ESSAYS ON THE ECONOMICS OF CRIME AND POLICING

by

Ariana Matsa

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Department of Economics

Birmingham Business School

College of Social Sciences

University of Birmingham

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Abstract

In this thesis we contribute to the debate on how economic incentives affect crime. As shown by theoretical models, deteriorating labour market opportunities can shift an individual's incentives to engage in legitimate or illegitimate acts. In the *first* chapter, using a panel data analysis, we empirically test the relationship between U.S. business cycles and burglary rates. We find that increasing benefits is more effective at reducing countercyclical crime than providing unemployment support for an extended period. The *second* chapter utilises a novel measure of income inequality and two measures to capture the incentives of the unemployed and low-income earners in a dynamic panel-data model to evaluate their effect on different types of crime in England and Wales. The findings strongly support the pervasive relationship between economic indicators and property crime, both in short- and long-run. Finally, the *third* chapter builds a predictive solvability model by examining how the presence and absence of factors, during the preliminary phase of the investigation, determine case solvability of fraud and cybercrime. The predictive capabilities of the model are assessed on an external validation sample and the findings show a high degree of accuracy.

Introduction

Advanced economies experience secular economic expansions, overlaid by transitory movements in economic activity. Changes in technology or positive supply shocks cause wide-ranging developments in social indicators. Likewise, short-term economic expansions and recessions, or so-called business cycles, might also cause fluctuations in criminal activity. Economic theory suggests that individuals are more likely to engage in criminal activities when illegal payoffs are high or legal compensation is low. It is further believed that incentives to commit crime are more likely to change when the individual experiences movements in permanent income than transitory earnings.

The first two chapters use various econometric techniques to analyse the relationship between economic incentives and crime. In particular, we examine how changes in legal returns of *at-the-margin* individuals affect crime rates.

Chapter 1 evaluates the effect of U.S. business cycles on burglary rates using a dynamic panel data model. To capture the effect of business cycles we use two economic indicators: unemployment compensation and income benefit payments. The model is estimated using the system GMM estimator. To account for the possible endogeneity of economic indicators and criminal justice factors included in the model, internal lags are used as instruments while also employing external instruments. Further, we take advantage of temporary benefit extensions during the latest recession to study how changes in the duration of unemployment benefits affect crime.

The empirical findings systematically show that increases in income benefits can reduce countercyclical crimes, which are more likely to be financially motivated. On the other hand, we find that longer unemployment durations cause increases in burglary rates. Overall, the results show that disadvantaged groups who experience longer spans of economic deprivation, such as long-term unemployed and low-income earners, are more likely to be financially motivated to engage in criminal activities. Thus, the findings show that increases of assistance payments, during recessionary periods, can reduce countercyclical crimes.

Chapter 2 uses a panel-data system GMM methodology to examine the short- and long-run effects of economic indicators on different types of crime in England and Wales. A novel Gini coefficient is constructed using micro-level data from the *Annual Survey of Hours and Earnings (ASHE)* to examine the relationship between crimes and income inequality. This is the first study to include an income inequality measure estimated at the same level of disaggregation as the level at which crime statistics are available. The chapter also uses unemployment and income benefits which we argue also affect the individual's decision on whether to engage in a criminal act rather than just the state of unemployment alone.

The empirical analysis provides tentative evidence in support of increasing income benefits to lower property crime rates. Also, higher levels of income inequality lead to increases in property crime. These effects are observed both in the short- and long-run. In fact, we find that the magnitude of the effect is larger during the long-term. From a policy perspective, these findings are particularly important as they uncover a dynamic relationship between economic indicators and property crime rates. The results suggest that contemporaneous small increases in benefit payments can have a considerable long-term negative effect on property crime. On the other hand, violent crimes do not seem to be affected by changes in economic indicators but violent offenders respond to changes in law enforcement variables.

The development of information technologies has stimulated an unprecedented growth of criminal opportunities. That is, it generated new ways to commit traditional crimes while creating entirely new types of crime. In light of the dramatic rises in fraud and cybercrime offences, while acknowledging the implicit resource constraint faced by police forces, *Chapter 3* develops a predictive solvability model that increases investigatory efficiency, by identifying preliminary investigative factors which forecast case clearance. The analysis utilises a rich, individual case-level dataset for fraud, administered by Warwickshire and West Mercia Police, to build the model. This is the first study to empirically identify solvability and case-limiting indicators for fraud and creating a forecasting model.

The findings indicate high predictive capabilities and ensure no wastage of scarce police resources. The accuracy of the model is also externally validated using a separate random sample. Despite analytical models being more rigorous and objective than human decision-makers, only rarely do police forces use statistical models to optimally decide investigative resource allocation. Nevertheless, developing this type of predictive model allows police forces to identify cases which have a slim probability of solvability and thus, need to be filed. In turn, this allows for effective allocation of limited resources to cases which have a higher chance of case clearance, as determined by the information obtained from the stages of initial investigation.

Chapter 1

Burglary Rates and The Business Cycle: A Panel Data Analysis

Abstract

The study examines the effect of business cycles on burglary rates by employing a dynamic panel data model which provides a multivariate explanation of burglary movements. The empirical analysis uses two economic indicators to approximate changes in business cycles, between 1983 and 2009. These are unemployment compensation and income benefit payments. Both variables better capture the financial motives of *at-the-margin* individuals. A system GMM is employed allowing for control of unobserved time and state fixed effects while also accounting for endogeneity issues. We also take advantage of temporary benefit extensions during the Great Recession and we re-estimate the model by restricting the sample between the latest business cycle, 2001-2009, and compare the results against previous business cycles. The empirical findings indicate that income benefits are negatively linked to burglaries whereas longer unemployment durations cause increases in burglary rates.

Keywords: business cycles; economic incentives; unemployment; income benefits; crime; system GMM

Glossary G.1

The following list of abbreviations, used in Chapter 1, is expanded below.

AB	Arellano-Bond serial autocorrelation test
DIFF GMM	Difference GMM estimator
GMM	Generalised Method of Moments estimator
OLS	Ordinary Least Squares estimator
SYS GMM	System GMM estimator
UI	Unemployment Insurance

1.1 Introduction

Business cycles are inherently linked to economic opportunities and thus, indirectly induce changes to individual behaviour. As Cook and Zarkin (1985) point out, various social indicators are pervasively affected by movements in economic activity, ranging from school enrolments to legal labour force participation. Unsurprisingly, criminal behaviour is also not immune to economic changes.

Historically, the literature finds this effect to be stronger for property crimes as they are more likely to be motivated by financial incentives (Raphael and Winter-Ebmer, 2001; Levitt, 1996, 1997, 2001). That is, during recessions, property crime rates are expected to increase.

This study demonstrates the countercyclicality[1] of burglary and provides a multivariate explanation of burglary movements by empirically exploiting the relationship between business cycles and crime. The dynamic model is estimated using a system GMM (SYS GMM) estimator which accounts for the endogeneity of economic indicators and law enforcement variables included in the model.

Economic theory (Becker, 1968; Ehrlich, 1973; Levitt, 1997) explains crime engagement through the lens of individual incentives, which depend on the costs and benefits of illegal activity[2]. In other words, under this framework, illegal markets are an alternative to legal job markets. Individuals decide whether to engage in criminal activities by comparing returns to legal and illegal activities. Returns to illegitimate activities depend on the expected crime payoff while also accounting for the probability of apprehension and being incarcerated (Draca and Machin, 2015).

[1] *Appendix A.1.2* presents a descriptive analysis confirming the countercyclicality of burglary rates.

[2] Consider for example two otherwise identical individuals, one is employed, and the other is unemployed. At that specific moment in time, the labour market offers lower payoffs to the unemployed individual. Thus, the unemployed has a decision to make, either commit a criminal offence by accepting illegal job opportunities or accept the lower return offered in the legal market. Economic theory predicts that the unemployed individual is more likely to accept illegal payoffs due to lower opportunity costs. On the other hand, although, the employed person faces the same dilemma because, higher legal payoffs are offered, the individual is less likely to accept illegal job opportunities (Becker, 1968).

By utilising data, collected from multiple sources, we build an empirical model based on the theoretical framework of Becker (1968) that includes variables aiming to capture economic incentives. In doing so, we extend the empirical work of scholars who use financial performance indicators, such as wages and Gross State Product (Gould *et al*., 2002; Arvanites and Defina, 2006), to assess the relationship between the economy and crimes. Although, unemployment rate is the most extensively studied economic factor, the literature is inconclusive about its relationship to crime[3]. Thus, we aim to provide an alternative perspective on the relationship between business cycles and crime. In doing so, we assess the link between *monetary* economic indicators, under a panel-data setting, which has not received much attention in the literature so far.

Therefore, the main contribution of this study is to evaluate the effect of economic incentives, as measured by changes in government financial assistance and income inequality, on burglary rates, over the latest three business cycles. The model controls for law enforcement factors and includes time and fixed effects. Unemployment and income benefits represent the two measures of financial assistance included in the model. The former encompasses the economic incentives of the unemployed whereas the latter captures low-income earners. Both variables represent disadvantaged groups of the population which face lower opportunity costs and thus, more likely to engage in criminal activities.

We believe that benefit measures are more equipped to capture incentives than other economic indicators such as, unemployment rate, as we argue that it is not the state of unemployment *per se* that increases the propensity of crime engagement. Rather, as advanced by the theoretical models, it is the expected illegal and legal returns that motivate an individual's decision making. Thus, we suggest that if these disadvantaged groups receive enough benefits[4] to offset the difference between legal and illegal opportunities, lower

[3] *Section 1.2* provides more details.

[4] As the decision to participate in a criminal activity is contingent on the returns to crime and employment (Witt *et al*., 1998; Machin and Meghir, 2004), it must also depend on the benefit system regulating transfers to low-income or unemployed individuals. These monetary transfers are important as they may act as an income effect (Bindler, 2017) while also influencing the ratio of returns-to-work against the returns-out-of-work (Machin and Meghir, 2004).

property crime such as burglaries will be committed. To the best of our knowledge, this is the first study to examine the effect of benefits on crime.

Our second contribution is methodological. The literature raises potential concerns of reverse causality and simultaneity which may lead to biased estimates. This is usually tackled by instrumenting the endogenous variables. However, such instrumental approaches restrict the analysis to a static specification to avoid the Nickell bias[5] (Nickell, 1981). Moreover, the literature usually instruments only either the law enforcement or socio-economic variables. Therefore, to address the endogeneity biases of both economic and law enforcement variables while accounting for the dynamics of criminal activity[6], we use internal lags as instruments while also including other external instruments in a SYS GMM framework[7]. To our knowledge, this is the first study to include external instruments[8] in this type of analysis.

The empirical analysis provides tentative evidence in support of increasing income benefits to lower burglary rates. Specifically, we find that increasing benefits, paid to low-income earners, by 10%, leads to a 1.2% reduction in burglaries. Also, the model estimates that higher probabilities of apprehension, proxied by police officer wages, lead to lower burglaries. However, we find that unemployment benefits are positively linked to burglary rates, contrary to our expectations. A closer examination of the findings demonstrates that extended durations of unemployment benefits led to prolonged periods of unemployment which positively affected burglaries.

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[5] Nickell bias refers to the dynamic panel bias which is not eliminated using fixed-effects, *FE,* or within-groups estimators (Nickell, 1981; Bond, 2002). These estimators follow a demeaning process, which subtracts the mean value of the dependent variable and each regressor, for each observation in the sample. As explained by Nickell (1981), this results in a correlation between the independent variables and error, creating a bias in the estimate coefficient of the lagged dependent variable. The bias cannot be minimised by increasing the number of individual units or panels.

[6] By including a lagged dependent variable in our model.

[7] As discussed, in detail, in *Section 1.4.3*, SYS GMM jointly estimates in a system level and first-differenced equations by utilising internal lags as instruments for endogenous variables. The estimator also allows the use of external instruments.

[8] The external instrument list includes economic and sociodemographic factors. These are, Gross State Product (GSP), effective interest rate, loan-to-price ratio, House-Price-Index (HPI), disposable income per capita, average unemployment insurance (UI) duration, a dummy capturing whether the state has minimum wage legislation laws, personal tax revenue-to-GSP ratio, poverty and employment rates; median age, percentage of black population, and finally, a variable constructed to capture educational attainment. See *Section 1.4.3* for more details.

This is shown by restricting the sample period to the latest business cycle, the Great Recession, where the U.S. government decided, as a mitigating mechanism, to temporarily extend the duration of unemployment benefits. Thus, we re-estimate the model by treating the latest business cycle as a separate event. As evident from previous empirical works, the policy, unintentionally, created longer spells of unemployment (Bradbury, 2014) and less job creation (Hagedorn *et al*., 2015), leading to higher job competition in the labour market and depreciation of human capital skills (Bindler, 2015). As a result, unemployed individuals experienced lower opportunity costs and thus, they were more likely to endure criminal behaviour[9]. That is, longer unemployment spells, partly caused by the extension of unemployment benefits, led to unemployment benefit exhaustion, even with benefit duration extensions.

Our interpretation of the empirical results is that *at-the-margin* individuals positively respond to increases in income benefits as they increase the opportunity cost of offending and thus, they are less likely to engage in criminal activities. On the other hand, disadvantaged groups also respond positively to policies which perpetuate their distressed economic condition, making them more likely to commit crimes.

The rest of the paper is organised as follows. *Section 1.2* reviews the literature. Data description is presented in *Section 1.3* while explaining why economic indicators better capture financial incentives of at-risk adults. Further, *Section 1.4* outlines the empirical model analysed whereas the findings are discussed in *Section 1.5*. In *Section 1.6* we perform two ex-ante forecasts as a robustness check, testing the predictive power of the model. Finally, *Section 1.7* concludes.

[9] The findings confirm the results of Bindler (2015) who finds that increased criminal engagement is partially explained by increased durations of unemployment.

1.2 Literature Review

Advanced economies experience secular economic expansions, overlaid by transitory movements in economic activity. Changes in technology or positive supply shocks cause wide-ranging developments in social indicators (Cook and Zarkin, 1985). Likewise, short-term economic expansions and recessions, encompassed by business cycles, might also cause social fluctuations. Thus, the vast analytical literature supports that both secular economic growth and short-term economic downturns provoke higher rates of crime.

Therefore, over the years, empirical research has investigated the relationship between crime movements and economic conditions. There is a plethora of hypotheses, statistical approaches and indicators of economic activity employed to explore the relationship between business cycles and crimes. Although, empirical studies often reach contradicting conclusions, there is a collective understanding: just as economic changes affect other aspects of social life, they also influence peoples' motives to engage in criminal acts.

Thomas (1927) is one of the first to study the link between economic conditions and crimes. The work focuses on Britain between 1857 to 1913. He finds that de-trended measures of burglary and robbery are strongly negatively (-0.44) related to an indicator of business conditions. This countercyclicality, of mainly property crimes, has stood up well in more recent studies which account for a multivariate explanation of crime tendencies by including various measures of economic indicators, sociodemographic factors and proxies for criminal justice variables (Cook and Zarkin, 1985).

From an economic perspective, the theoretical origins of this linkage are attributed to the seminal work of Becker (1968) and Ehrlich (1973) who characterise crime as a rational act. They suggest that individuals are more likely to engage in criminal activities when illegal returns are high or legal compensation is low. In other words, legitimate employment opportunities do matter when deciding whether to engage in a criminal activity and they are also considered procyclical as, the quality and quantity of legitimate job market opportunities is analogous to the state of the economy (Cook and Zarkin, 1985).

Hence, the literature considers employment as a significant determinant of crime. Not only because earning a fair wage discourages people from committing crimes due to a higher opportunity cost[10], but also because it dictates a structure in their lives. Specifically, a deteriorated job market – determined either in terms of job loss, reduced working hours or wage cuts – can severely affect the overall health of the economy (Arvanites and Defina, 2006. In turn, a deteriorating economy can negatively motivate other social attributes such as, crime engagement.

The majority of empirical analyses use unemployment rates as a proxy for economy's state. As the unemployment rate is considered procyclical (Cantor and Land, 2001), its employment aims to capture the uncertainty prevailing in the legal labour market. In an earlier study, Cantor and Land (1985), argue that it is unclear whether recessions generate increases in crimes since a slumping economy causes two opposing effects: the opportunity and the motivation effects. They support that the former has a negative effect on crime, since there are fewer opportunities to commit a crime during a recession. The argument is that more people are staying at home acting as a guardian to their property and themselves. They expect this effect to be contemporaneous. On the other hand, the motivational perspective refers to the increasing number of financially motivated offenders. The authors argue that the motivation effect is lagged by one period since people are not expected to engage into illegal activities as soon as the economy deteriorates. They believe that the existence of these two effects explains the inconclusive findings of the literature.

Nonetheless, this study has been criticised (Greenberg, 2001; Arvanites and Defina, 2006) not only due to its methodological approach (Paternoster and Bushway, 2001; p.396) but also for the arguments made. Greenberg (2001) is one of the main critics of this work. Among other argumentative and statistical issues, he argues that it is illogical to assume that people who are unemployed will not immediately experience economic distress but rather, as Cantor and Land (1985) propose, they will have enough savings and receive satisfactory welfare benefits without any effect on their financial motives, at least for a year. He argues that although the latter might be true, it is unreasonable to expect people who are *at-the-*

[10] Earning higher wages increases the opportunity cost of, both spending time in the execution of a crime and in prison, if caught.

margin of offending, such as unskilled or young individuals, to have sufficient funds to support themselves financially for an extended period.

Nevertheless, irrespective of motivational or guardianship effects, critics of unemployment rate argue that unemployment captures only a portion of individuals who are impacted by a deteriorating economy (Arvanites and Defina, 2006). Criminal motivation may spill over to under-employed individuals during economic strain (Chiricos, 1987; Paternoster and Bushway, 2001; Greenberg, 2001; Andresen, 2013). This suggests a potential underestimation of the impact of recessions on economy's condition in general, and on employability in particular (Arvanites and Defina, 2006). Thus, to effectively examine the ramifications of changing economic conditions on crime, the empirical analysis must include variables capturing the whole population domain (Cantor and Land, 2001). Also, it is important to recognise that business cycles are about change, not levels (Paternoster and Bushway, 2001). Therefore, the chosen empirical methodology should encompass factor fluctuation[11].

In addition, despite unemployment rates being the most widely used measure of economic activity, the literature is yet inconclusive about its effect on crime. Most national-level time series[12] analyses find a negative association between unemployment and crime (Cantor and Land, 1985; Land *et al*., 1990; Cohen and Felson, 1979), whereas cross-sectional and panel data[13] studies generally conclude that there is a positive relationship between the two (Burdett *et al*., 2001, 2004; Gould *et al*., 2002), particularly for property crime rates (Raphael and Winter-Ebmer, 2001; Levitt, 1996, 1997, 2001).

Levitt (1996, 1997) finds that a 1% rise in the unemployment rate leads to a 1-2%, contemporaneous, increase in property crime rates whereas violent crime rates remain unaffected. Raphael and Winter-Ebmer (2001) reach similar conclusions using a U.S. state-level panel dataset between 1992 and 1997. As unemployment is perceived to be endogenous, they instrument unemployment rates using prime defence contracts and state-

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[11] As explained in *Section 1.4.3*, the SYS GMM, our preferred estimator, jointly estimates equations in first-differences and in levels; allowing for business cycle fluctuations to be accounted for.

[12] Levitt (2001) suggests that national studies are 'at least crude' since all variation in the state/county level is removed.

[13] A panel data analysis is more appropriate for exploiting the effect of unemployment on crime since it allows for simultaneous variation over time and across sates; while controlling for year and state fixed-effects.

specific oil shocks. They find a strong positive effect on property crimes with a weaker effect on violent crimes.

