Understanding the Determinants of Crime: Expanding Gary Becker's original model to account for macroeconomic, sociological, and criminological variables

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A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfilment of the Requirements for the Degree

Bachelor of Arts

By:

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May 2023

Understanding the Determinants of Crime: Expanding Gary Becker's original model to account for macroeconomic, sociological, and criminological variables

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May 2023

Mathematical Economics

Abstract

This research aims to expand economist Gary Becker's original model of criminal utility by accounting for macroeconomic, sociological, and criminological variables. Additionally, this study hopes to also explore how Becker's utility function changes when looking at different categories of crime. This study analyzes these research questions by examining reports of crime in New York City from 2022 to 2023 and constructing a probit model to understand which variables are statistically significant for different types of crime. The existing literature posits that Becker's model can be further developed by studying social theory and criminology. This research corroborates current literature in the fields of economics, sociology, and criminology by determining that macroeconomic, sociodemographic, and criminological variables significantly impact the category of crime that occurs. It also finds significant differences between how these variables impact lower-level crimes compared to felonies.

KEYWORDS: (crime, inflation, unemployment, race, gender, age, income, utility)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

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Signature

Table of Contents

Acknowledgments

I would like to thank my incredible advisor Esther Redmount for all her support and advice. I would also like to thank the tireless support of my parents who always encourage me to achieve my goals. I also could not have completed this paper without the support and encouragement of my three furry editors Caesar, Nugget, and Reddy.

1. Introduction

Economics traditionally concerns the allocation of scarce resources, yet the discipline has evolved to apply principles of rationality outside the world of money and property. One of the primary economists who helped bridge economic thought with other disciplines, such as crime, was Gary Becker. Becker was the first economist to apply principles of rationality to the question: why does crime occur? His findings outline how an individual's decision to participate in criminal activity is governed by the same cost benefit analysis someone may use to decide what groceries to buy, or whether to walk or take the bus.

To quantify why crime occurs, Becker developed multiple models exploring both the role of the individual and the government. His primary model for understanding why individuals commit crimes relates back to a traditional utility model (equation 1 below). Becker contends "that a person commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities" (Becker & Landers, 1974). In his model of criminal utility, Becker outlines 3 key variables that determine whether a potential criminal will commit a crime: probability of being caught (p_j), penalty for potential crime (f_j), and income (Y_j). Becker defines income as both the monetary and psychological benefit a perpetrator receives from committing a crime. He then uses these factors to build a utility curve, outlining how a potential criminal would behave based on the three variables listed above.

$$EU_j = p_jU_j(Y_j - f_j) + (1-p_j)U_jY_j$$

Becker's work presents an excellent micro-economic approach to determining crime, but his model neglects two important considerations. First, that other factors, such as macroeconomic and sociological conditions, affect the likelihood of crime and second that this model may vary depending on the kind of crime a perpetrator intends to commit.

Becker's work has been expanded upon by other economists who have begun to incorporate macroeconomic factors that could impact the level of crime. This research has expanded Becker's model to include variables such as inflation and unemployment. For example, when analyzing property crime in the city of Los Angeles, economists concluded that economic factors that increase crime tend to be high inflation as well as high unemployment (Bechdolt 1975). Furthermore, other macroeconomists have analyzed how inflation affects property crime and found "a robust statistical link between inflation and … property crime rates" (Nunley et al., 2016). While this research helps expand Becker's original model, the scope of the research is limited to property crime and neglects to consider if these factors could affect other types of offenses.

While Becker's model has been adapted to include macroeconomic factors like inflation and unemployment, it also fails to include other variables such as victim characteristics that may affect a perpetrator's utility function. Sociological research supports the notion that specific trends that occur in crime can be explained by social theory. Social theory helps us to create a more in-depth model of crime by illustrating how some benefits or costs to crime are diminished or increased based on the social conditions of the time. Take for example, jaywalking. Jaywalking is technically a criminal offense, yet it is rarely enforced. This cultural knowledge then informs an individual's cost benefit analysis of whether to commit this offense.

Based on sociological research, we can model how specific victim demographics may alter the cost benefit approach originally proposed by Becker in the same way macroeconomists have amended his model in the past. Throughout my paper, I use sociological and economic research to help illustrate how specific factors may impact variables in Becker's original model depending on the type of crime.

In addition to sociological factors, I also incorporate framework created by criminologists. Criminologists tend to utilize a model of variance when looking at why crimes occur. A popular model to explain crime posits that crime occurs when "likely offenders, suitable targets, and the absence of capable guardians against crime" coalesce (Cohen & Felson, 1979). While this structure tends to consider a portion of crime being described by chance, it indicates that other significant variables, such as time or geography, factor into why crime occurs. I contend that the time and space when crimes occur are not just simply correlated, but rather reflect an individual maximizing their criminal utility curve by selecting time periods that decrease the likelihood of them being caught.

My research aims to explore a gap in economic, criminological, and sociological, modelling by investigating how different determinants of crime vary based on the type of offense. I hope to answer the research question, what macroeconomic and sociodemographic variables are significant predictors of the type of crime an individual will experience? To gain answers, I construct a model using the 2022-2023 criminal reports from the New York City Police Department (NYPD), in conjunction with macroeconomic statistics from the Department of Labour and the U.S. Census (census). New York City is ranked 11th in terms of crime rates in the United States and also has a large, diverse population (*Where Does New York Place in the U.S. News Best States Rankings?*, n.d.). Both of these facts, contribute to why I chose to use data from New York City for my research. My model combines both traditional analysis tools such as inflation and unemployment rates, while also accounting for sociological factors and factors from criminology that influence Becker's original utility curve. Past economic studies have neglected to account for the variation in independent variables across different types of crime. My model intends to highlight how specific independent variables may increase or decrease the likelihood of a specific crime occurring to highlight how different types of crime change a criminal's utility function.

2. Literature Review

To better understand which sociodemographic and macroeconomic factors impact a criminal's desire to commit a crime, I surveyed pre-existing literature from economics, sociology, and criminology. This review revealed that there are several key factors that increase an individual's likelihood of committing a crime and that these factors vary depending on the type of crime. This review outlines the following factors: gender, age, past incarceration and participation in criminal activity, inflation and unemployment, race, income and poverty, and time and geography. I then explain how these variables fit into a criminal's understanding of the cost benefit analysis proposed by Becker.

2.1 Gender

The literature around gender's effect on crime varies depending on the type of crime. The pre-existing literature distinguishes different motivations between higher level crimes, and lower-level crimes, depending on the victim's gender.

In recent years, both the disciplines of sociology and psychology have studied the motivations behind street harassment, a type of violation offense. Sociological and statistical research indicate that street harassment is an offense that mainly affects women (Kearl, 2018). Psychologists have posited that crimes such as street harassment stem from the harasser's desire to experience a feeling of social dominance (Walton & Pedersen, 2018). Sociological and psychological research portrays how there is an added psychological benefit to street harassment for perpetrators when the victim is a woman.