Although measures of income inequality and changes in wages have been less studied, the empirical findings are more compelling. Historically, wages have been negatively associated with crime whereas income inequality is positively linked to crimes. For instance, by considering the job opportunities of unskilled men, Gould *et al*. (2002) exploit the relation of unemployment and crime rates. As they explain unskilled men have a higher probability of engaging in criminal activities than any other population group. By studying the link of wages and crime, between 1979-1997, the authors find that half of the increase in crime rates (both violent and property) can be explained by wage trends. Also, although they show that both decreases in unemployment and increased wages contributed to the reduction of crime rates during the short-term (1993-1997). The authors suggest that raising wages is a more effective way to deter long-term crime trends than improving the employment prospects of unskilled men.

Kelly (2000) exploits the link between income inequality and crime. The empirical results showcase that, although property crime rates are not affected by inequality *per se*, they are positively and negatively affected by poverty rates and criminal justice factors, respectively. In contrast, they find no association between violent crime and poverty rates or police deterrence activity. Rather, they support that violent crime is affected by income inequality. In other words, the greater the income inequality, the higher the violent crime rates.

1.3 Data Description

This section describes data definitions and reports their sources; for more details see *Appendix A.1.1.1*. Using U.S. annual state-level data, a dynamic panel analysis between economic indicators and burglary rates is estimated. The empirical analysis covers the years of 1983 to 2009[14] for 50 states[15], allowing for three complete business cycles to be examined.

The dependent variable, burglary, is collected from the FBI's *Uniform Crime Reporting Statistics (UCR)*, as issued by the US Department of Justice. A burglary is defined as: "*the unlawful entry of a structure to commit a felony or theft*" (FBI UCR, 2016). There is no need for use of force to gain entry for a crime to be classified as burglary. The analysis includes burglary offences as a rate per 100,000 state population.

Further, we employ two economic indicators to approximate business cycles and test their link to burglary rates. First, weekly unemployment insurance (UI) compensation per unemployed recipient is used. It is a proxy for the number of beneficiaries, since not all individuals claiming unemployment compensation end-up receiving benefits – this is determined by the eligibility criteria set by each state. Both the amount of benefits paid out and the number of unemployed recipients is published by the *Employment and Training Administration* (*ETA*), part of the U.S. Department of Labor.

Unemployment compensation aims to provide "*temporary, partial wage replacement […] to involuntary unemployed individuals […]*" (Advisory Council on Unemployment Compensation, 1996). Further, according to Gabe and Whittaker (2012), reporting on behalf of the Congressional Research Service, UI payments aim to alleviate the poverty levels of individuals who receive them, particularly during or immediately after economic slumps. In

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[14] There is a twofold reasoning for choosing these years. First, state level data are unavailable for most of the explanatory variables in early 1980s. Second, we wanted to make sure that the sample captures three complete business cycles. Effectively, business cycles are defined from trough-to-trough, to allow for more recent data to be included in the dataset. That is, if instead peak-to-peak years are used, the latest data point available is year 2007 whereas by approximating business cycles by periods of trough, we are able to include data up to 2009.

[15] The District of Columbia is excluded as data were missing for many years.

addition, unemployment benefits are used as an economic stabiliser[16] during recessionary periods.

However, the US UI system has a unique structure[17]. Although it is a federal-state partnership, the UI system is mainly state funded[18] with states having "*a significant latitude to determine benefit standards*" (Fischer, 2017). States oversee the administration of UI programs, set benefit eligibility rules and tax rates. Since different monetary and non-monetary[19] eligibility requirements are set by each state, benefit recipiency varies vastly between states, rendering national averages as misleading[20] (Fisher, 2017; p.15). Fortunately, the panel data setting allows us to exploit these heterogeneities.

On the other hand, the federal government has, primarily, a regulatory role as it provides standardised guidelines for UI implementation and administers the program. Nevertheless, these guidelines are only indicative as states are not compelled to follow them. For example, although the federal government recommends that the duration of UI is, at least, 26 weeks; only nine states follow this standard with the remaining varying UI duration based on previous work experience. *Appendix A.1.1.3* presents the different durations offered by each state, between 1980 and 2010.

We expect that higher unemployment compensation is negatively linked to burglary, as individuals who are *at-the-margin* of offending will be less financially motivated to commit burglaries.

[16] Indicatively, during the Great Recession, it is estimated that the UI system, on average, generated $2 in economic activity for every dollar spent on UI benefits (Vroman, 2011). Part of this success is attributed to the system's design to extend benefit duration, after federal action.
[17] For a more detailed description of the structure of UI system, see Bindler (2015) and Fischer (2017).
[18] Nevertheless, if a state system is insolvent, the federal government fund UI programs by lending states. Alternatively, states can seek finance in the bond market. Indicatively, during the Great Recession, 36 state trust funds became bankrupt with the federal government offering $7 billion worth of grants to the states which subsequently have been distributed to the unemployed, in an effort to provide adequate support, in the form of unemployment benefits and obtain economic stabilisation (Fisher, 2017).
[19] Monetary requirements include the earnings earned prior to unemployment and the base period which assesses earnings and work whereas non-monetary requirements consist of job search and availability.
[20] As explained in *Section 1.4*, we employ a few different methodological approaches to control for this heterogeneity in the analysis. Unemployment durations are used as external instruments for unemployment benefits, the regression is estimated using heteroskedastic robust errors while including state fixed effects in the model. Nevertheless, this heterogeneity reinforces the usefulness of a panel data setting as it allows for state-fixed variations across time.

Nevertheless, we acknowledge that due to the wide-range state variations in eligibility, many part-time workers[21], who continuously work or individuals who are under-employed are discriminated against by the current UI program (Advisory Council on Unemployment Compensation, 1996). Therefore, to effectively assess the impact of business cycles on burglary, we also need to account for other disadvantaged groups which do not necessarily experience unemployment (Cantor and Land, 2001).

Thus, our model specification includes income maintenance benefits per $1k personal income as a second economic indicator. This measure aims to capture low-income earners who although they have a job, they may struggle financially, presumably lowering the opportunity cost of committing a financially motivated crime such as burglary. Income maintenance benefits consists of Supplemental Security Income (SSI) benefits, Earned Income Tax Credit (EITC), Additional Child Tax Credit, Supplemental Nutrition Assistance Program (SNAP) benefits, family assistance, and other income maintenance benefits, including general assistance. The data are drawn from the *Bureau of Economic Analysis* (*BEA)*.

Similar to unemployment benefits, income benefit payments intend to provide financial relief to disadvantaged groups of the population, reducing the likelihood of crime engagement motivated by economic difficulties. Both measures are adjusted for inflation and are used in the analysis as natural logarithms.

To our knowledge, this is the first study to examine the effects of unemployment compensation and income benefits on burglaries. Unemployment or under-employment translates into a loss of a stable income. Benefits paid out to these economically vulnerable groups help bridge the shortage of earnings created. Since theoretical economic frameworks predict that individuals engage in criminal activity when expected illegal payoffs exceed the expected gain from legal activities, we believe that these financial indicators are more appropriate in this type of analysis than economic factors (such as unemployment rates) as they better capture individual incentives.

[21] In the US, part-time or low-income workers are often excluded from the UI benefit system. In 2016, President Obama, at the State of the Union Address suggested modernisation of the UI system by expanding coverage to this group, among other proposals (The White House, 2016).

To address concerns about variables being strongly correlated, leading to biased regression estimates, we perform correlation and multicollinearity tests which are presented in *Appendix A.1.4*. As shown, the results provide reassurance about the variables included in the model.

Further, the model includes two law enforcement variables. To proxy police expenditure the total pay of full-time officers is divided by the number police officers. The data are obtained from the *Annual Survey of Public Employment and Payroll*, part of the Public Employment report series and published by US Census Bureau[22]. State prison populations are approximated using imprisonment rates[23]. This measure is used as a proxy for the severity of punishment and it is estimated as the number of sentenced prisoners[24], in each state, per 100,000 US residents. The data are obtained from the *National Prisoner Statistics Program*, issued by the Bureau of Justice Statistics.

Appendix A.1.3 presents the descriptive statistics.

[22] See, http://www.census.gov/govs/apes/index.html. To obtain data prior to 1992, we needed to contact the US Census Bureau to give us access to these historical data. No employment survey was conducted for 1996, since the base reporting period for measuring employment and payrolls was changed from October to March. This change became effective with the 1997 Census of Governments. Thus, the average number of police officers between 1995 and 1997 is used to fill in the gap for the missing data of 1996.

[23] The data are only disaggregated at the state level and not by type of offence. Although it would have been useful to know how many offenders have been incarcerated specifically for a burglary offence, we acknowledge that many criminals have been imprisoned for more than one offence. Thus, prison population calculations would have been magnified by the inclusion of individuals with multiple offences in different crime categories.

[24] Spending sentences longer than one year.

1.4 Methodology

1.4.1 Model Specification

To assess the relationship between burglaries and economic indicators, we estimate a dynamic model specification that links lagged burglary rate, unemployment and income maintenance benefits and relevant law enforcement variables. Thus, the empirical model is as follows:

$$burglary_{st} = \alpha burglary_{st-1} + \beta EconInd_{st} + \gamma LawEnf_{st} + \tau_t + \mu_s + \epsilon_{st}$$

for s = {1, . . . ,50} and t = {1, . . . ,27}[25]

$burglary_{st}$ is the variable of interest for state s in year t; $burglary_{st-1}$ is the lagged burglary rate; $EconInd_{st}$ denotes state-level unemployment and welfare benefits; $LawEnf_{st}$ denotes two law enforcement variables – police officers' pay, used as a proxy for police expenditure, and imprisonment rate, which captures the incapacitation and deterrence effects. The model also includes year (τ_t) and state (μ_s) specific fixed effects. μ_s controls for time-invariant, state specific unobservable characteristics while τ_t accounts for common shocks that affect all states, such as those propagated through financial crises. Finally, ϵ_{st} is a time-varying unobservable idiosyncratic shock.

The model specification includes a lagged dependent variable for two reasons. First, it captures crime persistence (Gould *et al*., 2002; Fajnzylber *et al*., 2002). That is, the crimes of yesterday are affecting the crimes of today. One of the main reasons is recidivism. Empirical research supports that prior crime engagement, increases the possibility of reoffending (Han *et al*., 2012) since ex-offenders are usually treated as such in the job market which in turn, lowers their legal labour opportunities and income. Second, accounting for crime persistence by using a dynamic specification is important as, it produces unbiased and consistent estimates (Bond, 2002). Also, according to Hale (1998) crime rates are affected over an

[25] There are 27 years in total (1983-2009). The model is estimated on the whole sample period as well as by business cycle.

extensive period of time. That is, if economic hardships trigger increases in burglary rates, this effect will persist for more than the recessionary period[26].

A positive, statistically significant value of α would support this dynamic setting. As demonstrated in *Appendix A.1.5.2*, we perform a simple first-order autoregressive model, AR(1), to examine crime persistence, as suggested by Blundell and Bond (2000) and Bond (2002). As shown in *Table A.1.5.2.1*, the burglary rate is highly persistent and thus, the use of a dynamic model specification is justified.

The above model is estimated over the whole sample period, 1983 to 2009 and it is re-estimated over the latest business cycle to examine whether burglary rates behave differently to changes in economic incentives across different periods. In turn, *Section 1.4.2* discusses the way in which the model is estimated.

1.4.2 System GMM (SYS GMM)

The dynamic panel data setting, the possibility of idiosyncratic shocks, and the potential endogeneity of economic indicators and law enforcement variables narrow our choices for a consistent estimator to examine the link between business cycles and burglary.

Firstly, by construction, the unobserved state fixed-effect, μ_s, is correlated with at least one of the regressors, $burglary_{st-1}$. Effectively, an endogeneity problem arises. Using Ordinary Least Squares (*OLS*) or Fixed Effects (*FE*) estimators to estimate *equation (1)*, produces biased estimates since they fail to effectively control for this correlation.

Secondly, economic indicators and criminal justice factors may be endogenous as well. For instance, higher unemployment rates may cause increases in crime whereas areas with high crime rates experience higher levels of unemployment. Wages can also be endogenous as it is highly likely that other factors – such as, education or parent's background – are correlated with both crimes and economic determinants. For example, less educated individuals or people coming from disadvantaged backgrounds are more likely to earn lower wages

[26] As shown in *Table A.1.2.1*, in the Appendix, on average, recessions last for one year.

(Freeman, 1991). This further suggests that these individuals may be in higher need of income support while being more susceptible to engage in criminal activities.

Further, law enforcement variables might also be endogenous. For instance, we do not know in which way the causation runs between the number of police officers and crime (Witt *et al*., 1999; Machin and Meghir, 2004). On one hand, more officers can lead to more effective investigation and subsequently, less crime. On the other hand, higher crime rates call for more police staff.

We strongly believe that not controlling for either or controlling for some potentially endogenous variables can still lead to biased estimates (Fajnzylber *et al*., 2002). In general, endogeneity arises either due to *reverse causation* between indicators and crime or due to *omitted variable bias*, or both (Field, 1990; Bindler, 2015). Not accounting for this possible endogeneity, produces biased and inconsistent parameter estimates. However, by controlling for endogeneity, the exogenous impact of these economic indicators on crime rates is isolated.

Traditionally, empirical studies control for endogeneity by employing instrumental variable estimators[27]. However, as explained above, standard instrumental variable estimators are not suitable for this study due to the dynamic nature of the model. Thus, to address these challenges, the system GMM (SYS GMM) estimator (Blundell and Bond, 1998; Bond, 2002) is employed. This is the first empirical study, to our best knowledge, that examines the effect of business cycles on crime and treats both set of factors, economic indicators and criminal justice variables, as endogenous.

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[27] For example, Raphael and Winter-Ebmer (2001) instrument unemployment rates with Department of Defence (DOD) annual prime contract awards for each state and a state-specific measure of oil price shocks. However, their regressions also include an incarceration rate without addressing potential endogeneity concerns. Another study, Gould *et al*. (2002), uses state unemployment rates, income per capita and non-college educated male weekly wages to examine the effect of changes on labour market opportunities on crime rates. Suspecting economic indicators being endogenous, they construct a Bartik instrument. The Bartik instrument averages national employment growth across industries using local industry employment shares as weights to produce a measure of local labour demand, which is not related to local labour supply. In other words, it isolates local labour demand changes. Nevertheless, their model also includes arrest rates, which are not controlled for endogeneity. Thus, it is possible that the estimated coefficients are biased. Other scholars account for the endogeneity of criminal justice factors but fail to control for the potential endogeneity of economic indicators and crime (Witt *et al*., 1999; Machin and Meghir, 2004).

SYS GMM allows to control for fixed effects and produces consistent and efficient estimates by addressing the inconsistency introduced by the dynamic setting (Nickell, 1981)[28]. The model jointly estimates *first-differenced* and *level* equations in a system. The estimator employs *lagged levels* to instrument equations in *differences* and uses *lagged first-differences* as instruments for *level* equations[29]. *Appendix A.1.5.1* discusses, in detail, the estimator's specific characteristics. Also, *Appendices A.1.5.2* and *A.1.5.3* present various tests demonstrating that the set-out assumptions[30] (Blundell and Bond, 2002) are satisfied and the use of the SYS GMM fits the purposes of this study while producing consistent and efficient estimates.

Further, the SYS GMM enables us to control for any endogeneity issues by employing both internal and external instruments. The *internal instrument set* consists of lag values of endogenous variables, known as, *GMM-type* instruments. *External instruments* are also employed, i.e. they are not included as explanatory variables but rather they are used as *IV-type* instruments. To our best knowledge, this is the first study to use the SYS GMM estimator by employing external instruments. Each type of instruments is explained in turn.

The GMM-type instruments are simply a list of instruments containing internal lags. For burglary, $t-3$ and $t-4$ lags are included whereas for economic indicators and law enforcement variables, only lags dated $t-3$ are used. To test instrument validity and to obtain further evidence to support the model specification, the Arellano-Bond's serial correlation test is used. Details are provided in *Section 1.4.2.1*.

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[28] Bond (2002) and Roodman (2009a, b) discuss in detail how system GMM deals with Nickell bias.
[29] Essentially, SYS GMM is an extension of the difference GMM (DIFF GMM), as it employs an additional level equation to estimate the model. That is, the DIFF GMM, developed by Arellano and Bond (1991) and Arellano and Bover (1995), estimates *equation (1)* in *first-differences* by using *lagged levels* as instruments for the potentially endogenous regressors. *Appendix A.1.5.1* discusses, in detail, the differences between the two estimators. To determine which of the two estimators fits the analysis better, Blundell and Bond (2002) outline a set of assumptions. If satisfied, the parameter estimates produced using the SYS GMM are more consistent and efficient than the estimated coefficients of the DIFF GMM. *Appendices 1.5.2* and *A.1.5.3* showcase that the conditions are satisfied.
[30] In brief, the assumptions of the SYS GMM require that the series is highly persistent, in both levels and first-differenced equations, while also being stationary in first-differences. To test for series persistence, Blundell and Bond (1998, 2000) and Bond (2002) suggest estimating simple first-order autocorrelation models, including year dummies, with all available lags; the results are presented in *Appendix A.1.5.2*. On the other hand, to test for series stationarity, we perform the Levin-Lin-Chu panel data unit root test. *Appendix A.1.5.3* validates stationarity in first-differenced equations.

On the other hand, the external instrument set includes other economic indicators and sociodemographic characteristics that are expected to be related with the endogenous explanatory economic variables, and uncorrelated with the error term, ϵ_{st}. In other words, these variables are not included in the model as explanatory variables but rather as instruments of the endogenous regressors.

The external instrument list includes economic factors such as: Gross State Product (GSP), effective interest rate, loan-to-price ratio, House-Price-Index (HPI), disposable income per capita, average unemployment insurance (UI) duration, a dummy capturing whether the state has minimum wage legislation laws, personal tax revenue-to-GSP ratio, poverty and employment rates. A sociodemographic set of factors is also included. This contains median age, percentage of black population, and finally, a variable constructed to capture educational attainment. All variables are included at the state level. *Appendix A.1.1.1* presents, in detail, the definition of each factor.

1.4.2.1 Instrument Validity and Specification Tests

As advanced earlier, the efficiency of system GMM depends on the validity of instruments. Inclusion of 'too many' instruments (Roodman 2009) causes instrument proliferation which in turn, produces biased estimates[31]. Further, including numerous instruments might significantly weaken the power of specification tests such as, the Hansen or the difference-in-Hansen tests, and thus, produce implausibly perfect p-values of 1[32] (Anderson and Sørenson, 1996; Roodman, 2006, 2009a, 2009b). The Hansen test of over-identifying restrictions assesses the *overall* validity of the instruments used whereas the difference-in-Hansen test examines the validity of the *additional* instruments[33] employed by the level equation (Blundell and Bond, 2000). The null hypothesis, of both tests, is that the model specification is correct.

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[31] Converging towards the biased estimates produced by the fixed-effect estimator.
[32] The statistic takes values between 0 and 1. Thus, a high p-value is regarded as a sign of validity of GMM estimation results (Roodman, 2009a).
[33] Compared to the DIFF GMM.

Accordingly, given the relatively modest cross-sectional dimension of our sample, we address our concerns of overfitting the model in two ways. Firstly, as advanced earlier, we limit the number of internal lags. Secondly, as suggested by Roodman (2009a, 2009b), the instrument list is *collapsed*[34].

Finally, to address concerns of autocorrelation in the model, rendering the instrument list invalid, we perform Arellano-Bond's (AB) serial correlation test. The null hypothesis is that the error term, ϵ_{st}, is not serially correlated. Failing to reject the null, provides support to the model specification. First-order autocorrelation is expected when including a lagged dependent variable in the model (Roodman, 2009b). If that is the case, the internal instrument list is valid only if lags are dated $t-3$ and longer.

All three specification tests are reported after the estimated coefficients. *Appendix A.1.5.4* provides additional details on the instrument validity and specification tests performed.

1.5 Results

As discussed in the previous section, the empirical analysis utilises data between 1983 and 2009 to estimate the model in *equation (1)*. The results are presented in *Table 1.1*. *Column (1)* presents the estimated coefficients for the whole sample period; whereas *columns (2) – (4)* display the findings for the latest recession, using three different variations of the unemployment benefit variable.

The AB autocorrelation tests show that there is serial autocorrelation of order 1 but not of order 2[35]. This suggests that the internal instruments used are valid, and the instrument list correctly starts from $t-3$ while providing further support to our model specification. Instrument validity and structural model specification are also tested using the Hansen and difference-in-Hansen tests of over-identifying restrictions. All tests verify the model's correct

[34] The *collapse* command produces an instrument list that consists of one instrument for each lag distance and instrumented variable. This option is available when using Roodman's *xtabond2* package in Stata.
[35] First-order serial correlation of the differenced residual is expected when the model includes a lag dependent variable; even if the error term, in levels, is serially uncorrelated (Roodman, 2009b).

specification and show that the *additional* instruments utilised by the SYS GMM are useful in the estimation.

Table 1.1: Regression Estimates, System GMM

	(1)		(2)		(3)		(4)	
	1983-2009		2001-2009					
Burglary,t-1	0.99	***	0.89	***	0.87	***	0.79	***
	(0.05)		(0.23)		(0.20)		(0.24)	
Av.Weekly UI Benefit per Total Unemployed	0.18	*	0.51	*				
	(0.09)		(0.29)					
Av.Weekly UI per Newly Unemployed					0.30			
					(0.22)			
Av.Annual UI per Newly Unemployed							0.15	
							(0.14)	
Income Benefits per $1k PI	-0.12	**	-0.34	**	-0.24	*	-0.36	**
	(0.05)		(0.14)		(0.14)		(0.14)	
Police Officer's Pay per employee	-0.16	**	-0.53		-0.51		-0.7	*
	(0.08)		(0.36)		(0.32)		(0.39)	
Sentenced Rate	0.01		0.07		0.05		0.09	
	(0.05)		(0.07)		(0.05)		(0.08)	
No of Instr	49		31		31		31	
AR(1) p-value	0.00		0.01		0.01		0.01	
AR(2) p-value	0.45		0.28		0.23		0.22	
Sargan	0.00		0.07		0.01		0.21	
Hansen	0.32		0.34		0.28		0.71	
Difference-in-Hansen								
all coefficients	0.18		0.27		0.25		0.76	
α	0.04		0.20		0.27		0.71	
β_{UI}	0.74		0.77		0.72		0.86	
$\beta_{Inc.Benef.}$	0.15		0.54		0.94		0.25	
$\gamma_{Pol.Off.}$	0.07		0.64		0.46		0.29	
$\gamma_{Sent.Rate}$	0.11		0.66		0.99		0.76	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All coefficients are in natural logs. Burglary rates are instrumented using $t-3$ and $t-4$ lags whereas for economic indicators and law enforcement variables only $t-3$ lags are used.

The lagged dependent variable is strongly statistically significant, as expected, in all model estimations. This showcases that prior engagement in burglary offences leads to higher rates of burglary[36]. This further demonstrates that, although the literature often neglects to include a crime lag, accounting for crime dynamics is important when estimating the relationship between economic conditions and crime. Also, the variable capturing the police officers' pay, used as a proxy for the probability of apprehension, has a negative effect on burglary. Indicatively, a 10% increase in officer wages is expected to reduce burglaries by 1.6%.

[36] This is true across all model specifications, presented in *columns (2) - (5)*.

From an economic perspective, the findings indicate that higher income benefits have a negative effect on burglary rates, as expected. Specifically, *column (1)* shows that a 10% increase in benefits, paid out to low-income individuals, leads to a 1.2% reduction in burglary rates, significant at the 1 percent level. This translates into, approximately, 13,000 less burglaries been committed for every 10% increase in income benefits.

However, the unemployment benefits variable has a positive coefficient, contrary to our expectations. Thus, we investigate this further. As during the Great Recession, the government decided to temporarily extend the duration of unemployment benefits, we restrict our sample period to the latest business cycle and the model is re-estimated.

The results are presented in *columns (2)* through *(4)*. *Column (2)* estimates the model using the same model specification as *column (1)*. Both economic indicators maintain their significance with the remaining variables having the expected signs. The findings show that the magnitude of the income benefits variable increases in size. Indicatively, during the Great Recession, a 10% increase in income benefits led to a 3.4% decrease in burglary rate, or, approximately, to 36,800 fewer burglaries.

Unemployment benefit payments also increase in magnitude during the latest business cycle and the coefficient still maintains its positive sign. As we find this odd, we try to interpret the results more carefully. The variable is a ratio of the total weekly unemployment benefits paid by states and the federal government to eligible recipients, divided by the number of total unemployed individuals. Thus, depending on the percentage change of the numerator and the denominator, the ratio can increase or decrease.

Nevertheless, it is the duration of unemployment benefits that was extended, not the amount of benefits paid. Also, the measure included in the model represents the *weekly* benefit amount received by unemployed[37]. Thus, we are confident that the percentage change of the denominator is larger, driving the ratio downwards. This could explain the

[37] One can argue that extending the duration of unemployment benefits suggests that the total benefit amount received while being unemployed will be higher. However, since our model includes weekly benefit payments, we manage to avoid this.

positive coefficient and further indicate that more unemployed individuals are linked to higher burglary rates.

In other words, eligible recipients were given unemployment benefits for an extended duration, effectively implying that they remained unemployed for a prolonged period. This further suggests that their condition did not change and neither did their incentives as, on a weekly basis[38], the amount of benefits received did not change.

The literature provides tentative evidence to support this explanation. Hagedorn *et al*. (2015) analyse the effect of different maximum durations between states, as a result of the extended unemployment benefit duration. They find that, unintentionally, the benefit extension led to significant increases in unemployment duration and reduced employment creation. Further, Bradbury (2014) utilises individual level data from the *Current Population Survey* (*CPS*) to examine the variations in duration of benefits, between 2005 and 2013. She finds that by extending benefits, individuals stayed unemployed longer, with non-beneficiaries abandoning the labour force altogether.

Bindler (2015) takes advantage of the quasi-experimental setting of unprecedented temporary benefit extensions, as a result of increased unemployment durations and exploits the relationship of unemployment duration and crime in the US, during the Great Recession. She finds that crime rates increased due to higher unemployment, driven by emergency benefit extensions. She further explains that, *ceteris paribus*, prolonged periods of unemployment lead to higher human capital deprivation and negative income effects, partially justifying higher tendencies of criminal engagement.

In addition, consider two unemployed individuals, one receives benefits whereas the other is long-term unemployed with exhausted unemployment benefits. Although, both are out of employment, the latter individual is more disincentivised and faces lower opportunity costs and thus, more likely to engage in criminal activities.

To examine this and evaluate whether it is, indeed, the increases in the number of long-term unemployed that drive the unemployment coefficient in *column (2)*; we re-estimate our

[38] In the U.S., unemployment benefits are paid weekly.

model using average *weekly* benefits per first payments[39], i.e. per *newly* unemployed. The first-payment component refers to the reference year, not to first-time unemployed individuals. By restricting the number of beneficiaries to first-benefit payment unemployed individuals, we aim to capture increases in the number of individuals who are forced into unemployment due to the economic recessionary phase. The results are presented in *column (3)* of *Table 1.1*. Although, the positive sign remains, the coefficient is no longer significant. Income benefits are still negatively significantly related to burglary rates. These results corroborate our previous findings. Newly unemployed are less financially motivated to engage in criminal acts.

Further, in *column (4)*, we re-estimate the model by including the average *annual* unemployment benefit amount per newly unemployed. This allows us to examine if changes in the *total* amount of benefits received, during unemployment, affect burglary rates. The estimates show that this relationship is not significant. That is, just because unemployed individuals end up with a higher lump-sum than initially anticipated, i.e. when they became unemployed, due to the extension of benefit duration, it does not change the fact that they struggle financially at that moment in time. Particularly when the weekly benefit amount is lower than the expected relative returns of illegal activities. The longer they remain unemployed, the more likely they are to engage in criminal activities due to lower opportunity costs. Nevertheless, the findings from this model specification, still, demonstrate that increases in income benefits, decrease burglary rates.

We acknowledge that it would have been interesting if we could isolate the effect of newly and long-term unemployed on crime, by estimating the average benefits received by each group. Unfortunately, we only have data on first-payments and total unemployment numbers with no distinction been made between the amount of benefits paid out to each group[40]. However, we perform further robustness checks that validate the aforementioned conclusions and provide support for the model specification. These are discussed in the next section.

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[39] *Figure A.1.1.2.3* in the Appendix demonstrates the growth rates of the weekly UI benefits.

[40] The numerator, in all measures, is the total amount of unemployment benefits paid to newly and long-term unemployed individuals.

1.6 Robustness Checks

As a robustness check, we re-estimate the model by including a measure of income inequality, at the state level, encompassing the entire income distribution. By including the Gini coefficient, we hope to capture the overall economic injustice which might not be accounted for when we only use the amount of benefits received by the unemployed and the low-income earners, and measure how that affects burglaries. A wider gap of economic injustice is expected to be associated with higher burglary rates.

This is based on sociological and economic theories which suggest that earnings inequality raises feelings of unfairness, prompting poorer individuals to reduce perceived income inequality by engaging in criminal activities (Runciman, 1966) whereas Wilson and Daly (1997) argue that high income inequality induces risk-seeking behaviour from people at the bottom of the income distribution. As advanced earlier, the economic perspective explains criminal engagement through economic incentives (Becker, 1968; Ehrlich, 1973) and suggests that criminal activity is an occupational choice which depends on the probability of apprehension. Thus, the economic theory predicts that more income inequality leads to higher crime rates.

Although the findings provide further support to our main results, because the movements in income inequality have *no* effect on burglary rates[41], we do not present the estimation results, but are available upon request.

[41] The insignificance of income inequality may be explained by looking at the overall trend of the Gini coefficient. As demonstrated in *Figure A.1.1.2.6*, there is a lot of variability throughout the business cycles.

Further, we compute two ex-ante forecasts to test how well the included regressors predict burglary trends. These are plotted against the actual burglary rates to assess the predictive capabilities of our model.

The first ex-ante forecast simply saves the predicted values, after model estimation, and plots them against the actual rates of burglary. As shown in the *Appendix A.1.6.1*, the fitted values mirror the actual values quite well, providing support for the model specification and indicating that the variables included in the model explain well the depend variable.

The second test is an ex-ante *dynamic* forecast. By compiling information from three sources: (1) the model, as presented in *equation (1)*; (2) equations for each endogenous economic indicator as well as its identity[42]; and (3) exogenous variables; we are able to perform this dynamic forecast. Since we want to test how well our model predicts future trends in crime and we have information on the actual burglary crime trends, we fabricate an out-of-sample sample. In other words, we end the *estimation-sampl*e in 2009; meaning that all the above estimations are performed over the period of 1983 to 2009. By default, using prior values of the endogenous variables, as computed from the forecast procedure, forecasts for 2010 and following years are dynamic forecasts. Having this setting, allows us to compare these forecasted values against the actual burglary rates of 2010 to 2014.

The model is estimated using the same specification as the one discussed in the empirical analysis. We still treat economic indicators as endogenous and thus, we create an instrumented equation for each one the factors by employing independent explanatory variables. The unemployment compensation equation is estimated using the log of average UI of newly unemployed as the dependent variable and with the contemporaneous percentage change of GSP per capita and the lag of disposable per capita and the average duration of UI compensation as the explanatory variables. To further address potential endogeneity issues between unemployment and the economic activity within the state, we instrument GSP growth using effective interest rate, loan-to-price ratio and House-Price-Index (HPI). All three regressors are statistically significant and the coefficients' signs are as

[42] An identity is a non-stochastic equation that expresses an endogenous regressor as a function of other variables in the model.

expected: GSP growth is negatively related to unemployment benefits while disposable income and duration of unemployment have a positive relationship with unemployment.

Further, we specify the income benefits equation in terms of the percentage change in benefits. We define income benefits as a function of its own first lag (positive) while also including a dummy capturing states having a minimum wage lower than the Federal minimum (negative), the growth in poverty rate (positive), the employment rate (negative), median age, the percentage of black population (positive), and the percentage of high-school graduates (positive). Again, all variables are significant and the estimated coefficients' signs are plausible.

The last instrumented equation estimates the income inequality based on the percentage change of disposable income, the economic growth as captured by the GSP, the cost of living proxied by HPI, the labour share, changes in tax policy[43] as captured by the log of personal tax revenue-to-GSP ratio and the median age[44]. Its coefficient estimates have plausible signs and significance.

Finally, we define all the exogenous variables before estimating the dynamic forecasts of the model. The findings are presented in *Appendix A.1.6.2*. As shown, the model performs quite well and accurately captures the burglary crime trends for most states. These dynamic forecasts provide further support to the model specification and the empirical findings presented.

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[43] Higher taxes are expected to be linked negatively with income inequality. Indeed, the model estimates prove that.

[44] Younger populations are considered to be more unequal societies, i.e. experience higher income inequality, than older ones. Probably, this is due to lower earnings disparities among older individuals.

1.7 Conclusion

This chapter estimates a dynamic panel data model to assess whether, and to what extent, business cycles affect the rate of burglary. The model is estimated using the SYS GMM estimator, allowing for unobserved heterogeneity and dynamic endogeneity. Both internal, i.e. lagged values, and external instruments are used to address potential endogeneity issues. To the best of our knowledge, this is the first empirical study to employ the SYS GMM estimator with external instruments.

The analysis uses two economic indicators, a measure of unemployment benefits and supplemental benefits paid to low-income earners, to capture the economic motives of disadvantaged groups who, historically, have been characterised as more susceptible to engage in criminal activities due to economic distress.

The empirical findings demonstrate that individuals can financially be motivated to commit crimes due to severe economic conditions which lower opportunity costs. The results are robust to different specifications and carry some noteworthy policy implications.

In all model specifications, the coefficient of income benefits is significantly negatively related to burglary rates. A 10% increase in income benefits leads to 1.2% decrease in burglary rates. The results suggest that increases in income benefits, paid to various low-income groups, can change the motives of people who are *at-the-margin*, leading to lower crimes being committed. By re-estimating the model, during the latest business cycle, 2001-2009, we find that the significance of the variable remains, and its magnitude almost triples in size to 3.4%. As the Great Recession is the most severe economic downturn among the three business cycles examined, the increasing elasticity leads us to believe that income benefit increases are more effective when economic crises are stronger.

Nevertheless, unemployment benefits, contrary to our expectations, are found to have a positive relationship with burglary. A closer examination of the findings reveals that the ratio is driven by the number of long-term unemployed. That is, by exploiting an unprecedented temporary extension of the duration of unemployment benefit, during the Great Recession, we find that longer periods of unemployment increase burglary rates.

That is, longer spells of unemployment lead to higher expected returns to illegal activities as human capital depreciates and expected future legal payoffs are lower due to higher job competition. This conveys increased probabilities of crime engagement due to lower opportunity costs. This argument is in-line with the economic theory (Becker, 1968; Ehlrich, 1973) and other empirical studies suggesting that increased unemployment rates are linked to higher crime rates especially, property crimes.

Thus, the findings indicate that increasing benefits is a more effective mechanism to reduce countercyclical crime than providing support for an extended period, as by implementing such policies the condition of economic distress of disadvantaged groups is perpetuated.

Appendix A.1

A.1.1 Sources and Data Description

A.1.1.1 Data Definitions and Sources

Appendix A.1.1.1: Description of Data Statistics

Data	Source	Published by	Available at	Description	Calculation
Dependent Variable					
Burglary	Uniform Crime Reporting (UCR)	*FBI*	state	per 100,000 mid-year population	$\frac{\text{\# of crimes x 100,000}}{\text{\# of mid-year state population}}$
Economic Indicators					
Av. Benefits per First Payments	Employment & Training Administration (ETA 5159)	*U.S. Department of Labor*	state	in $, real terms; benefits paid for all weeks compensated divided by the number of people who received first UI payments	$\frac{\text{UI compensation}}{\text{\# of first payments}}$
Av. Income Benefits	Personal Current Transfer Receipts (SA 35)	*Bureau of Economic Analysis (BEA)*	state	per $1k personal income, in real terms; it consists of income maintenance benefits including: Earned Income Tax Credit (EITC), Additional Child Tax Credit, Supplemental Nutrition Assistance Program (SNAP) benefits, family assistance, and other income maintenance benefits, incl. general assistance	$\frac{\text{Income Benefits x \\$1,000}}{\text{Personal Income}}$
Gini Coefficient	Current Population Survey (CPS)	*U.S. Census Bureau*	state	as an index; it captures earnings inequality for the entire income distribution	
Law Enforcement					
Police Officer's Pay	*Annual Survey of Public Employment and Payroll*	*U.S. Census Bureau*	state	per full-time police officer, in real terms	$\frac{\text{total pay for FT officers}}{\text{\# of police officers}}$
Imprisonment Rate	*National Prisoner Statistics Program*	*Bureau of Justice Statistics (BJS)*	state	per 100,000 residents; sentenced prisoners serving sentences longer than 1 year under the jurisdiction of state or federal correctional authorities	$\frac{\text{\# of sentenced prisoners x 100,000}}{\text{\# of mid-year state population}}$