Additionally, lower levels of crime such as misdemeanours tend to effect men and women at disproportionate rates. One example of this disparity is domestic abuse, with women experiencing domestic abuse at higher rates than men (Walby 2004). Some economic studies suggest that domestic violence may be perpetuated towards women for their participation in the work force. Researchers in India found that large public work programs that encouraged women to participate led to "male backlash", which resulted in higher levels of domestic abuse in the house (Kjelsurd & Sjurgard, 2023). This study indicates that there is also a psychological motivation behind these types of crimes, as shown by the male backlash these women experienced.

Higher levels of crime such as felonies begin to complicate this dynamic, as many felonies don't have a clear gender effect. Men in general are killed at a higher rate than women when looking at homicide (Korhonen 2024). Yet the overall level of violent crimes affects more women than men (Smith & Kuchta, 1993). Some sociologists have theorized that social constructs such as the patriarchy can be reinforced by spaces where there are more men than women, which causes the rate of femicide to increase (Drèze & Khera, 2000). Yet this study cannot highlight a clear psychological benefit the perpetrator experiences based on committing femicide, indicating that homicides tend to have a more complicated psychological cost benefit analysis, compared to lower-level crimes.

Both kinds of lower-level crimes such as violations and misdemeanours tend to show a clear psychological benefit to the perpetrators in terms gaining a feeling of power or satisfaction from the crime. However, the same body of evidence is not present for higher level crimes such as felonies.

2.2 Age

Becker's model identifies multiple variables which increase a perpetrator's desire to commit a crime. Two of those variables are the benefit a perpetrator receives, which is calculated both on the monetary and the psychological benefit they receive after committing the crime, and the likelihood they are caught. Unlike gender which grants psychological gratification to the perpetrator, the age of the victim tends to affect the likelihood of the perpetrator being caught. Literature surrounding the age of crime victims shows that different ages correlate to different types of crime.

The literature suggests that older individuals are the victims of lower levels crimes due to our cultural perception of them. In general, older people are believed to be easier to scam and more likely to be naïve (Blakeborough, 2008). While old age itself may not indicate that a person is actually less cognizant of their surroundings, this cultural belief portrays why many criminals may target older people for lesser crimes such as fraud (Mawby & Jones, 2006). These studies convey that older people are targeted for lower-level crimes because criminals believe they have less of a chance of being caught since they perceive older individuals as less aware.

The literature also shows that as the type of crime changes a new demographic emerges as victims: young men. One study in Brazil found that young men tended to be more likely to be homicide victims when they exceeded the age of majority (over the age of 18) but were under 25 years of age. This study also drew conclusions about how the victims of violent crimes were involved with criminal activity, which will be addressed later in this review when discussing participation in crime (Castro & Tirso, 2023). Another study from Britian also found that men ages 20-24 were more likely to be the victims of murder (Shaw et al., 2005). This trend may be explained by understanding that young men are more likely to be involved in criminal activity (Fitzgerald 2003). This cross over could limit young men's desire to report crimes, given that they are already involved in criminal activity themselves. This would decrease the perpetrators probability of being caught since they know their victim is less likely to go to the police.

2.3 Past Incarceration and Participation in Crime

Perhaps one of the most shocking factors linked to becoming a victim of crime is a history of incarceration. This factor is primarily related to the probability of being caught. The body of literature suggests past incarceration and active participation in crime expose individuals to being the victims of crime.

Psychological research indicates that individuals who are active in crime are less likely to report crimes committed against them to the police (Kidd & Chayet, 1984). This opens the door for them to become the victims of crimes. The Brazilian study which analysed the murder rates of young men, also concluded that men who participated in criminal activity put themselves at a higher risk of being the victim of homicide (Tunca 2019).

Additional research shows that this reluctance to report offenses is still present in former criminals (Bowleg et al., 2020). Sociological research has also shown that this population is also at a higher risk of being the victim of crime in general (Aaltonen, 2017).

General trends tend to show that past and present association with crime puts an individual at an increased risk at becoming the victim of crime in general. Psychological surveys highlight that these groups present a decreased level of risk for potential perpetrators as the victims are less likely to report the crime to the police.

2.4 Macroeconomic Factors

One of the key factors Becker's model focuses on is how perpetrators are often driven to commit crimes by a weighing the monetary benefit against the perceived cost of a crime. This line of reasoning demonstrates that when economic conditions worsen, more people would resort to property crime, as the benefits of crime sharply increase. A plethora of economic research indicates that this is exactly what occurs when both inflation and unemployment rise.

Research shows that there is a positive relationship between unemployment and the rate of crime (Tunca 2019). Economists have conducted further studies to illustrate that unemployment is correlated with a loss of income which perpetrators then try to supplement by resorting to criminal activity. These researchers found that after an individual is laid off "crime is lower during active benefits than during passive benefits and spikes at the end of benefit eligibility" (Bennett 2020). This illustrates that crime occurs due to the loss of monetary resources associated with employment, as crime spikes when those benefits are eliminated.

This is also true with a rise in inflation. One study looked at both unemployment and the rise of inflation in conjunction with property crimes and found that both caused the rate of property crimes to rise (Ralston 1999). Additionally, more studies analysed the impact of inflation on crime and found a positive relationship to inflation and crime in general (Hazra 2018).

Most of the research conducted around unemployment and inflation tend to look at nonviolent crimes such as property crimes or robberies, yet there has been no analysis of if these factors also correlate with more severe types of crimes like felonies. Given that most felonies do not have the same clear monetary benefits to perpetrators as lower-level property crimes, it's important to investigate if these factors do effect felonies, as this would complicate Becker's original theory.

2.5 Race

Race tends to effect two different parts of Becker's original model depending on the severity of specific offenses. Race much like gender is a factor that affects a perpetrator's psychological income in lower-level crimes, but higher-level offenses tend to signify that certain races are targeted due to probability of being caught.

Signs that race provides a psychological benefit to attackers is most apparent when looking at lower-level offenses. When looking at violation's crimes such as harassment it's important to remember that the crime contains a psychological benefit to perpetrators (Walton & Pedersen, 2018). Sociologists have expanded upon this theory to conclude that "street harassment for African Americans is not only sexualized but also racialized" (Krol 2019). This is also true for Hispanic Americans (Rodriguez 2017). This research means that the same psychological benefits that apply to harassment for women are also true for harassment committed against Black and Hispanic victims.