Appendix A.1.1.1 (cont'd): Description of Data Statistics

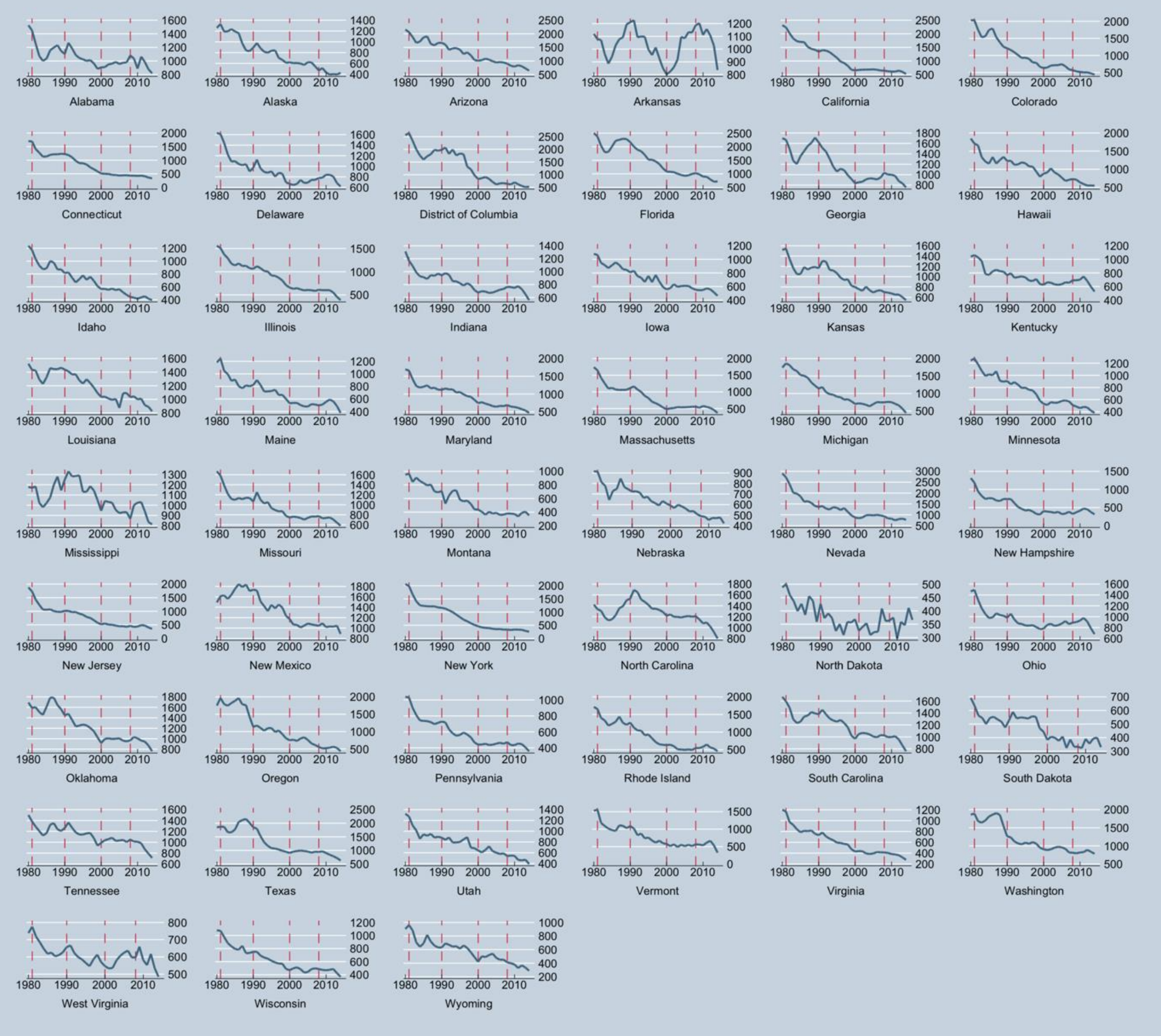
Data	Source	Published by	Available at	Description	Calculation
External Instruments					
Gross State Product (GSP)		*Bureau of Economic Analysis (BEA)*	state	per capita, in real terms; it measures all final goods and services produced within a state, capturing the economic activity	$\frac{\text{GSP}}{\text{\# of mid-year state population}}$
Effective Interest Rate	Montly Interest Rate Survey (MIRS)	*Federal Housing Finance Agency (FHFA)*	state	as a %; estimated based on conventioal single-family non-farm mortgage loans; it is the rate on a mortgage loan restated from the nominal interest rate with annual compount interest payable in arrears	
Loan-to-Price Ratio	Montly Interest Rate Survey (MIRS)	*Federal Housing Finance Agency (FHFA)*	state	as a %; estimated based on conventioal single-family non-farm mortgage loans; it express the cost of the loan w.r.t. how much the property is worth	
House Price Index (HPI)	Local House Price Dynamics	*Federal Housing Finance Agency (FHFA)*	state	index with a base of 100; capturing cumulative annual appreciation	
Disposable Income	Disposable Personal Income (SA 51)	*Bureau of Economic Analysis (BEA)*	state	per capita, in real terms; it represents income available to for spending or saving; it is the difference between personal income less current taxes;	$\frac{\text{disposable income}}{\text{\# of mid-year state population}}$
Average UI duration	Employment & Training Administration (ETA 5159)	*U.S. Department of Labor*	state	# of weeks compensated for the year divided by the # of individuals receiving first unemployment payment	$\frac{\text{\# of weeks compensated}}{\text{\# of first payments}}$
Minimum Wage	Wage and Hour Division (WHD)	*U.S. Department of Labor*	state	a dummy variable capturing states that offer minimum wages lower than the Federal Minimum Wage Rate or have no minimum state law in place	
Poverty Rate	Small Area Income and Poverty Estimates	*U.S. Census Bureau*	state	the ratio of families below 100% of poverty threshold to the total number of families	
Employment Rate	Local Area Unemployment Statistics (LAUS)	*Bureau of Labor Statistics (BLS)*	state	as a %; number of employed individuals - annual average	$\frac{\text{\# of employed x 100}}{\text{\# of civilian non-institutional pop}}$

Appendix A.1.1.1 (cont'd): Description of Data Statistics

Data	Source	Published by	Available at	Description	Calculation
External Instruments					
Personal Tax-to-GSP ratio	Personal Current Taxes (SA 50)	*Bureau of Econmic Analysis (BEA)*	state	as a ratio, in real terms; personal current taxes revenue divided by GSP; tax revenues includes all compulsory payments to the federal government	$\frac{\text{personal current tax revenue}}{\text{GSP}}$
Median Age	Population Estimates Program (PEP)	*U.S. Census Bureau*	state	a single index summarising the age distribution of state population	
Black Population	Population Estimates Program (PEP)	*U.S. Census Bureau*	state	as a % of the state population	$\frac{\text{\# of black individuals}}{\text{\# total state population}}$
High School Graduates	Current Population Survey (CPS)	*U.S. Census Bureau available at IPUMS*	state	as a % of 25+ population with a high-school diploma; data available at the individual level, using survey weights educational attainment is estimated	

A.1.1.2 Variable Trends

Figure A.1.1.2.1: Burglary Rate



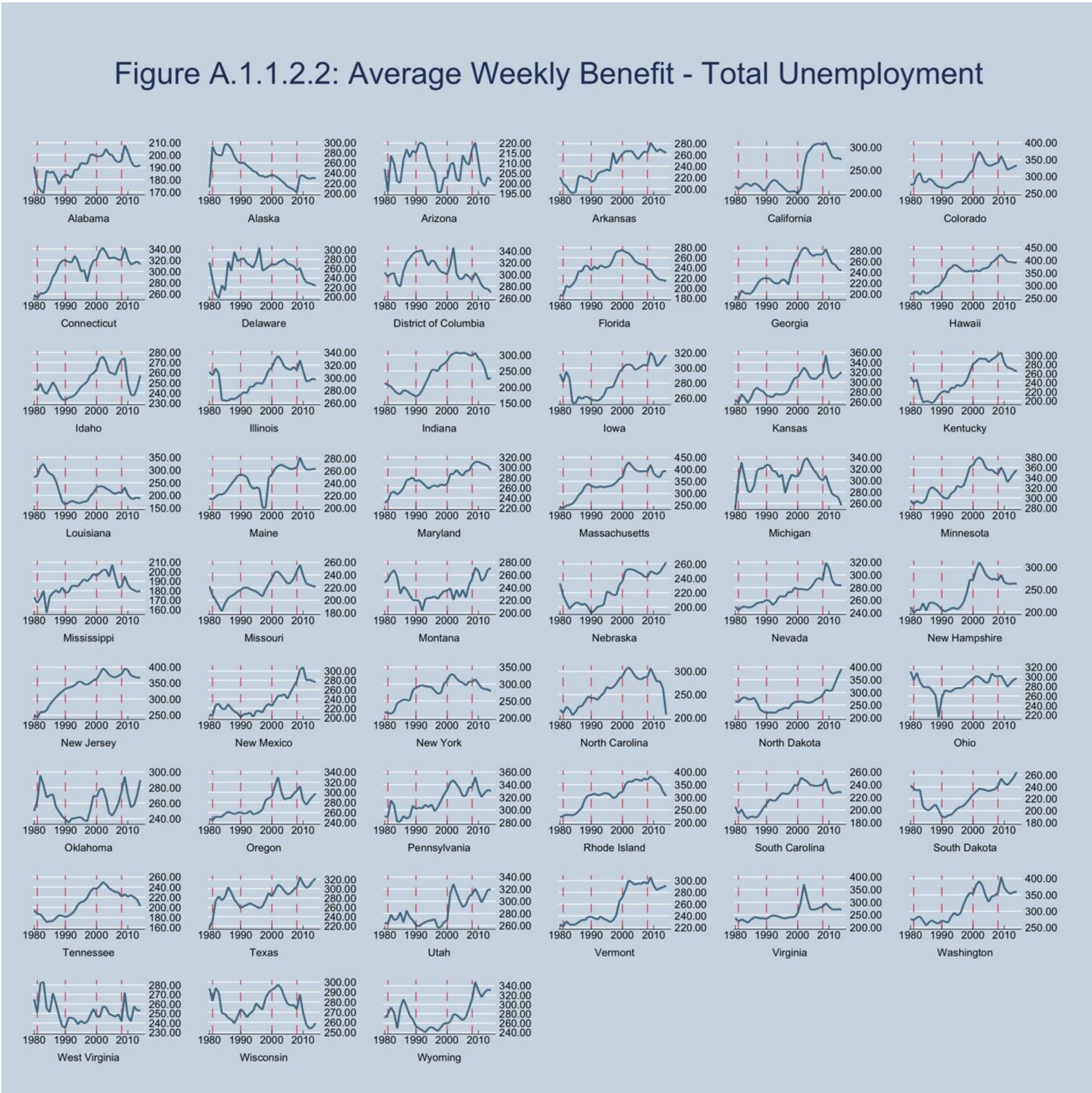


Figure A.1.1.2.2: Average Weekly Benefit - Total Unemployment
Alabama
Alaska
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
District of Columbia
Florida
Georgia
Hawaii
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
New Hampshire
New Jersey
New Mexico
New York
North Carolina
North Dakota
Ohio
Oklahoma
Oregon
Pennsylvania
Rhode Island
South Carolina
South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
West Virginia
Wisconsin
Wyoming

Figure A.1.1.2.3: Average Weekly Benefits per First Payment

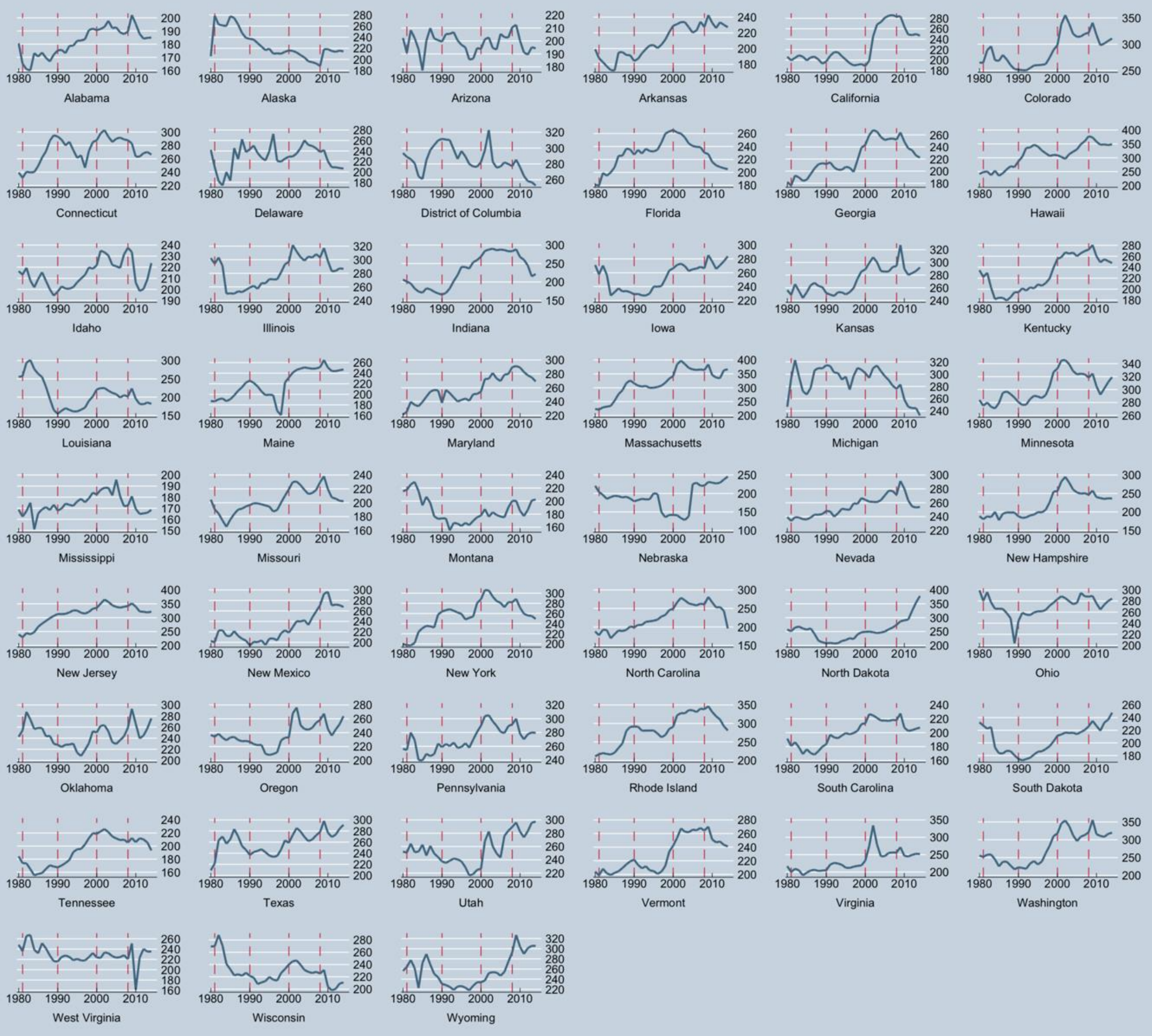


Figure A.1.1.2.4: Average Annual Benefits per First Payment

Figure A.1.1.2.5: Income Benefits per $1k Personal Income

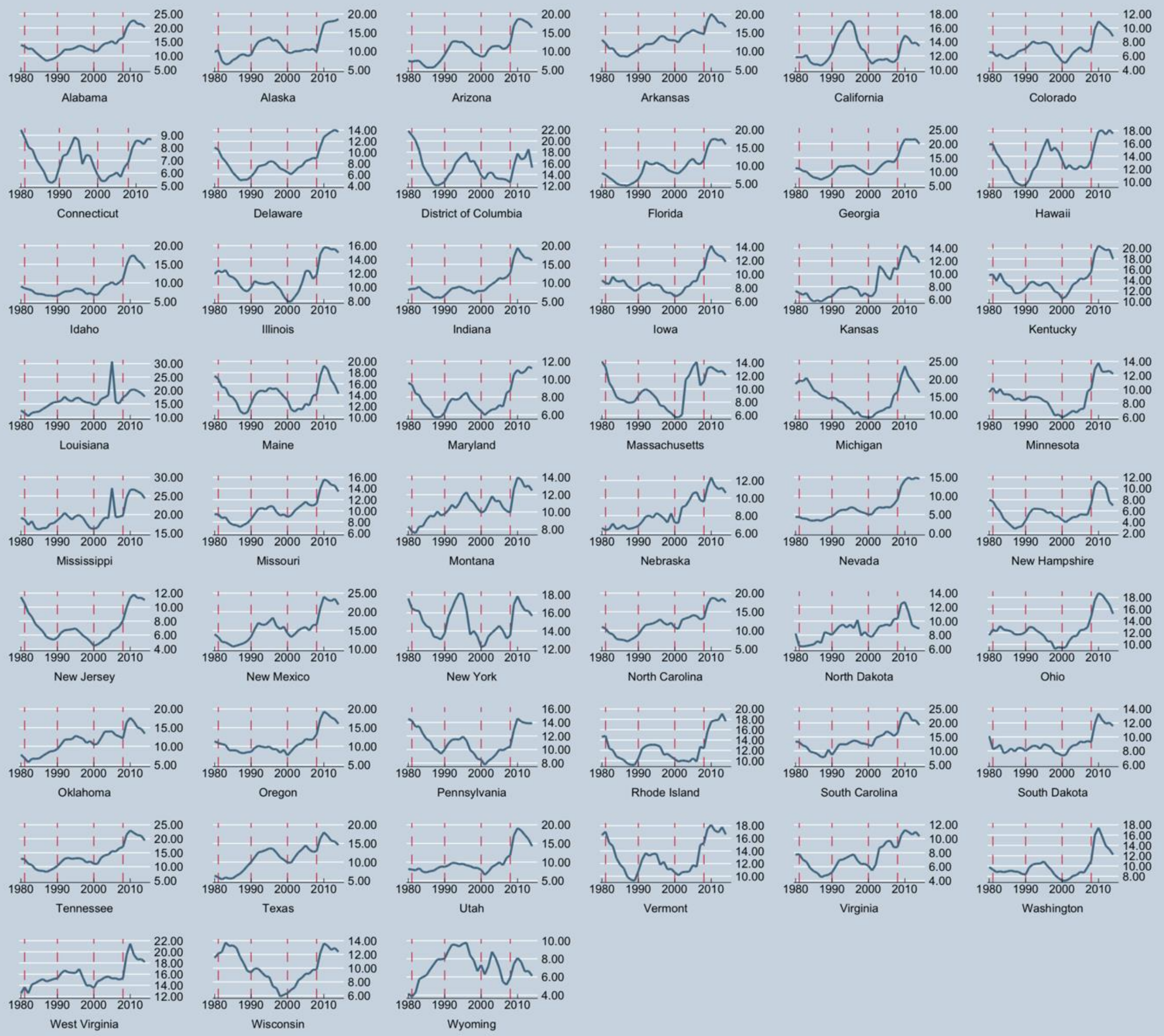
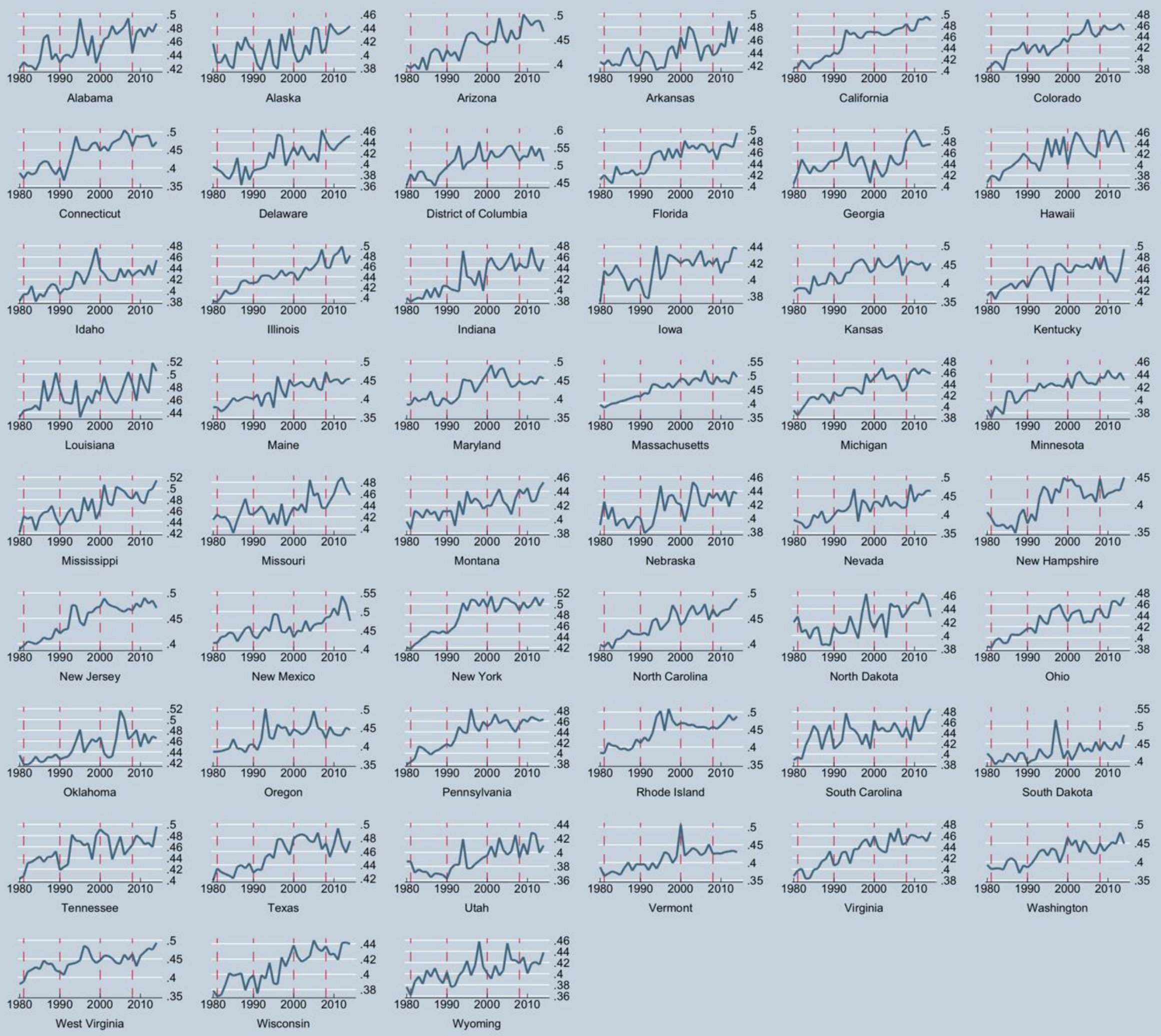


Figure A.1.1.2.6: Gini Index



A.1.1.3 Unemployment Insurance (UI) Benefit Duration

Table A.1.1.3: Minimum Unemployment Benefit Durations per State, 1980 to 2010

State	1980	1985	1990	1995	2000	2005	2010
Alabama	11+	11+	15+	15+	15+	15	15
Alaska	14	16	16	16	16	16	16
Arizona	12+	12	12+	12+	12+	12	12
Arkansas	10	12	10	9	9	9	9
California	12+-15	12+	14+	14+	14+	14	14
Colorado	7+-10	7+-13	13+	13+	13+	13	13
Connecticut	26	26	26	26	26	26	26
Delaware	11-18	18	24	24	24	24	24
District of Columbia	17+	17	26	20	20	19	19
Florida	10	10	10	10	26	9	9
Georgia	4	4	9+	9+	9+	9	6
Hawaii	26	26	26	26	26	26	26
Idaho	10	10	10	10	10	10	10
Illinois	26	26	26	26	26	26	26
Indiana	3+	9+	9+	14	8+	8	8
Iowa	15	11+	11+	11+	7+	9	9
Kansas	10	10	10	10	10	10	1
Kentucky	15	15	15	15	15	15	15
Louisiana	12	12	8	8	26	21	26
Maine	13+-25	7+-22	15+-22	21+-22	14+	14	22
Maryland	26	26	26	26	26	26	26
Massachusetts	9+-30	9+-30	10+-30	10+-30	10+-30	10	10
Michigan	11	15	15	15	15	14	14
Minnesota	13	11	10+	10+	10+	10	11
Mississippi	12	13+	13+	13+	13+	13	13
Missouri	10-13+	10	11+	11+	11+	16	8
Montana	8	8	8	8	8	8	8
Nebraska	17	17	20	20	20	17	1
Nevada	11	12+	12+	12+	12+	12	12
New Hampshire	26	26	26	26	26	26	26
New Jersey	15	15	15	15	15	1	1
New Mexico	18+	19	19	19	19		16
New York	26	26	26	26	26	26	26
North Carolina	13	13-26	13-26	13-26	13-26	13	13
North Dakota	12	12	12	12	12	12	12
Ohio	20	20	20	20	20	20	20
Oklahoma	20	20+	20+	20+	1+	18	18
Oregon	6	7+	6+	4+	4+	3	3
Pennsylvania	30	16	16	16	16	16	16
Rhode Island	12	12	15+	15+	15+	8	8
South Carolina	10	14	15	15	15	15	13
South Dakota	13+	18+	18+	15+	15+	15	15
Tennessee	12	12	12+	12+	12+	13	13
Texas	9	13+	9+	9+	9+	9	10
Utah	10-22	10	10	10	10	10	10
Vermont	26	26	26	26	26	26	26
Virginia	12	12	12	12	12	12	12
Washington	8+-25+	16+-30	16+-30	16+-30	16+-30	12	1
West Virginia	28	26	26	26	26	26	26
Wisconsin	1-12+	1-14+	13+	12+	12	12	14
Wyoming	12-26	12-26	12-26	12-26	12-26	11	11

A.1.2 Descriptive Analysis

Economic theory predicts that movements in economic activities are associated with changes in criminal behaviour. Specifically, for property crimes, as they are more likely motivated by financial incentives. This suggests that property crimes are countercyclical, indicating a higher growth rate during economic downturns.

To assess whether this is true, we examine the relationship of burglary rates across business cycles (Cook and Zarkin, 1985; Paternoster and Bushway, 2001; Bushway *et al*., 2015) by performing a descriptive analysis, before empirically evaluating the relationship between the two. However, in contrast to the above papers, which only estimate the national association of the two, we estimate and compare burglary growth rates between expansionary and recessionary phases across all 51 states.

Between 1973 and current date, the U.S. has experienced five complete business cycles[45], as shown in Table A.1.2.1. The table provides data on U.S. business cycles expansions (trough-to-peak) and contraction (peak-to-trough), as published by the *National Bureau of Economic Research* (*NBER*)[46]. Expansion is the period between the trough and the subsequent cyclical peak whereas contraction is the period between the *previous* peak and the trough of the *current* cycle. A complete business cycle is defined either from a peak-to-peak period or from trough-to-trough. As the data are annual, the start and the end of each business cycle is approximated.

According to Table A.1.2.1, the average contraction lasts for 12 months[47], while the average expansion lasts for about 71 months; leading to an average business cycle of 82 months. Appendix A.1.1.2 graphically represents the trends in burglary rates over the latest business

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[45] Data have been collected for 1980-1982 as well. However, due to the business cycle being too small (only 2 years), the estimates produced are not reliable and thus, excluded from this study. Serial correlation tests, used to determine from what lag the instrument list should start, indicate an autocorrelation of order 1. This calls for lag 3 and further to be used as instruments, which is no viable option.

[46] NBER has a long-lasting reputation on publishing data on business cycles. It approximates recessions by identifying "*a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales*" (NBER, 2018).

[47] Thus, a 1-year growth rate should be sufficient to capture the recessionary period and then compared against the rate of growth during economic expansion.

cycles.

Table A.1.2.1: Business Cycle Expansions and Contractions (1975-2018)

				Length (months)		
		Expansionary Period	**Business Cycle Reference**	**Contraction**	**Expansion**	**Cycle**
Trough	*Peak*	*Trough-to-Peak Interval used in Estimations*		*Previous Peak Current Trough*	*Trough to Peak*	*Peak from Previous Peak*
	Nov-1973					
Mar-1975	Jan-1980	1975-1979	BC1	16	58	74
Jul-1980	Jul-1981	1980-1981	BC2	6	12	18
Nov-1982	Jul-1990	1983-1990	BC3	16	92	108
Mar-1991	Mar-2001	1991-2000	BC4	8	120	128
Nov-2001	Dec-2007	2002-2007	BC5	8	73	81
Jun-2009				18		
Average				12	71.0	81.8

Notes: The reference dates of business cycles are identified by the *National Bureau of Economic Research (NBER)*. Peak and trough are the highest and lowest points of each business cycle. Contraction is the period from the *previous* peak to current trough whereas expansion is the period form trough to peak of the *current* business cycle. The duration of a complete business cycle is estimated either by peak-to-peak or by trough-to-trough.

This descriptive approach treats each cycle as an independent event which takes place under unique conditions. This context allows us to assess the impact of the post-peak economic recession on burglary by estimating the average annual burglary rate of growth over the period of expansion. Then, this is compared against the percentage change during economic downsizing, i.e. between peak and the subsequent trough. As shown in the table above, on average, the recessionary period lasts one year.

Therefore, to determine whether burglary rates increase or decrease during recessions, we estimate the percentage change of the *year after* the last peak. For instance, as shown in Table A.1.2.1, BC1 is between 1975 and 1980[48]. The trough-to-peak interval which represents the expansionary phase of the business cycle is between 1975 and 1979; whereas the recessionary period is the next year, 1980. A burglary growth rate during expansion (trough-to-peak) that is higher than the rate of growth in the subsequent recessionary year (peak-to-trough) indicates a procyclical crime; giving support to the opportunity theory. On

[48] Trough-to-trough period is between March 1975 and July 1980.

the other hand, burglary is countercyclical when the average rate of growth, during years of economic expansion, is lower than the growth rate of post-peak slump. This provides support to the motivational theory; which states that recessions increase the rate at which crimes are committed (Paternoster and Bushway, 2001).

As demonstrated in Table A.1.2.2, over the latest five business cycles (BC1 – BC5), burglary increases more during contractions than periods of economic growth; confirming that burglary rate is countercyclical.

The statistics indicate that burglary grew during periods of economic distress in all but one business cycle, BC2 (1980-1982). This post-war recession is a well-known exception which has puzzled scholars over the years (Cook and Zarkin, 1985). Since this business cycle is not included in the empirical analysis, due to data availability, we do not try to explain these paradoxical results.

Nevertheless, Table A.1.2.2 demonstrates that burglary grew 11%, on average, during BC1; around 2% during BC3 and BC4; and approximately 1% over the latest recession, BC5. This also showcases the overall burglary drop over recent years, as displayed in *Appendix A.1.1.2*.

By performing a state-level descriptive analysis, we can examine the wide-ranging effects of business cycles across states which are not visible when compounded in a national figure. For instance, during BC1, states such as Alabama, Iowa, Mississippi, Montana, New Jersey and New York; experienced increases over 17% whereas the national average was only 11%. The analysis indicates that 49 out of 51 states experienced increases in burglary rates during that year of economic distress. Over BC3, the lowest rate of growth was 0.03% in Wisconsin, whereas Missouri had the highest rate, 17.59%. Overall, the recession increases the rate at which burglaries are committed in 34 states. Over BC4 and BC5, the same pattern is observed. However, in the latest recession, BC5, only 25 states experienced higher growth rates during the economic slump than the expansionary period – this is examined more closely in the empirical analysis.

In general, the findings demonstrate the usefulness of a panel data setting since it unveils differences across years and states that national studies fail to capture. Also, the estimations provide evidence for the motivational theory and reinforce the notion that burglary is a countercyclical type of crime.

Table A.1.2.2: Crime Movements over 5 Business Cycles

	Reference Business Cycle									
	1975-1979 ***(BC1)***		**1980-1981** ***(BC2)***		**1983-1990** ***(BC3)***		**1991-2000** ***(BC4)***		**2002-2007** ***(BC5)***	
States	Annual Growth Trough to Peak (%)	Next Year (%)	Annual Growth Trough to Peak (%)	Next Year (%)	Annual Growth Trough to Peak (%)	Next Year (%)	Annual Growth Trough to Peak (%)	Next Year (%)	Annual Growth Trough to Peak (%)	Next Year (%)
United States	**2.08**	**11.39**	**4.60**	**-9.66**	**-2.24**	**1.61**	**-5.07**	**1.78**	**0.35**	**0.95**
Number of states in which the growth in burglary rate during expansion was less than the growth rate in the next year	**49**		**4**		**32**		**34**		**25**	
Alabama	2.64	18.60	6.81	-13.41	-1.30	14.97	-1.74	0.28	1.29	10.27
Alaska	3.37	-8.93	-1.68	-10.66	-3.18	9.50	-3.29	-2.38	-1.56	-13.66
Arizona	-5.67	7.95	1.86	-8.77	-1.19	-3.74	-4.67	2.12	-1.38	-4.73
Arkansas	-2.00	13.68	5.01	-0.61	1.78	1.29	-3.89	2.69	5.62	5.09
California	-0.33	5.93	1.28	-9.75	-4.89	3.89	-6.73	2.29	-0.50	-0.57
Colorado	-2.63	13.17	6.61	-13.91	-4.15	-4.18	-6.18	2.08	-1.17	-3.57
Connecticut	0.90	9.84	4.66	-16.61	-1.57	-2.98	-8.28	-2.42	-1.80	-3.38
Delaware	-3.97	6.74	2.74	-10.25	-4.55	16.19	-3.17	-2.99	2.54	4.65
District of Columbia	3.07	24.83	14.11	-11.53	-1.66	4.61	-7.66	3.98	-3.77	-4.11
Florida	-1.60	16.36	5.57	-14.36	1.06	-7.59	-6.66	-0.61	-1.19	3.21
Georgia	0.54	6.60	2.50	-10.42	1.36	-6.47	-6.29	2.10	1.74	9.76
Hawaii	-0.19	2.22	-2.65	-2.98	-3.01	0.50	-2.97	3.34	-3.67	3.08
Idaho	0.31	15.25	4.99	-12.07	-2.67	1.57	-3.23	0.35	-2.82	-6.90
Illinois	0.82	8.26	2.59	-9.11	-3.08	5.36	-4.55	-4.08	-1.18	4.17
Indiana	-3.68	12.26	0.63	-6.84	-1.66	3.58	-3.16	3.22	0.84	4.48
Iowa	3.09	17.07	7.98	-11.21	-1.88	2.98	-3.14	3.13	0.12	-3.83
Kansas	-0.68	14.41	7.95	-12.91	-1.47	12.02	-3.47	-4.99	-0.26	-4.86
Kentucky	-1.34	14.42	8.25	-3.13	-3.32	3.87	-1.88	5.83	-0.14	5.55
Louisiana	5.87	9.10	1.62	-0.68	0.29	-1.84	-3.17	0.32	1.45	-5.59
Maine	-4.15	3.04	4.10	-15.83	-2.78	9.66	-4.00	1.05	-0.69	-2.71
Maryland	1.73	12.49	5.13	-14.49	-2.77	3.37	-3.89	3.64	-2.51	4.45
Massachusetts	-1.49	8.46	1.57	-13.70	-2.84	4.89	-7.90	5.10	1.54	0.61
Michigan	-5.33	15.51	11.22	-2.63	-5.57	3.75	-4.64	2.52	0.81	0.03
Minnesota	-1.67	11.96	7.25	-7.47	-3.03	-5.91	-5.07	-3.65	1.95	-11.02
Mississippi	5.95	21.09	10.18	1.14	1.09	6.45	-2.57	10.20	-1.81	-6.94
Missouri	-0.92	15.36	5.11	-12.12	-3.14	17.59	-3.18	2.34	0.09	1.35
Montana	-2.08	18.34	9.98	-12.65	-1.98	-26.16	-3.73	-7.32	-1.52	5.07
Nebraska	2.07	12.53	6.11	-11.10	-0.92	0.39	-1.91	-4.16	-1.72	-3.83
Nevada	3.69	3.06	-1.56	-11.54	-6.67	2.67	-4.04	-3.74	2.47	-3.93
New Hampshire	8.93	9.50	-0.08	-20.33	-2.85	-0.01	-4.94	-3.91	0.41	-15.92
New Jersey	1.43	17.28	4.78	-17.45	-3.96	-0.15	-6.35	5.36	-4.03	8.54
New Mexico	-3.33	0.74	4.41	0.98	0.93	-0.90	-3.65	-8.97	-0.13	-1.29
New York	1.29	18.01	7.31	-16.06	-4.30	-2.43	-8.73	-9.09	-3.65	-0.03
North Carolina	0.44	9.74	1.84	-2.07	2.16	10.58	-2.16	2.10	-0.56	0.83
North Dakota	-3.56	5.92	4.22	-8.35	-0.13	-12.61	-2.19	4.36	1.83	0.69
Ohio	0.39	13.91	7.89	-12.32	-3.36	7.40	-2.16	8.99	0.34	3.24
Oklahoma	-0.74	14.79	4.33	0.95	-1.02	2.12	-4.34	8.61	-0.77	1.85
Oregon	-4.11	8.60	10.55	-9.01	-5.03	3.58	-3.84	2.46	-3.34	-9.15
Pennsylvania	-1.14	11.08	5.20	-12.68	-2.51	-1.30	-4.77	0.30	0.39	4.48
Rhode Island	1.98	10.72	3.57	-15.39	-0.88	-11.30	-6.60	1.98	-4.22	11.50
South Carolina	-3.03	10.88	3.22	-6.57	-0.78	5.40	-3.37	8.22	-0.28	-0.39
South Dakota	-1.39	10.55	1.10	-11.42	-0.56	11.83	-2.83	6.10	-2.40	0.36
Tennessee	-0.81	15.97	4.08	-6.91	0.00	7.99	-2.21	4.86	-0.51	4.31
Texas	2.04	3.46	2.19	0.06	0.19	-2.65	-6.77	5.52	0.02	-0.99
Utah	-0.15	12.13	4.28	-13.17	-2.53	-4.59	-2.73	-5.71	-0.14	-8.46
Vermont	10.86	-3.24	-0.54	-24.46	-0.72	-6.18	-5.75	-10.63	0.57	9.84
Virginia	-1.52	11.08	4.08	-16.62	-3.43	7.11	-5.00	2.14	-0.80	-0.24
Washington	1.02	4.41	3.01	-11.20	-3.08	-2.17	-3.14	-2.49	-1.16	-0.75
West Virginia	1.99	15.97	10.46	-7.38	-1.03	1.48	-1.72	-2.52	2.01	0.03
Wisconsin	1.08	13.70	6.52	-8.86	-3.02	0.03	-4.51	6.09	0.22	-2.01
Wyoming	0.26	4.62	5.48	-8.13	-3.47	9.70	-3.67	19.42	-1.55	-8.78

Nevertheless, although this descriptive analysis compares relative magnitudes of growth rates across business cycles and states; it does not provide an explanation as to why burglary rates are, on average, increasing during economic slumps (Cook and Zarkin, 1985). In other words, it only demonstrates whether and how changes in economic conditions affect burglary.

Thus, as demonstrated in *Section 1.4*, we attempt to empirically determine why this is the case by employing variables which capture economic incentives and control for law enforcement factors that could be linked to crime engagement. As explained in *Section 1.3*, we believe these variables are able to capture changes in economic opportunities and extensively, changes in an individual's behaviour, as induced by movements in economic conditions. This enables us to empirically assess the relationship between business cycles and burglary rates.

A.1.3 Summary Statistics

Table A.1.3.1: Descriptive Statistics

	Obs	Mean	Std.Dev.	Min.	Max.
Burglary Rates	1,350	6.74	0.40	5.73	7.74
Av. UI Benefits per newly Unemployed	1,350	5.47	0.19	4.86	5.99
Income Benefits per $1k Personal Income	1,350	-1.15	0.36	-2.38	0.00
Police Officer's Wages	1,350	8.37	0.22	7.90	9.04
Sentence Rate	1,350	9.11	1.29	5.86	12.07

Notes: All variables are in natural logs.

A.1.4 Correlation and Multicollinearity Tests

Table A.1.4.1: Bivariate Correlation Test, 1983-2009

	Burglary		UI		IncBen		PolOff		Sent
Burglary Rates	1								
Av. UI Benefits per newly Unemployed	-0.2874	***	1						
Income Benefits per $1k Personal Income	-0.1519	***	0.1953	***	1				
Police Officer's Wages	-0.1750	***	0.5925	***	0.2301	***	1		
Sentence Rate	0.2443	***	0.1151	***	0.3783	***	0.2276	***	1

Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.1.4.2: Multicollinearity (VIF) Test, 1983-2009

	VIF	1/VIF
Burglary Rates	1.26	0.7921
Av. UI Benefits per newly Unemployed	1.65	0.6061
Income Benefits per $1k Personal Income	1.26	0.7966
Police Officer's Wages	1.62	0.6180
Sentence Rate	1.38	0.7265

Notes: VIF stands for *variance inflation factor.*
1/VIF is the tolerance level, used to check colinearity.
VIF values greater than 10 or 1/VIF lower than 0.1 indicate merit for further investigaton.