Violent crimes such as felonies tend to occur to some racial demographics more than others. One study looked at both Black and White Americans and analysed the different rates between offenders and victims. The researchers found that Black Americans tend to be at a much higher risk of becoming the victim of homicide, sexual assault, and aggravated assault (Pallone & Hennessy, 2008). Further research also highlights that specific subsections of Black Americans are at a higher risk of being the victim of violent crimes in general (Harrell 2007). Research found that individuals who were Black men, Black and unmarried, as well as Black and living in urban areas were more likely to be the victims of violent crimes (Harrell 2007). This background is coupled with sociological studies that indicate that Black men are often perceived as disposable within our current culture (Smiley 2016). This mentality portrays that perpetrators are more likely to target Black men because they worry less about a fear of being caught.

Research also shows that recognizing specific racial difference is vital to understanding why perpetrators target specific racial groups. One piece of research studied the effect of lumping Asian Americans with other minority groups when analysing crime. The study did this to help understand which minority demographics are more likely to be targeted for crimes. The research found that by grouping Asian Americans and with other minority groups such as Native Americans or Hispanics, researchers diluted the effects of crime towards the group. This signals that there are different risk rates associated with being Asian, Native American, or Hispanic (Roberts 2023). This research illustrates that crimes are not just committed against minority groups because they are minorities but rather that our cultural understanding of race, varies from group to group.

A survey of the literature shows that specific races such as Black Americans and Hispanic Americans tend to be more likely to be the victims of harassment-based crimes due to the psychological benefit it grants perpetrators. Race also seems to play a role in higher level crimes such as felonies but for different reasons. Higher level offenses tend to occur due to worry about being caught as opposed to the perpetrator gaining psychological gratification from the crime.

2.6 Income and Poverty

When considering income, one might assume that this factor only affects the Y_j variable in Becker's model, but economic research reveals that income and poverty are also associated with a criminal's concern for being caught.

One of the first studies that directly looked at how income level impacted the rate of crime came from noted economist Steven Levitt. The study found that in the mid-1970s lower income areas were less likely to experience burglary compared to higher income areas (Levitt, 2007). These findings align with Becker's original model, as perpetrators choose higher income neighbourhoods to rob to increase their Y_j value.

Levitt's study also looked at higher level crimes such as murder and his findings reflect that how increasing Y_j is not always a factor in why individuals commit certain crimes. Levitt also found that other crimes had a different relationship with income, observing that media income of household was inversely correlated with murder in Chicago. Levitt's work demonstrates that the level of income perpetrator receive is only part of the equation when looking at different levels of crime, and that perpetrators choose lower income areas when committing higher level crimes to avoid detection.

Most economic studies tend to expand beyond income when considering crime. One study found that both levels of poverty and income inequality tend to increase the level of crime in a nation (Sugiharti et al., 2023). This study also concluded that crime in these countries rose in higher income areas as opposed to lower income locations because of the income inequality. Another study which observed burglary in South

Africa, found similar results. This indicates that rich precincts tend to be the targets of burglary when income inequality rises, but when the income level of those precincts falls, less burglaries occur (Thorton 2023). All of these studies support Becker's model and express that criminals choose their targets in order to maximum the income they receive.

Another way in which income inequality can be measured when analysing crime is through looking at the interactions between welfare and crime. Research finds that eliminating welfare spending in impoverished areas tends to increase the rate of crime, specifically property crime (Melander & Miotto, 2023). This reasoning holds with Becker's original model which demonstrates that individuals will resort to crime if there are higher benefits to perceived costs. In this case the lack of resources due to the elimination of certain welfare stipends increases the value of the benefits an individual would receive from committing a crime.

A survey of data around income and poverty reveals that perpetrators choose locations to maximize the profit they receive from committing a crime or to avoid detection depending on the level of crime.

2.7 Time and Geography

Referring to Becker's model, I review past criminology data around time and geography to emphasize how these variables impact the likelihood of a perpetrator being caught.

Both time of day and time of year appear to be vital determinants of the probability of criminal being caught. A study from the Netherlands found that robberies increase during the winter due to criminals utilizing the increased periods of darkness to avoid detection (Van Koppen & Jansen, 1999). This aligns with economic reasoning and demonstrates how time of year can decrease the probability of being caught, thus could increase crime.

Current criminological research also indicates that geographical locations are chosen by criminals to maximize their success at completing crimes and that they are not random areas. Geographical research has shown that while there are no “hot spots” for crime in general, specific types of crime due tend to be concentrated together (Sherman et al., 1989). This shows that the geographical location of crime is also not just due to chance, but rather reflects a calculation made by criminals to decrease the likelihood of them being caught.

Past research on time and geography emphasizes how these variables are correlated with a criminal’s risk of being caught, which will affect the p_j variable of Becker’s model.

3. Theory and Methodology

Becker’s original model (depicted below) considers three primary factors to determine the utility function for if an individual commits a crime. He outlines that the utility function is dependent on p_j, his probability of conviction per offense, f_j his punishment per offense, and Y_i the income he receives for committing the offense. He the defines income as the “monetary value plus psychic value” an individual receives for committing a crime (Becker 1968).

$$EU_j = p_j U_j(Y_j - f_j) + (1-p_j)U_j Y_j$$

I assert that the function for EU_j contains further hidden variables that affect the output and make up p_j as well as Y_j. The factors from sociology and criminology I account for in my data, help to explain either a criminal’s perception of the likelihood they will get caught, or the monetary/psychic benefit they gain from a crime. This leads to my first hypothesis: Conditions explored in macroeconomics, sociology, and criminology will impact the likelihood a crime is committed. Furthermore, I assert that these hidden variables have different values depending on the type of crime an individual is committing. This leads to my second hypothesis: violations, misdemeanours, and felonies will each have different coefficients for each variable. These variables can shift the utility function based on the different type of crime. Below I outline my hypothesis which depicts how the three different types of crime observed in my data are affected by the independent variables I select to use in my model.

3.1. Proposed Changes to Becker's Model: Violations

Violations

$$EU_j = p_j U_j(Y_j - f_j) + (1-p_j)U_j Y_j$$

$p_j = g(\textit{Time of Month, Hour of Day, Age})$

$Y_j = k($*Gender Female, Face Black, Race Black Hispanic, Race White Hispanic, Race Asian, Race White, Unemployment Rate, Inflation Rate, Median Income of Neighborhood)*

The New York City Penal code defines a violation as "an offense, other than a 'traffic infraction', for which a sentence to a term of imprisonment in excess of fifteen days cannot be imposed" (New York Penal Law § 10.00 [3]). Additionally, a quick survey of the violations category in the dataset shows that the majority of violations are made up of one offense, harassment in the second degree. Out of the 58,413 data points only 282 offenses were not defined as harassment in the second degree.

In the model above I break down Becker's three variables and expand on them to account for the influence of other factors that affect income (monetary and psychic gain) and the probability of being caught. The majority of the factors that affect income were added to that portion of the equation due to their effect on psychological gratification, which Becker includes in his original Y_j definition. I summarize the hypothesized effects of each variable on the level of violation offenses in the table below.