A.1.5 Econometric Modelling

A.1.5.1 System GMM vs Difference GMM

A dynamic panel data setting is adopted to capture relationship between economic indicators and crime. Estimating a dynamic model, by construction, causes endogeneity issues since $crime_{state,t-1}$ and μ_{state} are correlated. In effect, conventional linear panel-data estimators, such as OLS[49] and within-groups/fixed effects[50], yield biased and inconsistent parameter estimates[51] since they fail to effectively control for this correlation.

Thus, to avoid the above problems, we consider two estimators, the difference (DIFF GMM) and the system GMM (SYS GMM). Both DIFF GMM and SYS GMM account for the endogeneity in the model by instrumenting $crime_{state,t-1}$ and other potentially endogenous regressors with variables uncorrelated with area specific fixed effects. The DIFF GMM eliminates unobserved specific effects by taking first-differences. It corrects for endogeneity in *difference* equations by using *lagged levels* as instruments. The SYS GMM incorporates an additional set of equations, in *levels*, using *lagged first-differences* as instruments while using lagged levels to instrument equations in first-differences. That is, the model is estimated in both differences and levels, *jointly*, in a system.

Assuming (1) the error terms are serially uncorrelated and (2) regressors are endogenous; the DIFF GMM estimator follows these two moment conditions:

$$E\left[crime_{state,t-\tau}\left(\Delta e_{state,t}\right)\right] = 0 \qquad for\ \tau = 2..,t-1,\ \ t = 3,\dots,T \tag{2}$$

$$E\left[\mathbf{x}_{state,t-\tau}\left(\Delta e_{state,t}\right)\right] = 0 \qquad for\ \tau = 2..,t-1,\ \ t = 3,\dots,T \tag{3}$$

Thus, provided that there is no AR(1), valid instruments for the equations in first-differences are lags dated $t-2$ and earlier. Although asymptotically consistent, the DIFF GMM is not

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[49] OLS does not control for the correlation between the error term and lagged dependent variable, giving rise to Nickell bias. This correlation between a regressor and the error violates an important assumption necessary for the consistency of OLS (Fajnzylber *et al*., 2002a, 2002b; Roodman, 2009b, Blundell and Bond, 2000).

[50] Although, the within-groups estimator tries to correct for this endogeneity by transforming the data to remove unobserved area fixed effects; the estimator is inconsistent when T is fixed and does not eliminate Nickell bias entirely (Nickell, 1981; Bond, 2002; Drukker, 2008; Roodman, 2009b).

[51] The estimates reflect the short-term relationships between the dependent variable and the regressors (Levitt, 2001).

ideal within the context of this study. Firstly, it eliminates area-specific fixed effects, making it impossible to examine the cross-state relationship between crime and economic indicators. Further, the difference GMM estimator suffers from large finite sample biases when lagged instruments are only weakly correlated with and contain little information about the endogenous variables in first-differences equations. Weak instruments are more prevalent when the dependent variable and the regressors are highly persistent, series are stationary and when T is small (Blundell and Bond, 2000)[52].

SYS GMM reinforces these issues by exploiting more moment conditions and adds a *levels* equation to complement the DIFF GMM. It requires for the series to be highly persistent and stationary, i.e. $E\left(\Delta crime_{state,t}\,\mu_{state}\right) = 0$ and $\left(\Delta \mathbf{x}_{state,t}\,\mu_{state}\right) = 0$. Thus, it requires the first-differences of both the dependent and independent variables to be uncorrelated with the area-specific effects. Correlation between the *levels* of the corresponding variables and the state fixed effects is allowed. Effectively, lagged differences are valid instruments for the levels equations (Arellano and Bover, 1995; Blundell and Bond, 1998). Assuming endogenous regressors, the SYS GMM estimator is more informative and its performance improves compared to DIFF GMM[53] when the below *additional* moment conditions hold:

$$E\left[\Delta crime_{state,t-\tau}\left(\varepsilon_{state,t}\right)\right] = 0 \qquad for\ \tau = 1,\ \ t = 3, \dots, T \tag{4}$$

$$E\left[\Delta \mathbf{x}_{state,t-\tau}\left(\varepsilon_{state,t}\right)\right] = 0 \qquad for\ \tau = 1,\ \ t = 3, \dots, T \tag{5}$$

Hence, at $t-2$, SYS GMM estimator combines equations in first-differences and levels into a joint system. It utilises lagged levels of endogenous variables as instruments for equations in differences while using lagged differences to instrument endogenous variables in level equations.

This methodology allows to investigate both short- and long-run dynamics of the link between crime rates and economic factors. To determine which of the two estimators fits the analysis better, Blundell and Bond (2002) outline a set of assumptions. If satisfied, the

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[52] Appendices A.1.5.2 and A.1.5.3 perform various empirical tests to examine and prove that SYS GMM is the most appropriate estimator for this study.

[53] Blundell and Bond (1998) demonstrate that the system GMM has better asymptotic and finite sample properties compared to difference GMM.

parameter estimates produced by the SYS GMM are more consistent and efficient than the estimated coefficients of DIFF GMM. The assumptions of SYS GMM require that the series is highly persistent, in both levels and first-differenced equations, while also being stationary, in differences. These are examined in *Appendices A.1.5.2* and *A.1.5.3*.

A.1.5.2 Testing for Series Persistency

To test for series persistence, Blundell and Bond (1998, 2000) and Bond (2002) suggest estimating simple first-order autocorrelation models, including year dummies, with all available lags. As shown in Table A.1.5.2.1, the burglary rate, the economic indicators and the law enforcement variables considered are highly persistent[54]. This provides the first indication that lagged levels, employed by DIFF GMM, are weak instruments for the differenced equations. In other words, under this framework, DIFF GMM produces biased estimates.

As advanced in *Appendix A.1.5.1*, SYS GMM is more efficient than DIFF GMM when the series is highly persistent and stationary (in differences). Using simple AR(1) models including year dummies[55] can test for the series persistence. As shown in the tables below, crime rates are highly persistent. The results reassure us that the first assumption made by Blundell and Bond (1998) for the use of SYS GMM, that the series is persistent, is satisfied.

As shown, for the crime rates, both DIFF and SYS GMM estimators suggest a very high autoregressive coefficient, above 0.9 for most crime rates. Since there is an autocorrelation of order 1, the preferred specification is to use SYS GMM including instruments from the third lag and further. Further, arrest rates, young male population, population density show a high persistence, around 0.9. Unemployment compensation and police expenses are also persistent but to a lesser degree; around 0.6. Imprisonment rates have a coefficient of 0.7 (SYS, t-2 columns). Notice that they do not experience autocorrelation of order 1 and thus, the instrument set can include instruments from second lag and further.

[54] Various estimators (OLS, within-groups, and variations of DIFF and SYS GMM) are employed to compare series persistence across different estimation frameworks.

[55] Accounting for heteroskedastic robust errors; allowing observations to be independent across states (clusters) but not necessarily within states.

Table A.1.5.2.1: AR(1) Model Estimates, 1983-2009

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS levels	within groups	one-step DIFF t-2	one-step DIFF t-3	one-step SYS t-2	one-step SYS t-3	two-step DIFF t-2	two-step DIFF t-3	two-step SYS t-2	two-step SYS t-3
Burglary Rate,t-1	0.99^{***}	0.89^{***}	0.76^{***}	0.74^{***}	0.87^{***}	0.97^{***}	0.70^{***}	0.68^{***}	0.87^{***}	0.99^{***}
	(0.00)	(0.02)	(0.07)	(0.07)	(0.06)	(0.04)	(0.10)	(0.12)	(0.07)	(0.05)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.24	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.44	0.69	0.46	0.47	0.45	0.48	0.49	0.49	0.49	0.50
Sargan			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen			0.27	0.23	0.17	0.17	0.27	0.23	0.17	0.17
Diff-in-Hansen all					0.01	0.12			0.01	0.12
Unemp.Benefits,t-1	0.97^{***}	0.82^{***}	0.94^{***}	0.91^{***}	1.05^{***}	0.93^{***}	0.97^{***}	0.95^{***}	1.08^{***}	0.95^{***}
	(0.01)	(0.02)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)	(0.05)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.08	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.61	0.68	0.52	0.50	0.53	0.50	0.51	0.51	0.53	0.51
Sargan			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen			0.28	0.21	0.42	0.27	0.28	0.21	0.42	0.27
Diff-in-Hansen all					1.00	0.66			1.00	0.66
Inc.Benefits,t-1	0.95^{***}	0.87^{***}	0.98^{***}	0.96^{***}	0.98^{***}	0.96^{***}	0.98^{***}	0.97^{***}	0.99^{***}	0.96^{***}
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.78	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.36	0.34	0.51	0.51	0.51	0.51	0.51	0.51	0.50	0.50
Sargan			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen			0.04	0.03	0.05	0.03	0.04	0.03	0.05	0.03
Diff-in-Hansen all					0.80	0.29			0.80	0.29
Gini Coeff,t-1	0.68^{***}	0.26^{***}	0.22^{***}	0.30^{**}	0.21^{***}	0.32^{**}	0.21^{***}	0.17	0.19^{***}	0.21
	(0.04)	(0.04)	(0.04)	(0.14)	(0.04)	(0.13)	(0.04)	(0.19)	(0.04)	(0.20)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
AR(2) p-value	0.46	0.72	0.33	0.82	0.28	0.89	0.23	0.48	0.19	0.60
Sargan			0.09	0.11	0.08	0.13	0.09	0.11	0.08	0.13
Hansen			0.23	0.22	0.30	0.17	0.23	0.22	0.30	0.17
Diff-in-Hansen all					1.00	0.12			1.00	0.12
Police Off. Pay, t-1	0.99^{***}	0.78^{***}	0.55^{*}	0.68^{***}	0.79^{***}	1.03^{***}	0.45	0.65^{***}	0.82^{***}	1.01^{***}
	(0.00)	(0.04)	(0.28)	(0.17)	(0.08)	(0.05)	(0.30)	(0.20)	(0.08)	(0.04)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.00	0.01	0.03	0.00	0.00	0.00	0.06	0.00	0.00	0.00
AR(2) p-value	0.40	0.05	0.14	0.07	0.03	0.05	0.16	0.07	0.04	0.04
Sargan			0.00	0.02	0.02	0.11	0.00	0.02	0.02	0.11
Hansen			0.63	0.86	0.43	0.92	0.63	0.86	0.43	0.92
Diff-in-Hansen all					0.13	0.95			0.13	0.95
Impr.Rate,t-1	1.03^{***}	0.96^{***}	0.93^{***}	0.93^{***}	1.05^{***}	1.04^{***}	0.93^{***}	0.93^{***}	1.05^{***}	1.04^{***}
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
No of Instr			50.00	49.00	52.00	51.00	50.00	49.00	52.00	51.00
AR(1) p-value	0.10	0.14	0.06	0.04	0.03	0.03	0.04	0.04	0.03	0.03
AR(2) p-value	0.05	0.05	0.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Sargan			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen			0.04	0.03	0.06	0.03	0.04	0.03	0.06	0.03
Diff-in-Hansen all					1.00	0.94			1.00	0.94

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All variables are in natural logs, except the Gini coefficient which is multiplied by 100. All equations include a full set of set of state specific effects and yearly dummies. Sample period 1983-2009 for 50 PFAs (excl. District of Columbia). The reported standard errors are robust to heteroskedasticity. *Columns (1)* and *(2)* estimate the model using OLS and within-groups estimators, respectively. *Columns (3), (4), (7)* and *(8)* report the estimated results using the difference GMM in one- and two-step specifications. Respectively, in *columns (5), (6), (9)* and *(10)* the model is estimated using system GMM in one- and two-step variations. Instruments, for the difference equations, in *columns (4), (6), (8) (10)* include lags from *t-3* to *t-4*. Instruments, for the difference equations, in *columns (3), (5), (7)* and *(9)* include lags from *t-2* to *t-4*.

A.1.5.3 Testing for Series Stationarity

The second condition set-out by Blundell and Bond (1998)[56] for the use of SYS GMM supports that increases in efficiency can be achieved when also the stationarity requirement is also satisfied (Yasar, 2003; Roodman, 2009a, 2009b). This assumption concerns the *additional* equation in levels. In other words, it requires that the dependent variable, in *differences*, is stationarity. The *differences* of the right-hand side variables should not be correlated with the state-specific effect, i.e. no unit root in differences. Correlation between the *levels* of the corresponding variables and the state fixed effects is allowed, i.e. can have unit root in levels. Essentially, this test ascertains that when the explanatory variable is stationary, lagged differences are valid instruments for equations in levels.

To test for the series stationarity, the Levin-Lin-Chu panel-data unit root test[57] is implemented. As shown in Table A.1.5.3.1, the series are stationary in *first-differences* and have a unit root in *levels*.

Therefore, SYS GMM is our preferred estimator as both tests, of autocorrelation and stationarity, provide tentative evidence to support the usefulness of the additional set of internal instruments utilised by the level equation.

Table A.1.5.3.1: LLC Unit Root Test, 1983-2009

	(1) First Differences	(2) Levels
Burglary Rate	0.00	0.01
Unemployment Benefits	0.00	0.03
Income Benefits	0.01	1.00
Police Officers Pay	0.00	0.00
Sentence Rate	0.00	0.00

Notes: LLC stands for Levin-Lin-Chu test. The null hypothesis is that panel contains unit root whereas the alternative is that panels are stationary.

[56] First outlined by Arellano and Bover (1995)

[57] The Im-Pesaran-Shin test is also used and confirms the results.

A.1.5.4 Specification Tests and Instrument Validity

As advanced earlier, the efficiency of system GMM depends on the validity of instruments. Inclusion of 'too many' instruments (Roodman 2009) causes instrument proliferation. In other words, overfitting the model produces biased estimates[58]. In effect, we perform various specifications tests to ensure instrument validity and correct model specification.

Further, including numerous instruments might significantly weaken the power of specification tests, such as the Hansen test, by producing implausibly perfect p-values of 1[59] (Anderson and Sørenson, 1996; Roodman, 2006, 2009a, 2009b). The Hansen test of over-identifying restrictions assesses the *overall* validity of the instruments used. Specifically, it determines whether the structural model specification is correct. Therefore, if the test reports p-values of 1, the simplest and most effective way[60] to avoid instrument proliferation is to limit the number of lags used as instruments.

Further, using the difference-in-Hansen test, we examine the validity of the *additional* instruments (compared to the DIFF GMM) of the level equation when estimating the model using SYS GMM (Blundell and Bond, 2000). The null hypothesis denotes that the subset of instruments employed by the level equations is valid (Roodman, 2009a). However, as with the Hansen test, a high instrument count, weakens the test.

Accordingly, given the relatively modest cross-sectional dimension of our sample, we address our concerns of overfitting the model in two ways. Firstly, as advanced earlier, we limit the number of internal lags. Secondly, as suggested by Roodman (2009a, 2009b), the instrument list is *collapsed*[61].

Finally, to address concerns of autocorrelation in the model, rendering the instrument list invalid, we perform Arellano-Bond's (AB) serial correlation test (Arellano and Bond, 1991). The test ensures instrument validity by examining whether the idiosyncratic disturbance

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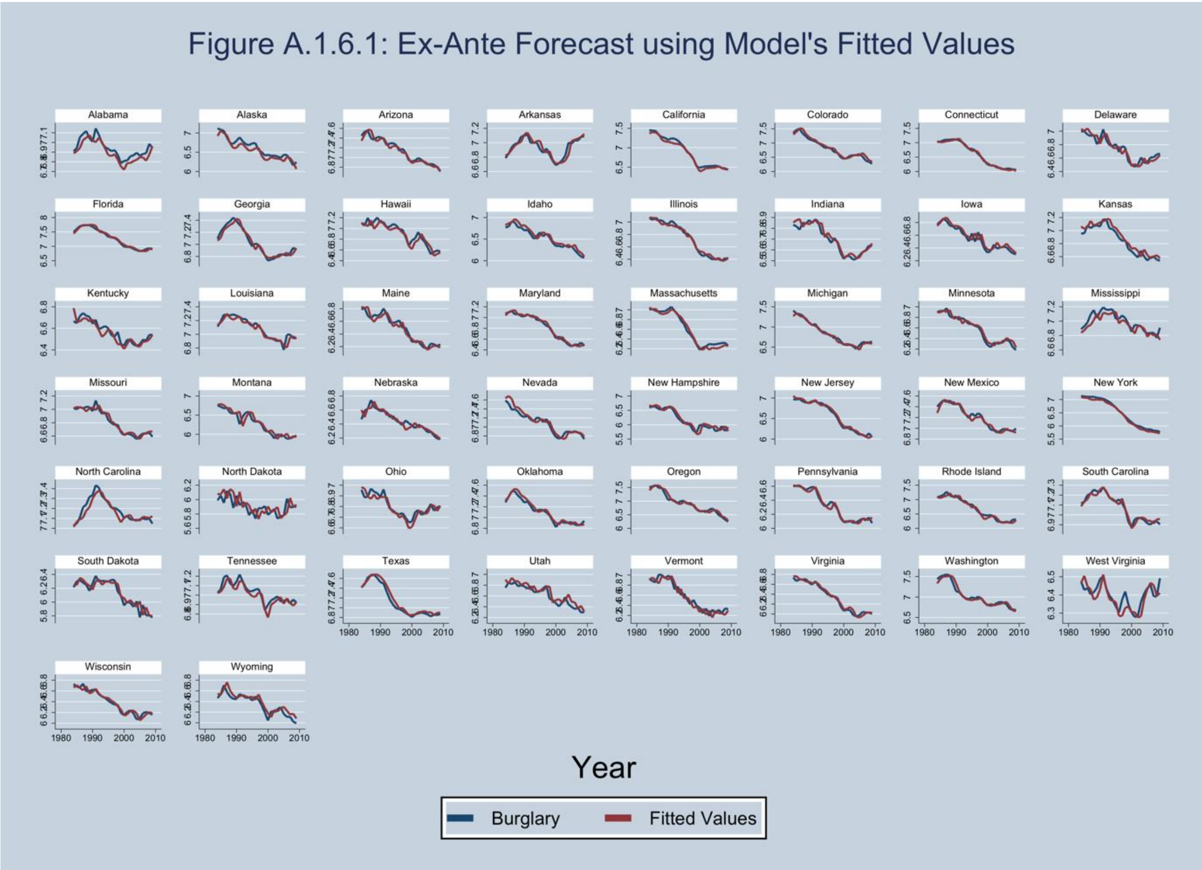
[58] Converging towards the biased estimates produced by the fixed-effect estimator.
[59] The statistic takes values between 0 and 1. Thus, a high p-value is regarded as a sign of validity of GMM estimation results (Roodman, 2009a).
[60] For an extensive discussion of all the methods that can be used to avoid instrument proliferation, read Roodman (2009a).
[61] The *collapse* command produces an instrument list that consists of one instrument for each lag distance and instrumented variable. This method makes the instrument count linear in the time dimension of the sample. This option is available when using Roodman's *xtabond2* package in Stata.

term, ϵ_{st}, is serially uncorrelated. The null hypothesis is that the error term, ϵ_{st}, is not serially correlated. Failing to reject the null, provides support to the model specification.

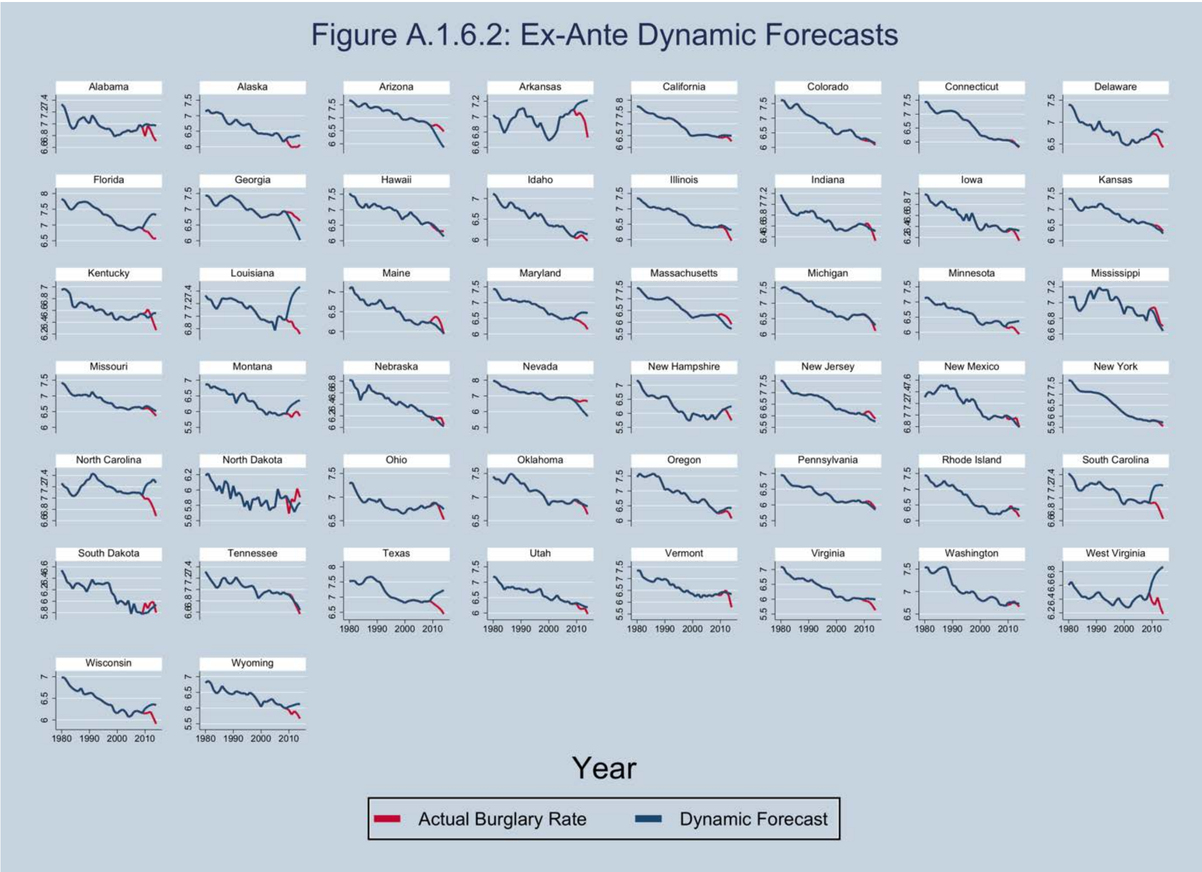
Nevertheless, first-order serial correlation of the differenced residual is common when the model examined is dynamic (Roodman, 2009b; Fajnzylber *et al*., 2002). Fortunately, this endogeneity issue can be easily resolved by restricting the number of lags that are included in each instrument set. That is, if the above argument is true, i.e. there is AR(1) but not AR(2), in order to instrument the lagged dependent variable, the instrument matrix in *differences* must include instruments from the third lag, $\Delta crime_{st-3}$, onwards; while the instrument set in *levels* should include instruments from lag 1, $crime_{st-2}$, and further. If the test indicates the existence of second-order autocorrelation, then even longer lags should be considered (Roodman, 2009b).

A.1.6 Forecasting

A.1.6.1 Ex-ante Forecasting



A.1.6.2 Ex-ante Dynamic Forecasting



Chapter 2

The Impact of Economic Incentives on Crime in England and Wales: A Panel Data Analysis

Abstract

This study utilises a panel data of violent and property crime rates, for a sample of 42 Police Force Areas (PFA) in England and Wales for the period 2000/01-2011/12, to analyse the impact of economic indicators on crime rates. A novel Gini coefficient is constructed using micro-level data from the *Annual Survey of Hours and Earnings (ASHE)* to examine the relationship between crimes and income inequality. Jobseeker's allowance (JSA) and income support (IS) benefits are used to capture specific disadvantaged groups of the population who, traditionally, have been linked to crimes. A panel-data based system GMM methodology is used to estimate a dynamic model of crime rates. This estimator controls for unobserved PFA-specific effects, the existence of measurement error and the joint endogeneity of lagged crime rates, economic indicators and law enforcement variables. The results show that economic indicators affect crime both in the short- and long-run with the impact being stronger in the long-run. Property crimes and robbery are affected by changes in JSA, IS and income inequality, whereas violence against person and sexual offences are not but are affected by law enforcement factors.

Glossary G.2

The following list of abbreviations, used in Chapter 2, is expanded below.

SYS GMM	System GMM estimator
DIFF GMM	Difference GMM estimator
GMM	Generalised Method of Moments estimator
OLS	Ordinary Least Squares estimator
ONS	Office for National Statistics
PFA	Police Force Area
ASHE	Annual Survey of Hours and Earnings
JSA	Jobseeker’s Allowance
IS	Income Support benefits
LA	Local Authority
AB	Arellano-Bond serial autocorrelation test
IV	Instrument Variable estimator

2.1 Introduction

Economic models of crime have analysed how financial incentives affect criminal participation. According to Becker (1968)[62], individuals are utility maximisers and decide whether to engage in a criminal activity by assessing the returns from available legal and illegal opportunities. The returns to legitimate activities are determined by expected returns to a specific activity. Likewise, returns to illegitimate activities depend on the expected crime payoff but they are discounted by the probability of apprehension and incapacitation[63] (Draca and Machin, 2015).

In this framework, deteriorating labour market opportunities can shift an individual's incentives to engage in legitimate or illegitimate acts (Raphael and Winter-Ebmer, 2002; Machin and Meghir, 2004). Further, the literature supports the view that this theoretical framework better describes property crime offenders, as property crime is usually assumed to be financially motivated[64].

This chapter empirically reassesses the link between economic incentives and crime. Our contribution is threefold. First, the crime-inequality link is re-examined using a Gini coefficient from micro-level data. Second, specific economic indicators are used to capture the incentives of the unemployed and economically disadvantaged. Third, we explicitly account both for the dynamic nature of crime and potential endogeneity of all regressors in the crime equation. We discuss each in turn.

We re-examine the relationship between crime and income inequality by constructing a novel Gini coefficient, at the police force area (PFA) level, using micro-level data. To our knowledge this is the first study to include an income inequality measure estimated at the same level of disaggregation as the level at which crime statistics are available. Most studies

[62] Becker's (1968) analysis is abundantly generic in terms of what constitutes a criminal activity. It is not limited to violent and property felonies but rather, covers all different kinds of violations; such as traffic violations, tax evasion, white-collar crimes and others.
[63] An apprehended offender loses access to legal earnings and thereafter, faces labour market discrimination upon release and expects lower wages.
[64] The empirical findings confirming this are discussed, in detail, in *Section 2.2*.

use a national[65] figure to control for income inequality (Han et al., 2013) or an inter-quantile measure (Witt et al., 1998; 1999, Wu and Wu, 2012). A national measure of inequality is restrictive and limiting in a panel setting since it does not allow for earnings inequality to be measured at the area level. The alternative measure, the inter-quantile wage rate, is estimated as the ratio of the upper to lower quantiles. Although it can be measured at the PFA level[66], it omits the middle class since, it accounts only for the upper and lower quantiles of the wage distribution, meaning that the largest proportion of the population is left out.

Second, this paper makes use of unemployment and income benefits which we argue affect the individual's decision on whether to engage in a criminal act rather than just the state of unemployment alone[67]. That is, the income received during a period of unemployment, through unemployment benefits, (or, through government benefit payments even for the employed, if a low-earner) is what crucially affects the costs and earnings of an individual's decision-making, not the state of unemployment or poverty *per se*.

These monetary transfers are important since they may act as an income effect (Bindler, 2017) while also influencing the ratio of returns-to-work against the returns-out-of-work (Machin and Meghir, 2004). To the best of our knowledge, this is the first study to examine the effect of benefits on crime[68], in England and Wales.

We consider two income measures when a person is unemployed or under-employed: jobseeker's allowance (JSA) and income support (IS), respectively. JSA is paid to individuals who are actively seeking employment whereas IS is a governmental support subsidy paid to low-earners. These two income measures are both significant determinants of crime and better measures of legal alternatives than the unemployment rate – particularly for

[65] Captures the whole United Kingdom: Scotland and Northern Ireland included; while the studies focus on England and Wales.

[66] By aggregating wage-quantiles from the Local Authority (LA) level.

[67] Unemployment does affect this calculation, as demonstrated by previous research, but empirical evidence documents a weak link between unemployment and crime, despite the intuitive appeal of the above theoretical argument. On the other hand, research examining the relationship between crime and earnings reports stronger effects, presumably because changes in returns to activities better capture shifts in individual's incentives (Grogger, 1998; Gould et al., 2002; Machin and Meghir, 2004).

[68] Field (1990) is the only other paper that, in our knowledge, tests the link between unemployment benefits (by also including unemployment rates in the same regression) and crime. However, it is a national time-series study between 1950 and 1987. Although 12 crime categories were considered, unemployment benefits are only included in the regressions for thefts from vehicle and violence against the person. See *Appendix A.2.3* for more information.

individuals who are struggling economically, forcing them on the brink of offending.

Thus, higher benefit payments may reduce crime by altering the relative incentives linked to engaging in legal and illegal activities, during the un(der)employment state. Further, since violent behaviour may be less akin to economic incentives, property crimes and robbery are expected to have a stronger link to economic indicators compared to violent crimes (Raphael and Winter-Ebmer, 2002; Machin and Meghir, 2004; Malby *et al*., 2012).

Finally, the literature often overlooks three important issues when examining the link between economic activity and crime. *First*, the dynamic nature of crime is generally ignored[69]. Crime trends tend to be persistent over time indicating that crime depends to a large extent on its past realisations. A lagged crime variable is included in the model to account for crime's persistence. *Second*, many of the explanatory variables are possibly endogenous, i.e. it is likely that crime itself affects these regressors. Thus, estimating this dynamic model using OLS or fixed-effects estimators produces biased estimates. *Third*, unobserved area-specific fixed effects, such as measurement error, might be correlated with both the dependent variable and the regressors (Fajnzylber et al., 2002b; Yasar, 2003) leading to biased estimates.

To account for these issues, an instrumental variable procedure used in dynamic panel data models, known as the system GMM (SYS GMM) estimator, is employed. The SYS GMM utilises the dynamic properties of the data to generate valid instruments by employing internal lags. The model estimates, *jointly*, equations in levels and in first-differences. The *levels* equations employ lagged instruments in *differences* whereas the equations in *first-differences* use lagged *levels* as instruments. Thus, the joint endogeneity of all three economic indicators – JSA, IS and Gini coefficient – and law enforcement variables is addressed by instrumenting[70] current values with past realisations that are not correlated with the error term. Further, although the inclusion of the lagged dependent variable is expected to mitigate any concerns of omitted-variable bias, we also include observable

[69] Exceptions are Machin and Meghir (2004) and Han *et al*. (2013).

[70] The validity of the instrument list is tested using Sargan/Hansen tests and Arellano-Bond test for serial autocorrelation. The null hypothesis, in both tests, gives support to the model specification.

demographic variables and control for area and year fixed effects. Finally, this methodology allows one to estimate both the short- and long-run effects of economic indicators on crime.

The findings indicate significant effects of economic indicators on crime, both in the short-run and the long-run. In fact, the percentage changes in the long-run are emphatically larger in magnitude. Specifically, the findings indicate that, in the short-run, a 10% increase in unemployment benefits leads to a 1.2%, 0.7% and 1.2% reduction in robberies, burglaries and thefts, respectively. These effects become significantly stronger in the long-run for all three crimes with the reductions amounting to 3.2%, 2.5% and 2.2%, respectively. Income support payments are only significant for robbery, as a 10% increase can lead to a 12% and 32% decrease in the short- and long-term. Furthermore, income inequality has a significant positive effect on robbery and thefts. A 10% higher income inequality can lead to 0.9% and 0.6% increase in robbery and thefts, respectively. Both effects significantly increase in size over the long-run, to 2.4% and 1.1%, respectively.

In line with the literature, we find that violent crimes are not affected by economic incentives. In contrast, violent crimes are more responsive, both in short- and long-run, to changes in the probabilities of apprehension and sentence lengths than property crimes[71]. Higher detection rates lead to lower violent crimes whereas longer sentences increase the occurrences of violence against the person. Additionally, robberies and burglaries (in the long-run) are positively affected by the number of police officers. Finally, in line with earlier research, a larger proportion of male juveniles has a positive effect on robberies, burglaries (in the long-run) and thefts.

The structure of the rest of the chapter is as follows. In *Section 2.2*, a detailed literature review, with particular emphasis on empirical work undertaken for England and Wales, is presented. In *Section 2.3* the data, covering 42 police force areas in England and Wales, are described while in *Section 2.4* the empirical methodology used is discussed. In *Section 2.5*,

[71] Probability of apprehension is proxied by including a ratio of PFA residents to police officers and detection/conviction rates. Average sentence lengths capture the severity of punishment, once apprehended. Correlation and multicollinearity tests indicate that inclusion of both variables does not create any issues. See *Appendix A.2.4.2*.

the empirical findings are presented while *Section 2.6* discusses the findings from various robustness checks. Finally, *Section 2.7* concludes.

2.2 Literature Review

Economic models[72] consider crime as an alternative to legal job markets. That is, the propensity of criminal engagement depends on changes in the expected costs and benefits of illegitimate activity and the expected returns from legal job opportunities (Becker, 1968; Ehrlich, 1973, 1981, 1996; Levitt, 1997). In general, these economic models look at crime and employment in a similar way; both require time and generate income (Ehrlich, 1973; Witte and Tauchen, 1994; Grogger, 1998; Fagan and Feeeman, 1999; Raphael and Winter-Ebmer, 2002; Machin and Meghir, 2004; Lochner, 2004, 2010).

The paper of Becker (1968)[73] is the first formal effort of an economist explaining why individuals engage in criminal activities. He posits crime as a rational decision[74]. Under this framework, direct and indirect economic incentives affect crime participation. The direct effect comes in two complementary forms, *alternatives* and *returns* to crime, whereas *deterrence* and *incapacitation* effects can indirectly affect crime participation (Draca and Machin, 2015). The direct effect accrues from a cost-benefit assessment of participating in legal or illegal activities. The model demonstrates that individuals compare their payoffs gained in each activity to decide whether it is beneficial to commit a crime.

However, if they do engage in criminal activities, offenders face a probability of apprehension – that is the indirect effect. Consequently, earnings coming from illegal activities are discounted by the risk of getting caught and the possible sanctions that may

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[72] For comprehensive reviews, see Chiricos (1987), Freeman, 1999, Webster and Kingston (2014), Draca and Machin (2015).
[73] Ehrlich (1973, 1981, 1996), Block and Heineke (1975), Levitt (1997), Lochner (2004, 2010) Machin and Meghir (2004) and others have extended and/or modified this model. Pyle (1995) reviews the evolution of economic theory in detail.
[74] Although, this notion – of the criminal following rational judgements – may strike many as unrealistic, as Friedman (1953) suggests, it is the theory's predictive power that matters, not the realism of its assumptions. Empirical research has demonstrated that criminals respond to changes in opportunity costs, in the likelihood of apprehension, the severity of punishment and other related factors; effectively giving support to this economic approach. Thus, whether a criminal's actions are rationally calculated or not, the underlying proposition is that economic circumstances induce criminal behaviour. This argument is intuitively appealing and based on the premise that individuals respond to incentives (Raphael and Winter-Ebmer, 2002).

follow. The model predicts that if the expected net gains exceed the expected net costs of offending, then the individual will commit a crime. In general, the model forecasts that, *ceteris paribus*, higher illegal payoffs increase crime whereas higher legal returns, higher probability of apprehension and stricter sanctions, if caught, lead to less crimes.

2.2.1 Crime and Unemployment

To measure the direct effect on crime, researchers considered various economic indicators and, by far the most widely used is the unemployment rate (Field, 1990, p.7). This is unsurprising since, both crime and unemployment have traditionally been at the top of the political agenda in an effort to keep them as low as possible (Hale and Sabbagh, 1991; Carmichael and Ward, 2000). Despite researchers studying extensively the link between these two variables, the evidence is mixed or as Freedman (1999) describes it "*fragile, at best*". Nevertheless, comprehensive literature reviews (Chiricos, 1987; Freeman, 1983, 1999; Freeman and Rodgers, 1999; Papps and Winkleman, 2000; and Draca and Machin, 2015) indicate that more often than not there is a positive link between unemployment and crime. A summary of the literature for England and Wales can be found in *Appendix A.2.3*.

Older studies use national-level time-series data[75]. However, this level of aggregation is uninformative since it does not allow for the useful local variation of unemployment and crime to be explored (Chiricos, 1987; Pyle and Deadman, 1994; Levitt, 2001; Draca and Machin, 2015). Recent empirical studies are more refined and allow for area-specific variation by using panel data[76]. Yet, several of these studies focus on the *contemporaneous* link between unemployment and crime. However, the lagged relationship is also important as the impact of unemployment on crime may not be instantaneous.

A popular view, first described by Cantor and Land (1985)[77], is that unemployment causes two opposing effects: the motivational and opportunity effects. On the one hand, the

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[75] Wolpin (1978), Field (1990), Hale and Sabbagh (1991), Pyle and Deadman (1994, 1997), Hale (1998) and Saridakis (2011).

[76] Witt *et al.* (1998, 1999), Carmichael and Ward (2000, 2001), Machin and Meghir (2004), Wu and Wu (2012) and Han *et al*. (2013).

[77] The study of Cantor and Land (1985) has been criticised by many scholars (Hale and Sabbagh, 1991; Hale, 1991; Greenberg, 2001). Among them, Hale and Sabbagh (1991), using annual time-series for the UK (1949-1987), demonstrate that the Cantor and Land's model is susceptible to changes in model specification and technique specification. They support that there is a strong positive link between unemployment and crime.

motivational effect is in-line with the predictions made by economic models (Carmichael and Ward, 2000). Due to high unemployment, legal labour market opportunities are limited and the opportunity cost of engaging in criminal activity is lower (Willis, 1983; Witt *et al*., 1999). Thus, the motivational effect predicts a positive relationship between unemployment and crime (Hale and Sabbagh, 1991; Witt et al., 1998, 1999; Carmichael and Ward, 2000, 2001).

On the other hand, the *opportunity effect*, predicts a negative link between the two. When unemployment is high; fewer goods are circulated and consumed in the economy and consequently, there is less to steal (Field, 1990; Witt *et al*., 1999; Winter, 2008). In addition, higher levels of unemployment imply that more people stay at home; protecting themselves (due to a lower possibility of encountering an offender) and their belongings. This is also known as the guardianship effect.

The interaction of these two opposing effects may explain why the net effect of unemployment on crime is found to be ambiguous (Pyle and Deadman, 1994; Witt et al. 1999). While national time-series studies tend to find the weakest link between the two (Chiricos, 1987), empirical analyses conducted at lower levels of aggregation find a stronger positive relationship between unemployment and (property) crime. Witt et al. (1998, 1999) examine the relationship between male unemployment rate and property crime and find a strong positive link between the two. Carmichael and Ward (2000, 2001) test the relationship between adult and young unemployment with crime and find that the latter has a stronger motivational effect. However, using more recent data (2002-2007), Wu and Wu (2012) fail to find a significant link between male unemployment and crimes[78], for both property and violent.