Table 1: Predicted Signs for Violation Model

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	+
Unemployment Rate	Month by month data generated by the U.S. Department of Labor	+
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	+
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-
Race: American Indian	Binary Variable, 1= Indigenous victim	**NA**
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

As stated in the literature review, the gender of a victim being a woman is highly correlated with crimes of harassment (Kearl 2018). Additionally, the literature suggests that gender is an important factor in harassment crimes because it satisfies a psychological urge within the perpetrator, so I classify this variable as being part of Becker's income. I expect the gender of a victim being female to have a positive correlation with violation offense based on previous research. I also expect to see that if an individual is Black there will be a positive correlation with violations. Based on the literature, I also expect to see that inflation and unemployment increase violations, as they would make the income effect more desirable (Melander & Miotto, 2023). I also predict that violations will increase in as neighbourhood income rises. This is consistent with previous economic research (Levitt 1999).

The other aspect I hypothesize will be impacted by my independent variables is a perpetrator's perception of being caught. As seen in the literature, certain aspects such as the age of victim or time a crime occurred tend to factor into if perpetrators believe they will be caught. For violations, I expect that an increase in victims' age will increase the level of violations based on our cultural perceptions of age (Blakeborough, 2008). I also expect that time of day and time of the year will be positively correlated with an increase in violations, as criminals attempt to maximize their utility curve by minimizing the chance they will be caught (Van Koppen & Jansen, 1999).

3.2. Proposed Changes to Becker's Model: Misdemeanours

Misdemeanors

$$EU_j = p_j U_j(Y_j - f_j) + (1-p_j) U_j Y_j$$

$$p_j = g(\text{time of month, hour of day, median income of neighborhood, age})$$

U_j = *r(unemployment rate, inflation rate)*

Y_j = *k(gender female, race Black, race Black Hispanic, race White Hispanic, race Asian, race White, age)*

Misdemeanors are considered more serious than violations but don't rise to the level of severity of felonies. The dataset categorizes specific crimes such as criminal mischief, criminal trespassing, petty larceny, and assault as misdemeanors. Taking these definitions into account, I expect the explanatory variables to behave the same way as they did in the violations model. While there is more diversity within the misdemeanor category, many of the same behavioral principles such as psychological gratification or probability of being caught mirror what occurs in violations. Below I include a table which predicts the type of impact these independent variables will have on the likelihood of misdemeanors.

Table 2: Predicted Signs for Misdemeanor Model

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	+
Unemployment Rate	Month by month data generated by the U.S. Department of Labor	+
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	+
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-

Race: American Indian	Binary Variable, 1= Indigenous victim	**NA**
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

3.3. Proposed Changes to Becker's Model: Felonies

Felonies

$$EU_j = p_j U_j(Y_j - f_j) + (1-p_j)U_j Y_j$$

p_j = *g(time of month, hour of day, median income of neighborhood, age, gender female, race Black, race Black Hispanic, race White Hispanic, race Asian, race White)*

Y_j = *k(unemployment rate, inflation rate)*

Felonies are the highest level of crime an individual can be charged with and includes offenses such as murder, kidnapping, possession of stolen property, or sex crimes. It's important to note that within the New York legal system and throughout America, many crimes escalate from a misdemeanor to a felony due to the amount of money or the level of violence involved in the crime. I summarize my predicted values for how the independent variables affect felonies in the table below.

Table 3: Predicted Signs for Felony Model

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	-

Unemployment Rate	Month by month data generated by the U.S. Department of Labor	**NA**
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	**NA**
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-
Race: American Indian	Binary Variable, 1= Indigenous victim	**NA**
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

Based on the literature related to felonies, I move some variables from the income category to the probability of being caught category. Additionally, I hypothesize that some variables will no longer have a positive coefficient. The first significant change I make is moving gender, median income, and all race categories to the probability of being caught portion of the model. While this movement will not change how the utility curve is moved by these variables, it is important to note that for felonies a criminal's motivation changes from experience of a psychological income effect to concern about the probability they are caught. Additionally, I believe the sign of these variables will change. The literature indicates that men are more likely to be the victims of murder which makes up a large portion of the felony offenses (Korhonen 2024). It also shows that as median income decreases perpetrators commit more high-level crimes (Levitt 1999). I also hypothesize that age will be inversely correlated with felonies, showing that as age decreases the likelihood of a felony increases. Ample research shows that young people are more likely to be the victims of felonies such as murder, so I contend that the sign will shift to be negative when looking at felonies.

When constructing my model for felonies, I reclassify my race-based variables under a perpetrator's probability of being caught. Sociological research shows violent crimes typically affect Black and Hispanic individuals at higher rates than other races, so I hypothesize there will be a positive correlation between race being Black and Hispanic and felonies (Harrell 2007). I also believe that as time of day and year increases felonies will increase, as later months and hours are associated with more felonies, since this decreases a criminal's chance of being caught (Van Koppen & Jansen, 1999).

In terms of variables that affect the income level of the individual, I contend that both inflation and unemployment will not have an effect on felonies as there is not significant research to indicate that these variables motivate criminals outside a monetary context.

3.4. Probit Model Background

To evaluate which of my independent variables affect the different models of crime, under Becker's model, I created a probit model to identify the signs and significance of my variables in relation to each type of crime. Given that the list of offenses I selected for my dependent variable increase in intensity, I organize my model as follows:

$y_i = 1$, represents the probability of a violation occurring

y_i =2, represents the probability of a misdemeanour occurring

y_i =3 represents the probability of a felony occurring

$$y_i = 1,2,3$$

Pr(y_i = 1) = β1 (*Gender_Female*) + β2 (*Race_Black*) + β3 (*Race_Black_Hispanic*) + β4 (*Race_White_Hispanic*) -β5 (Race_White) - β6 (*Race_Asian*) + β7 (*Age*) + β8 (*Time_Month*) + β9 (*Time_Hour*) - β10(*Median_Income*) + β11(*Unemployment_Rate*) + β12(*Inflation_Rate*)

Pr(y_i = 2) = β1 (*Gender_Female*) + β2 (*Race_Black*) + β3 (*Race_Black_Hispanic*) + β4 (*Race_White_Hispanic*) - β5 (Race_White) - β6 (*Race_Asian*) + β7 (*Age*) + β8 (*Time_Month*) + β9 (*Time_Hour*) -β10(*Median_Income*) + β11(*Unemployment_Rate*) + β12(*Inflation_Rate*)

Pr(y_i = 3) = β1 (*Gender_Female*) + β2 (*Race_Black*) + β3 (*Race_Black_Hispanic*) + β4 (*Race_White_Hispanic*) - β5 (Race_White) +-β6 (*Race_Asian*) + β7 (*Age*) + β8 (*Time_Month*) + β9 (*Time_Hour*) + β10(*Median_Income*) + β11(*Unemployment_Rate*) + β12(*Inflation_Rate*)

After surveying the literature, I hypothesized that all the listed variables will be significant in the model. I specifically break down the rationale for each variable above. The probit model will help to identify how variables effect the probability of each type of crime occurring as opposed to just surveying the relationship between the variables and crime.

4. Results and Analysis

4.1 Data Background and Cleaning

To examine the effects of macroeconomic and sociological factors on different types of crime, I utilize data collected from the New York Police Department of reported crimes that occurred from 2022-2023. Each data point in the dataset represents a criminal complaint filed in the city of New York during the 2022-2023 year. The data includes information about the type and location of the crime, the time of enforcement, and demographic information about both the suspect and victim.

In addition to the original data gathered from the NYPD, I supplemented it with macro-economic data from the U.S. Bureau of Labor Statistics, as well as from the American Community Survey conducted by the U.S. Census. The U.S. Bureau of Labor generated both the unemployment rate and the inflation rate per month for New York City. These variables were added to the data set by the month they occurred. The original data set also included the borough in which the crime was committed. Using this information, I included median incomes generated for each New York Borough and combined them with the original data set. Previous studies in both economic and sociological research used reports of crimes as a source for their studies which lead me to use the data from the NYPD.

The total sample size for the data was 415,000 observations, but significant data were missing surrounding demographic information of victims such as age, race, or gender. To prepare the data for analysis I eliminated all observations with null inputs in any of the variables I used in my model. To make the data more digestible for Stata to process, I eliminated variables that would not be useful in my model such as response time for individual crimes or jurisdiction number.

From the NYPD data set I isolated a set of possible independent variables: complaint date, complaint time, victim's age, victim's race, and victim's gender. The data also included multiple measures to explain the type of crime that occurred. These ranged from the specific legal offense to the overall category of crime. The specific legal offenses were based on the New York penal code. For example, a crime would be listed as "harassment 2" indicating that the reported offense violates section 240.26 of the penal code. This type of classification of crime was incredibly detailed and did not provide a concrete way to measure the intensity of different offenses. A second variable within the dataset classified crimes into one of three categories: violations, misdemeanours, and felonies. Both misdemeanours and felonies match the legal definition of what constitutes those crimes in the state of New York. Violations are non-criminal offenses, but can still be punishable by arrest, fines, or jail time. For example, harassment falls into this category. This variable provided a simpler and distinct classification of crime, so it I opted to utilize it instead of the penal code definition.

4.2 Data Checks

Prior to testing my model using regression, I reviewed the independent and dependent variables to understand each variable and to ensure that the data were clean and accurate. For example, when reviewing each dummy variable in my dataset, the only values present were 0 and 1. This check indicated that I encoded my dummy variables correctly. Also, the averages of my dummy variables did not show that one group was significantly smaller than the rest, with the exception of the dummy variable created for indigenous victims. This variable had a mean of .006 indicating that very few of these incidents occurred, relative to other races.

This is not a reflection on the rate of crime against indigenous people in New York City but reflects the small population of indigenous people in New York City. The indigenous population is very low and therefore there are few incidents of crime compared to other races. Below is a table outlining the summary statistics of the variables that I evaluated and included in my model.

Table 4: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Median Income	75,000	17,000	46,000	96,000
Unemployment Rate	5.4	.23	4.5	7.8
Inflation Rate	4.1	1.2	2.5	6.7
Month	5.2	2.6	1	12
Hour	13	6.6	0	23
Age	40	14	17	65
Gender: Female	.53	.50	0	1
Race: White	.20	.40	0	1
Race: Black	.35	.48	0	1
Race: Asian	.11	.32	0	1
Race: Indigenous	.0063	.080	0	1
Race: Black Hispanic	.064	.25	0	1
Race: White Hispanic	.26	.44	0	1

I found no outliers in my data around median income, unemployment, or inflation. An additional step I took to make sure I evaluated my data for bias, came from comparing the number observations for different types of crime. My total data contained 278,694 observations broke down into three categories: violations, misdemeanours, and felonies. My data contained 58,617 offenses classified as violations, 124,207 offenses classified as misdemeanours, and 95,870 classified as felonies. While the number of violations is lower compared to misdemeanours, the relative amount of each type of crime was not great enough to bias the data.

After a general survey of the data, I created correlation tables to analyse if multicollinearity was present. Any value greater than or equal to 0.5 indicates that the variable is affected by multicollinearity. I expected to see elevated numbers within my race dummy variables as I completed this test with all variables included. This can bump up the correlation due to repeated correlations which include redundant information. As shown below, even with the inclusion of all the dummy variables, none of the independent variables rise to a level greater than 0.5. This indicates that the regression will not suffer from multicollinearity. There are some elevated values between the racial dummy variables which is to be expected when looking at all the variables together. While the correlation table does not show multicollinearity for any of the variables, I will remove the dummy variable for indigenous victims from my model to avoid redundancy in my model.

Table 5: Correlations Between Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1 Gender: Female	1.000												
2 Median Income	-0.047	1.000											
3 Month	-0.001	-0.003	1.000										
4 Unemployment Rate	0.004	-0.001	-0.061	1.000									
5 Inflation Rate	0.007	-0.000	.623	-0.158	1.000								
6 Hour	-0.008	-0.011	0.004	-0.004	-0.005	1.000							
7 Age	-0.075	0.016	0.012	0.005	0.001	-0.008	1.000						
8 White	-0.059	0.189	0.005	-0.004	0.004	0.004	0.100	1.000					
9 Indigenous	-0.036	0.006	0.003	0.002	0.000	-0.000	-0.000	-0.039	1.000				
10 Asian	-0.103	0.113	0.002	0.001	0.001	0.011	0.019	-0.174	-0.028	1.000			
11 Black	0.107	-0.080	0.006	0.000	0.006	-0.005	0.005	-0.367	-0.059	-0.261	1.000		
12 Black Hispanic	-0.006	-0.123	0.009	0.002	-0.011	0.002	-0.042	-0.131	-0.021	-0.093	-0.197	1.000	
13 White Hispanic	0.020	-0.095	0.004	0.002	-0.004	-0.007	-0.085	-0.298	-0.048	-0.212	-0.447	-0.160	1.00

4.3 ANOVA Check

To begin my analysis, I measured the variation of my independent variables with each other to understand if any strong correlations existed. I measured the correlations using an ANOVA table and organized the findings into the data tables below.

Table 6: ANOVA Table

Crime Type	Coefficient	Standard Error	Significance
Median Income	0	0	***
Month: base 1	0	.	
2	.13	.006	***
3	-.44	.01	***
4	-.403	.014	***
5	-.67	.016	***
6	.016	.02	
7	-.31	.016	***
8	-.19	.015	***
9	-.55	.014	***
10	-.26	.029	***
11	-.32	.023	***
12	-.35	.014	***
Unemployment Rate	-1.4	.009	***
Inflation Rate	-.19	.006	***
Hour of crime			
1	-.032	.01	***
2	-.005	.01	
3	-.013	.011	
4	.003	.011	
5	-.041	.012	***
6	-.12	.012	***
7	-.20	.01	***
8	-.21	.009	***
9	-.21	.009	***
10	-.2	.009	***
11	-.21	.009	***
12	-.14	.008	***
13	-.19	.009	***
14	-.2	.008	***
15	-.17	.008	***
16	-.17	.008	***
17	-.15	.008	***
18	-.15	.008	***
19	-.15	.008	***
20	-.14	.008	***
21	-.13	.009	***
22	-.104	.009	***

23	-.061	.009	***
Age of Victim	-.001	0	***
Victim Race White	.10	.017	***
Victim Race Asian	.12	.017	***
Victim Race Black	-.008	.017	
Victim Race Black Hispanic	.053	.017	***
Victim Race White Hispanic	.046	.017	***
Victim Gender Female	-.15	.003	***
Constant	10.557	.068	***

Based on both my findings from the ANOVA table and my past research on what components factor into crimes being committed, I theorize that the variables gender of victim, age of victim, race of victim, time of day when crime occurs, time of month when crime occurs, inflation rate, unemployment rate, income level per borough, will determine if a crime is a violation, misdemeanour, or a felony. My ANOVA table indicates that I can reject the null hypothesis for every variable except from one race variable and a few sections of hour and month. The race variable was the dummy variable indicating that the individual was indigenous. The table also demonstrates that the time from 2 am to 4 am was not significant. The only month that had a p value greater than 0 was June.

4.4 Probit Model Results and Marginal Effects

To understand the impact each independent variable has on different types of crime; I construct a probit model. This differs from traditional OLS, and instead uses a maximum likelihood functioned related to the normal distribution curve to generate the model. The results of the probit model are shown below.

Table 7: Probit Model Coefficients and Significance

Crime Type	Coefficient	P-Value	Significance
Median Income	0	0	***

Unemployment Rate	-.88	0	***
Time of Day	-.006	0	***
Time of Year	-.007	0	***
Inflation Rate	-.03	0	***
Age of Victim	-.001	0	***
Victim Race White	.11	0	***
Victim Race Asian	.166	0	***
Victim Race Black	-.064	.018	**
Victim Race Black Hispanic	.063	.025	**
Victim Race White Hispanic	.038	.162	
Victim Gender Female	-.258	0	***

The table indicates that all the variables in the model apart from race being white Hispanic are significant determinants of the level of crime that occurs. The table also shows that factors such as the victim's race being White, Asian, or Black Hispanic tends to be positively associated with the severity of crime increasing. On the other hand, the factors such as age, race being Black, unemployment rate, inflation rate, time of day, and time of year all would cause the level of criminal offense to decrease. Unlike OLS, the coefficient values from the original model do not give a one-to-one ratio to how each independent variable effect the level of crime, only that these variables are significant and have a positive or negative correlation with the overall escalation of crime from violation to felony. To find those values I calculated the marginal effects each independent variable had on different levels of crime and represented the results in the chart below.

Table 8: Marginal Effects Coefficients

Variable	Violation	Misdemeanou*r*	Felony
Median Income	3.4e-07	1.01e-07	-4.40e-07
Unemployment Rate	0.25	.074	-.32

Inflation Rate	.0084	.0025	-.011
Month	.0019	.00057	-.0025
Hour	.0017	.00051	-.0022
Age	.00032	.000094	-.00041
Gender: Female	.07	.022	-.094
Race: White	-.030	-.011	.041
Race: Black	.018	.0051	-.023
Race: Asian	-.044	-.018	.062
Race: Black Hispanic	-.017	-.0059	.023
Race: White Hispanic	-.011	-.0033	.014

The chart gives a more detailed breakdown of how certain variables affect whether specific types of crime occur. It also highlights how some variables even change signs when going from lower levels crimes to felonies, indicating that specific variables affect different types of crime in different ways. The chart shows that multiple variables increase the level of violations and misdemeanours but decrease the likelihood of a felony. The variables median income, unemployment rate, inflation rate, time of year, time of day, age, gender being female, and race being black all remain positive for violations and misdemeanours before becoming negative for felonies. Additionally, the inverse is true for the other variables race being Black Hispanic, White, and Asian all remain negative for violations and misdemeanours, but change signs for felonies. I address the implications of these results and how they relate to my theory in my discussion section.

5. Discussion

5.1 Aims and Findings

This study investigates how to expand Becker's original utility function in two ways. First, it looks to evaluate if other variables studied in sociology and criminology factor into Becker's original model, and second it explores the difference in Becker's model across different types of offenses. I examined three types of offenses in this study: violations, misdemeanours, and felonies. Violations are defined as "an offense, other than a 'traffic infraction', for which a sentence to a term of imprisonment in excess of fifteen days cannot be imposed" (New York Penal Law § 10.00 [3]). Whereas misdemeanors are defined as "a criminal offense that is punishable by no more than a one year 'definite' sentence which would be served in a local jail, not state prison" and a felony is defined as "an offense for which a sentence to a term of imprisonment in excess of one year may be imposed" (New York Penal Law § 10.00 [4], [5]). These definitions helped me to select a probit model to analyze my data. This study modernizes Becker's model, by incorporating sociology and criminology theories, two fields which have greatly contributed to economic theory in recent years. It also expands current economic studies of crime, by differentiating between lower-level crimes and felonies.

My first overarching hypothesis was that factors such as age, race, gender, time of year, time of day, inflation, unemployment, and median income of neighbourhood, would all impact what type of crime occurred. My second hypothesis was that different types of offense would have different coefficients for each model. I elaborated on this by predicting the different signs I expected to see in my final models, based on the literature I reviewed. The results from my probit model supported my first two hypotheses. The first model indicated that all of the independent variables I selected were significant in predicting which level of crime occurred. Furthermore, my marginal results demonstrated that different independent variables, had different effects on predicting the type of crime that occurred. As for my more detailed predictions, the majority of the signs I predicted were confirmed by my probit models with some notable exceptions, which I expand upon in further sections below. When evaluating my results, I did notice a significant pattern. The primary pattern found for every significant variable, was that the variable either caused violations and misdemeanours to increase and felonies to decrease, or that the variable caused felonies to increase, and violations and misdemeanours to decrease. This means that any variable that increases violations and misdemeanours will decrease felonies, as well as the other way around. I continue by discussing how these patterns relate to current literature in the field, to explain why certain variables behave this way.

5.2 Race, Age, and Gender

The majority of the results around race, gender, and age support pre-existing literature about the nature of perpetrators and how they target victims for particular crimes.

My results show that as age increases, older populations are more likely to be the victim of lower-level crimes such as violations or misdemeanours. This is consistent with research from both psychology and sociology that shows that older individuals are more likely to be targeted due to stereotypes that these individuals are less aware. Moreover, the results also show that as age decreases, an individual is more likely to be the victim of a felony. This is also consistent with previous literature that reveals that young people are more likely to be the victims of violent crimes such as murder.

The same is also true for gender. My model demonstrates that if a victim is woman, they are more likely than a man to be the victim of violations and misdemeanours. This doesn't indicate that being a woman means you cause more misdemeanours or violations to occur, but rather that being a woman puts you at an elevated risk for being the victim of these kinds of crimes. It's also important to note that, while there is a positive correlation between being a woman and lower-level crimes, the relationship changes when looking at felonies. This result is supported by literature about why perpetrators choose their victims. For lower-level offenses such as violations, a perpetrator increases his utility function by harassing a woman, based on the psychological gratification he gains, but as the severity of the crime increases so does the level of punishment. This explains why perpetrators are willing to risk getting caught for lower-level offenses, but when the crime rises to the level of felony the psychological benefit no longer outweighs the cost of committing the crime.

The results for race confirm some of the previous findings from other literature but dispute particular findings around the rate of violent crime against Black Americans. The results show that Black Americans are more likely to be the victims of violations and misdemeanours compared to other races. This also signals that all other races, besides Black individuals are more likely to be the victims of felonies. This finding partially clashes with current literature in the field. As stated in the literature review, Black Americans are more likely to be the victims of violent crimes such as murder or rape which are classified as felonies, yet that was not shown in my results. A possible explanation for this may be the classification of race created by the NYPD versus the standard used by America as a whole. In the previous research I review, there was a breakout between Black Americans and Hispanic Americans which was not present in my data. Most research classifies an individual as either Black or Hispanic and does not account for individuals who fit into both of these categories. This may explain why Black Hispanic individuals are more likely to be the victim of felonies and also why Black victims with Black Hispanics removed do not reflect the findings from the literature.

5.3 Median Income, Inflation Rate, and Unemployment Rate

Median income, inflation rate, and the unemployment rate all behaved in accordance with the pre-existing literature. The results reveal that lower-level crimes such as violations or misdemeanours tended to increase when the median income of a neighbourhood went down, which supports Levitt's research from 1999. The results also signal that as median income rises, the likelihood of felonies decreases. This also mirrors Levitt's findings, indicating that more violent offenses tend to occur in lower income areas. The inflation rate and unemployment rate results also support current economic research. Both results show that when inflation and unemployment rates rise lower-level crimes increase. This reflects the current economic theory that as economic conditions worsen more individuals resort to crime to raise their income level. This can mean both their psychological income and their monetary income as defined by Becker. The results also further demonstrate that felonies decrease when unemployment and inflation rates rise, portraying that these economic conditions are more impactful to lower-level offenses.

The findings for this portion of the independent variables further illustrate the relevance and theory behind Becker's original model. It demonstrates that when the cost of an offense is relatively low (such as in the case of a violation or misdemeanour) perpetrators are more swayed by economic downturn, but when a crime is particularly costly (such as a felony which could result in 20 years in prison) the economic downturn does not have the same effect.

5.4 Time of Year, and Time of Day

Both the results from time of year and time of day are also consistent with findings from previous literature in the field. The analysis shows that as it gets later in the year and later in the day violations and misdemeanours increase. This corroborates current literature from both economics and criminology. Both disciplines explain that potential criminals often execute their crimes later in the day and year as to avoid detection by using natural darkness which lowers the probability they will be caught. Given that felonies occur more often earlier in the year, this suggests that more serious crimes may not be reliant on perpetrators needing dark conditions to avoid detection. This is understandable for higher level crimes, since in many cases these offenses may be driven by a specific gain or motive that supersedes the minor benefit of avoiding detection though darkness.

5.5 Policy Implications

These results show a difference in the cost to criminals for lower-level offenses compared to higher level crimes such as felonies. A clear pattern emerges that women, Black individuals, and older individuals are more likely to be the victims of lower-level crimes. Based on Becker’s model this is due to the marginal benefit of these crimes outweighing the cost which is compiled by the probability of being caught and the penalty for these crimes imposed by the government. In order to decrease the rates of these lower-level crimes occurring, the New York City Police Department should consider re-allocating their resources. If more patrol officers were dispatched to lower-level neighbourhoods (which often correspond to neighbourhoods of colour), this would raise an offender's probability of being caught. By increasing this value, the marginal benefit perpetrators gain from committing these crimes be it psychological or monetary, would be outweighed by the probability of being caught.

Another improvement could come from the judicial system, as opposed to the police force. Another variable in Becker's model is f_j which represents the penalty for a crime. When it comes to lower-level crimes such as harassment, the penalty is relatively low compared to other types of crime. If law makers were to upgrade the penalty for harassment from a small fine or minimal time in jail, this could also decrease the frequency of this offense.

5.6 Limitations and Further Research

While this analysis does provide support that more sociological and criminology-based factors should be considered in an economic model of crime, there are ways to improve these findings. As stated in the literature review, one major factor that often contributes to certain individuals being the victim of crime is if they are actively participating in crime or were criminals in the past. This information could not be analysed for this research as there was no way to correlate which victims had a criminal past. Another limitation came from the analysis of time of year and time of day. In order to create an accurate probit model, there had to be a limited number of dummy variables. I prioritized qualitative variables such as race and gender over numeric variables such as hour of day, but this did mean my results for time of year and time of day have limited application. Further research could explore if specific seasons lead to an increase in felonies, as well as if certain periods such as the middle of the night vs. the afternoon are more prone to higher or lower-level offenses.

Additionally, the further breakdown of crimes into specific types of felony offenses could provide more insight as to why those crimes occurred. The purpose of this study was to verify that different types of offenses had a different relationship to specific independent variables, but this type of research could be expanded by looking at specific types of felonies. This might help determine if there are significant variables that change when looking at different kinds of offenses such as murder or rape. Moreover, given the often-complex nature of felonies it should warrant its own model with different crimes to understand exactly how each of the independent variables relate to the likelihood of different offenses occurring and if a behavioural model such as Becker's applies to every kind of felony.

5.7 Conclusion

The results from my analysis indicate that demographic information and criminological factors affect both the probability of being caught and income variables in Becker's model. The data also reveals that different independent variables affect crime at higher or lower rates depending on the type of offense. This aligns with current research by economists, sociologists, and criminologists. Furthermore, this grants more credibility to the evolution of economics incorporating more behavioural models based on sociological and psychological reasoning. Becker's model is improved by accounting for more variables which help to expand his original model. More detailed models also create opportunities to help the victims of crime by understanding why criminals commit specific offense so we can refine our allocation of police resources to protect more people. This research helps to expand Becker's model both in terms of the variables it considers and the crimes it applies to. The three-models developed for this study highlight that certain independent variables affect the likelihood of whether a crime is a violation, misdemeanour, or felony. It contributes to current economic theory by recognizing that these variables influence both the psychological and monetary benefit to perpetrators and the probability a perpetrator is caught. This research also establishes that these independent variables may change signs when they influence different categories of crime.

6. Appendix

6.1 Tables

Table 1: Predicted Signs for Violations

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	+
Unemployment Rate	Month by month data generated by the U.S. Department of Labor	+
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	+
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-
Race: American Indian	Binary Variable, 1= Indigenous victim	**NA**
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

Table 2: Predicted Signs for Misdemeanours

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	+
Unemployment Rate	Month by month data generated by the U.S. Department of Labor	+
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	+
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-
Race: American Indian	Binary Variable, 1= Indigenous victim	**NA**
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

Table 3: Predicted Signs for Felonies

Variable	Measure	Predicted Sign
Median Income	Median income generated by the American Community Survey.	-
Unemployment Rate	Month by month data generated by the U.S. Department of Labor	NA
Inflation Rate	Month by month inflation rate generated by the U.S. Department of Labor in 2022 dollars.	NA
Gender	Binary variable, 1=female victim	+
Age	Average of age range assigned to victim	+
Race: Black	Binary variable, 1=Black victim.	+
Race: White	Binary variable, 1=White victim	-
Race: Asian American or Pacific Islander	Binary Variable, 1=AAPI victim	-
Race: American Indian	Binary Variable, 1= Indigenous victim	NA
Race: Black Hispanic	Binary Variable = 1 Black Hispanic Victim	+
Race: White Hispanic	Binary Variable = 1 White Hispanic Victim	+
Month	Month when the crime occurred. 1 represents January while 12 represents December.	+
Hour	Hour when crime occurred, running from 0 to 23. 0 represents 12:00 AM, and 23 represents 11:00 PM.	+

Table 4: Summary Statistics of Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Median Income	75,000	17,000	46,000	96,000
Unemployment Rate	5.4	.23	4.5	7.8
Inflation Rate	4.1	1.2	2.5	6.7
Month	5.2	2.6	1	12
Hour	13	6.6	0	23
Age	40	14	17	65
Gender: Female	.53	.50	0	1
Race: White	.20	.40	0	1
Race: Black	.35	.48	0	1
Race: Asian	.11	.32	0	1
Race: Indigenous	.0063	.080	0	1
Race: Black Hispanic	.064	.25	0	1
Race: White Hispanic	.26	.44	0	1

Table 5: Correlation Table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1 Gender: Female	1.000												
2 Median Income	-0.047	1.000											
3 Month	-0.001	-0.003	1.000										
4 Unemployment Rate	0.004	-0.001	-0.061	1.000									
5 Inflation Rate	0.007	-0.000	.623	-0.158	1.000								
6 Hour	-0.008	-0.011	0.004	-0.004	-0.005	1.000							
7 Age	-0.075	0.016	0.012	0.005	0.001	-0.008	1.000						
8 White	-0.059	0.189	0.005	-0.004	0.004	0.004	0.100	1.000					
9 Indigenous	-0.036	0.006	0.003	0.002	0.000	-0.000	-0.000	-0.039	1.000				
10 Asian	-0.103	0.113	0.002	0.001	0.001	0.011	0.019	-0.174	-0.028	1.000			
11 Black	0.107	-0.080	0.006	0.000	0.006	-0.005	0.005	-0.367	-0.059	-0.261	1.000		
12 Black Hispanic	-0.006	-0.123	0.009	0.002	-0.011	0.002	-0.042	-0.131	-0.021	-0.093	-0.197	1.000	
13 White Hispanic	0.020	-0.095	0.004	0.002	-0.004	-0.007	-0.085	-0.298	-0.048	-0.212	-0.447	-0.160	1.00

Table 6: ANOVA Table

Crime Type	Coefficient	Standard	Significance

		Error	
Median Income	0	0	***
Month: base 1	0	.	
2	.13	.006	***
3	-.44	.01	***
4	-.403	.014	***
5	-.67	.016	***
6	.016	.02	
7	-.31	.016	***
8	-.19	.015	***
9	-.55	.014	***
10	-.26	.029	***
11	-.32	.023	***
12	-.35	.014	***
Unemployment Rate	-1.4	.009	***
Inflation Rate	-.19	.006	***
Hour of crime			
1	-.032	.01	***
2	-.005	.01	
3	-.013	.011	
4	.003	.011	
5	-.041	.012	***
6	-.12	.012	***
7	-.20	.01	***
8	-.21	.009	***
9	-.21	.009	***
10	-.2	.009	***
11	-.21	.009	***
12	-.14	.008	***
13	-.19	.009	***
14	-.2	.008	***
15	-.17	.008	***
16	-.17	.008	***
17	-.15	.008	***
18	-.15	.008	***
19	-.15	.008	***
20	-.14	.008	***
21	-.13	.009	***
22	-.104	.009	***
23	-.061	.009	***
Age of Victim	-.001	0	***
Victim Race White	.10	.017	***
Victim Race Asian	.12	.017	***
Victim Race Black	-.008	.017	
Victim Race Black Hispanic	.053	.017	***
Victim Race White Hispanic	.046	.017	***
Victim Gender Female	-.15	.003	***
Constant	10.557	.068	***

Table 7: Probit Model Coefficients and Significance

Crime Type	Coefficient	P-Value	Significance
Median Income	0	0	***
Unemployment Rate	-.88	0	***
Time of Day	-.006	0	***
Time of Year	-.007	0	***
Inflation Rate	-.03	0	***
Age of Victim	-.001	0	***
Victim Race White	.11	0	***
Victim Race Asian	.166	0	***
Victim Race Black	-.064	.018	**
Victim Race Black Hispanic	.063	.025	**
Victim Race White Hispanic	.038	.162	
Victim Gender Female	-.258	0	***

Table 8: Marginal Effects by Crime

Variable	Violation	Misdemeanour	Felony
Median Income	3.4e-07	1.01e-07	-4.40e-07
Unemployment Rate	0.25	.074	-.32
Inflation Rate	.0084	.0025	-.011
Month	.0019	.00057	-.0025
Hour	.0017	.00051	-.0022
Age	.00032	.000094	-.00041
Gender: Female	.07	.022	-.094
Race: White	-.030	-.011	.041
Race: Black	.018	.0051	-.023
Race: Asian	-.044	-.018	.062
Race: Black Hispanic	-.017	-.0059	.023
Race: White Hispanic	-.011	-.0033	.014

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