Unemployment rate is a rather problematic economic indicator and the mixed evidence may be occurring for a number of reasons. By definition, unemployment excludes individuals who are labour force inactive as well as under-employed[79] (Chiricos, 1987; Greenberg, 2001; Andresen, 2013). The former relates to individuals who either stopped looking for a job or who never searched for full-time employment because they never believed they could secure one. Effectively, unemployment rates do not accurately account for the real level of

[78] However, they do find a correlation between crime and fraud (negative), drug and other crimes (positive).
[79] For instance, individuals on non-discretionary part-time employment.

unemployment (Arvanites and Defina, 2006). Further, it excludes low-wage earners and thus overlooks that work and crime are not mutually exclusive (Machin and Meghir, 2004). That is, crimes can be committed by both the employed and the unemployed, despite differences in incentives. Inevitably, many researchers turned their focus into other economic indicators such as wages and poverty rates. The findings indicate an unambiguous relationship between economic variables and crime.

2.2.2 Crime and Earnings

Machin and Meghir (2004) suggest that wages are better suited to capture economic incentives and utilise a panel of 42 police force areas in England and Wales, between 1975 and 1996, to prove it. They use two wage measures, based on the 25th percentile of the *overall* and *retail trade wage* distribution, to explore the relationship between property crime and the labour market opportunities for less skilled workers. Their findings predict a strong link between low-wage workers and property crime (crime against the property and vehicle crimes).

Other researchers study the link between income inequality and crime. The theory predicts that, the greater income inequality, the higher the incentive to commit a crime since individuals at the bottom-end of the distribution experience lower opportunity costs, in terms of earnings and conviction. Witt *et al*. (1998, 1999) define wage inequality as the ratio of the 90th to 10th decile of manual male gross weekly earnings. They find that increases in relative wages reduce property crimes. Likewise, Wu and Wu (2012) define income inequality as the ratio of the 10th to 90th percentile of male wage for 10 regions in England and Wales between 2002-2007. Using random effects, they find evidence to support that property crimes (robbery included) – which are more likely to be affected by economic incentives – and male income inequality are positively related. Saridakis (2011) tests the long-run relationship between poverty rate and violent crimes in England and Wales. He finds that a positive relationship exists only for aggravated assault.

2.3 Data Description

A dynamic panel model for England and Wales is estimated using data collected from various sources. The panel dataset is disaggregated at 42[80] Police Force Areas (PFAs) between 2000/01 to 2011/12. *Appendix A.2.1.1* summarises the definitions, the sources, and the disaggregation level of each variable and explains how each factor is constructed.

Five different categories of violent and property crimes are examined. Violent crimes include violence against the person, sexual offences and robbery whereas property crimes cover burglary and thefts. Crimes are in per capita terms, i.e. measured as the number of recorded crimes per 1,000 PFA residents. The annual data are obtained from *Home Office*.

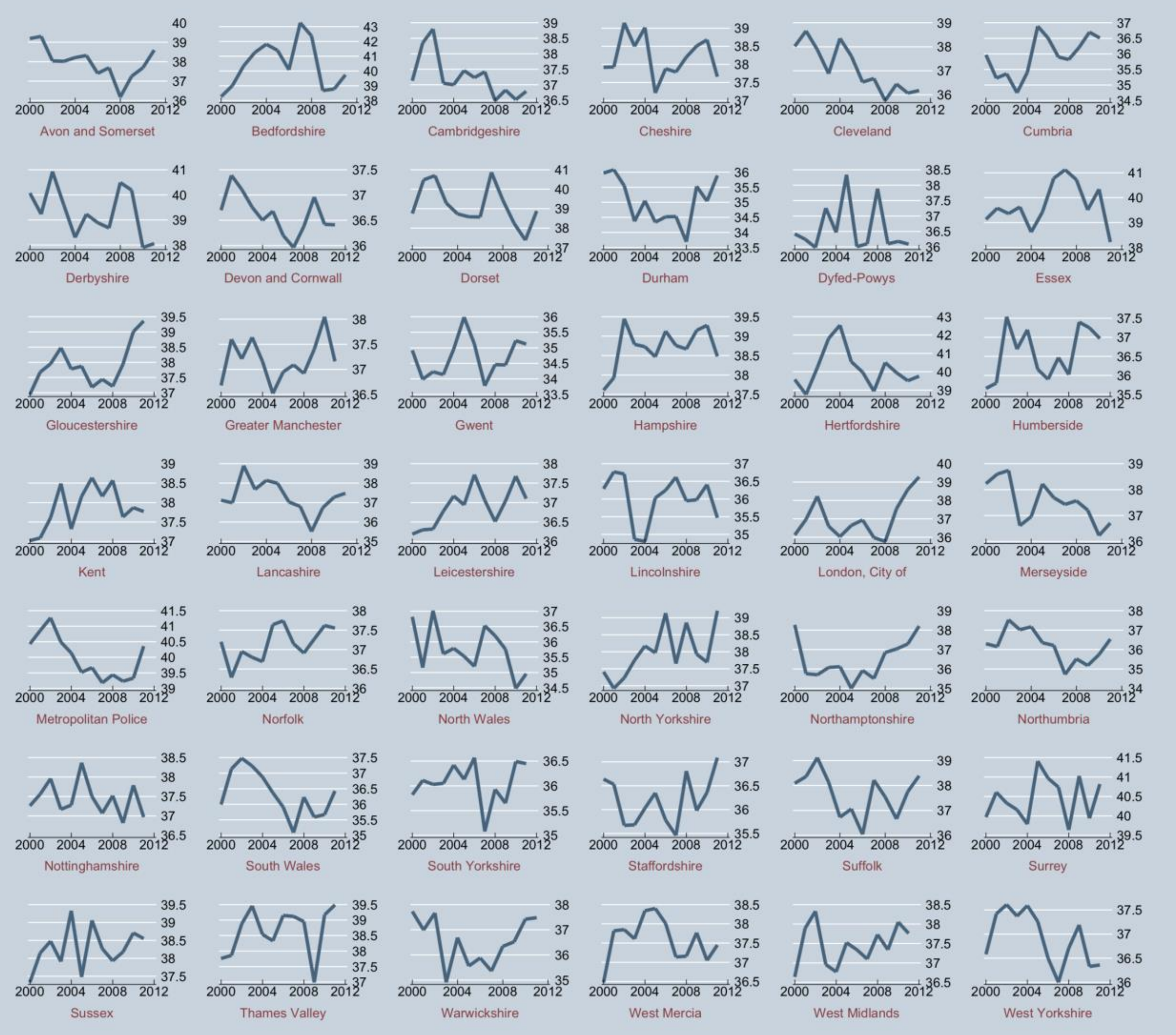
Unemployment benefits per unemployed are measured by dividing JSA expenditure by the number of JSA recipients whereas low-income benefits are calculated by dividing the total weekly IS payments by the number of IS claimants. The latter variable aims to account for low-wage earners, not captured by the unemployment benefits variable. For both variables, the data are obtained from the *Benefit Expenditure and Caseload Tables*, published by the Department for Work and Pensions, and are estimated at the PFA level. For more details about these variables, see *Appendices 2.1.2* and *2.1.3*.

The study also uses a Gini coefficient, constructed specifically at the PFA level, using individual level data from the *Annual Survey of Hours and Earnings (ASHE)*. *Appendix A.2.1.4* provides more details on how this variable is constructed.

The advantages of this constructed inequality index are the following. Firstly, it is a full-information measure since it considers all parts of the population distribution. Secondly, it facilitates a direct comparison between populations at the PFA level, irrespective of their sizes. As shown in *Figure 2.1*, income inequality varies quite considerably across PFAs. By using a national figure, all of this variation will not be accounted for in the empirical model. Hence, compared to the alternatives, this measure better represents the income inequality within society.

[80] The financial district of London, reported as the City of London, is excluded from the analysis due to its unique heterogeneity and the low resident population causing crime rates to inflate.

Figure 2.1: Gini Coefficient



As mentioned earlier, criminals respond to changes in their income. JSA and IS payments, can affect the opportunity cost of committing a crime, as for many un(under)employed might be the only source of legal income. Additionally, by including a measure of income inequality, we are able to capture a wide range of disadvantaged groups. As explained above, in England and Wales, Income Support benefits are given to specific low-income groups of the population. In effect, individuals who are low-income earners but do not fill the programme's threshold criteria, are left out from the analysis. Thus, we hope that these excluded groups are picked up by the constructed Gini coefficient, as it captures the income inequality prevailing in each PFA.

We expect that increases in income and unemployment benefits will negatively affect financially motivated crimes. On the other hand, increases in the Gini coefficient indicate increases in income inequality which effectively imply that the distribution of income widens. Thus, the opportunity costs of poorer people are lower. That is, low-income earners have a lower opportunity cost of participating in an illegitimate activity and have less to lose, in terms of earnings obtained from legal activities (e.g. wages). Correlation and multicollinearity tests[81] confirm that inclusion of these three economic indicators is appropriate. The results are presented in *Appendix A.2.4.2.*

The model also accounts for law enforcement factors. The baseline model includes a ratio of population per police officer – an indicator of police's strength – and detection rates[82] – a percentage measure of recorded offences that have been 'cleared-up' by the police. Data for the former are obtained from the yearly publication of *Police Statistics*, issued by the Chartered Institute of Public Finance and Accountancy (CIPFA) whereas data for the latter are obtained from the *Criminal Statistics*, part of the annual Home Office Statistical Bulletin.

Alternative measures, include conviction rates (ratio of the number of sentenced offenders to recorded crimes) and the average length of custodial sentence (determinate custody sentence divided by the total months spend in custody). Both variables were provided by the Ministry of Justice, part of the *Justice Statistics Analytical Services*.

Our preferred specification also controls for young male population[83], aged 15-24 years old. The data are obtained from Nomis where *Mid-Year Population Estimates* by age and sex are published. Young males are expected to have a positive relationship with crime rates.

Alternately, to test for the robustness of the results, population density (dividing the area, in hectares, by 1,000 resident population) and educational attainment (as a percentage of

[81] Correlation and multicollinearity tests for thefts is represented, but similar results are obtained when using different crime rates.

[82] This variable is available by type of offence. Vehicle detection rates are not available. Thus, thefts detection rates are used; since vehicle detections are included in there.

[83] Empirical research finds that young men have lower risk aversion and are more likely to commit crimes than any other group of the population; since the opportunity cost of committing crime is lower for younger individuals than adults, in terms of lost earnings and incapacitation. Youth usually receive more lenient prison sentences (Levitt, 1998a) while earning lower wages in the legal labour market (Reuter *et al*., 1990; Freeman, 1999; Levitt and Lochner, 2001).

working age population with NVQ4+[84] qualifications) are also used. Population density data are obtained from *Police Statistics*, published by the Chartered Institute of Public Finance and Accountancy (CIPFA) whereas data on education are collected from the *Labour Force Survey* for the period of 1997 to 2003 and from the *Annual Population Survey* for 2004 to 2014. Both surveys are published by Nomis. Data on young males and education attainment are available at the LAs and are aggregated up to the PFA level.

All variables included in the regressions are in natural logarithms, except for the Gini coefficient which is multiplied by 100 to obtain percentage changes since, it ranges between 0 and 1. *Appendix A.2.4.1* provides summary statistics for all variables used in the analysis.

2.4 Empirical Methodology

2.4.1 Modelling Issues and Estimation Method

The estimation method chosen enables one to control for various estimation problems that many empirical studies suffer from. *Firstly*, the effect of unobserved variables that mainly vary across PFAs but not much over time is being controlled for by including area-specific fixed effects (Fajnzylber *et al*., 2002b; Yasar, 2003). *Secondly*, we consider that past crime itself is a significant determinant of criminal behaviour. Empirical findings document crime's persistence[85]: the crimes of yesterday are affecting the crimes of today (Fajnzylber *et al*., 2002b; Hale, 1998 p.694). As Witt *et al*., (1999) explain, people participating in crime have the tendency "*to continue in it even after the circumstances that led them to turn to crime have changed*". In general, prior engagement in criminal acts, can positively affect reoffending[86].

Secondly, the model specification controls for the joint endogeneity of the economic indicators and criminal justice factors. The endogeneity arises either due to *reverse*

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[84] National Vocational Qualification.
[85] The coefficient of lagged crime rates from our AR(1) tests, reinforces that finding; see *Appendix 2.5.2*.
[86] This is also known as recidivism.

causation between these indicators and crime rates or due to *omitted variable bias*, or both (Field, 1990; Bindler, 2017). By not accounting for this possible endogeneity, biased and inconsistent parameter estimates may be produced. However, by correcting for this joint endogeneity, the exogenous impact of these economic indicators on crime rates is isolated.

Generally, scholars acknowledge and control for the potential endogeneity of law enforcement variables, such as deterrent and incapacitation effects but neglect to address the endogeneity of economic indicators when estimating their models. From the aforementioned papers testing the link of economic variables on crime in *England and Wales*, **none** takes into consideration the bi-causality of these variables (see *Appendix 2.3*). Some researchers, such as Raphael and Winter-Ebmer, 2001[87] and Gould *et al*., 2002[88], acknowledge the potential endogeneity and, using instruments, they control for it. However, they fail to do so for law enforcement variables. Others, such as Machin and Meghir (2004) and Witt *et al*. (1999), account for endogeneity of law enforcement variables but do not control for the possible endogeneity of economic indicators. Not controlling for either, or controlling for some endogenous variables can, still, lead to biased estimates[89] (Fajnzylber *et al*., 2002b). To the best of our knowledge, this is the first study examining the link between economic incentives and crime, in England and Wales that treats economic indicators as endogenous.

To address the above issues and to explore short- and long-run dynamics between economic indicators and crime, the instrumental variable (IV) Generalised Method of Moments (GMM) of Blundell and Bond (1998), known as the system GMM (SYS GMM), is employed. This estimation method is an extension to the difference GMM (DIFF GMM) developed by Arellano and Bond (1991) and Arellano and Bover (1995).

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[87] Raphael and Winter-Ebmer (2001) instrument unemployment rates with Department of Defence (DOD) annual prime contract awards for each state and a state-specific measure of oil price shocks. In their regressions, they also include an incarceration rate without addressing potential endogeneity concerns.

[88] Gould *et al*. (2002) use state unemployment rates, income per capita and non-college educated male weekly wages. Suspecting economic indicators being endogenous, they construct a Bartik instrument. The Bartik instrument averages national employment growth across industries using local industry employment shares as weights to produce a measure of local labour demand, which is not related to local labour supply. In other words, it isolates local labour demand changes. However, their model also includes arrest rates, which are not control for endogeneity and might be a source of bias.

[89] Depending on the sign of the reverse causality, their effects on crime rates would be over or under estimated.

The SYS GMM exploits the dynamic properties of the data to generate appropriate instrumental variables by using exogenous internal lags as instruments[90] (Fajnzylber et al., 2002b). The model estimates *first-differenced* and *level* equations jointly in a system. The estimator employs *lagged levels* to instrument equations in *differences* and uses *lagged first-differences* as instruments for *level* equations. The model allows to use instruments dated $t-2$ $(t-1)$ and earlier for equations in levels (first-differences), provided there is no serial autocorrelation of order 1. If AR(1) exists then, the instrument list should include longer lags to be valid. *Appendix 2.5.1* presents the econometric modelling in more detail.

SYS GMM is more efficient than DIFF GMM when the series is highly persistent (overall) and stationary (in differences). The dataset is examined to determine whether the series for crime, economic indicators and criminal justice variables are persistent. To test for series persistence, simple first-order autocorrelation models including year dummies[91] are estimated. As shown in the tables of *Appendix A.2.5.2,* crime rates are highly persistent across all estimators. This suggests that lagged levels provide weak instruments for the differenced equations, i.e. DIFF GMM suffers from large sample bias[92].

Blundell and Bond (1998) show[93] that efficiency can be increased when series are also stationary (Yasar, 2003; Roodman, 2009a, 2009b). This additional assumption gives rise to the level equations. Thus, when the explanatory variables are stationary, lagged differences are valid instruments for equations in levels. To test for series stationarity, the Levin-Lin-Chu panel-data unit root test[94] is implemented. As shown in *Appendix A.2.5.2*, the series are stationary in *first-differences* and have a unit root in *levels*.

Thus, both tests indicate that the series is persistent and stationary. As a result, in the context of this study, the use of SYS GMM is more appropriate than DIFF GMM since it provides more efficient and consistent estimates.

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[90] Internal lags are used because this approach assumes that no good external instruments – correlated with the regressor but uncorrelated with the source of endogeneity – exist outside the immediate dataset. Nevertheless, the estimator allows for the inclusion of external instruments (Roodman, 2009b).
[91] Accounting for heteroskedastic robust errors; allowing observations to be independent across states (clusters) but not necessarily within states.
[92] When series are highly persistent, and T is small, the bias becomes more severe (Yasar, 2003).
[93] First outlined by Arellano and Bover (1995).
[94] The Im-Pesaran-Shin test is also used and confirms the results.

Nevertheless, the consistency of the coefficient estimates depends on the validity of instruments used. Inclusion of too many instruments, known as instrument proliferation (Roodman, 2009a, 2009b), can produce biased estimates. Thus, we perform various specification tests – as suggested by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (2000) – to verify whether the instruments used are valid[95]. These are presented in *Appendices A.2.5.2* and *A.2.5.3*.

2.4.2 Model Specification

The equation below is based on Becker's (1968) economic model of crime. The theoretical framework predicts that engagement in criminal activity is contingent on the earnings obtained through legal activities, their incentives and factors associated with the likelihood of arrest and length of punishment. These are captured by the inclusion of economic and law enforcement variables. The following linear dynamic model specification is estimated using SYS GMM[96]:

$$crime_{PFA,t} = \alpha crime_{PFA,t-1} + \beta EconInd_{PFA,t} + \gamma LawEnfor_{PFA,t} + \delta C_{PFA,t} + \tau_t + \mu_{PFA} + \epsilon_{PFA,t} \quad (1)$$

where $e_{PFA,t} = \mu_{PFA} + \epsilon_{PFA,t}$, for $PFA = \{1,\ldots,42\}$ and $t = \{1,\ldots,13\}$

where $crime_{PFA,t}$ is the crime rate in each PFA in year t; $crime_{PFA,t-1}$ is the lagged crime rate; $EconInd_{PFA,t}$ represents a set of economic indicators (that is, JSA, IS and Gini coefficient); $LawEnfor_{PFA,t}$ includes law enforcement variables; $\delta C_{PFA,t}$ is a set of demographic controls; τ_t is a vector of year dummies; $e_{PFA,t}$ is the cross-section error term which captures two effects: (1) μ_{PFA}, the unobserved time-invariant PFA-specific effects and (2) $\epsilon_{PFA,t}$, the time-varying unobservable idiosyncratic error.

The explanatory variables in the preferred model specification are: the lagged crime rate, the average JSA per unemployed, the average weekly IS received per claimant, the Gini

95 As shown in *Section 2.5.1* and *Appendix A.2.5.2*, the tests indicate autocorrelation of order 1; which is expected. Therefore, for the instrument list to be valid we use instruments dated $t-3$ and earlier in our preferred specification.

96 The dynamic model is also estimated using OLS, within-groups estimator and difference GMM in order to compare and contrast the empirical findings reached by each.

coefficient, the population per police officer, detection rates, the average sentence length and the percentage of young males (15-24 year olds). All variables, except for young male population, are treated as endogenous in the empirical analysis.

2.5 Results

2.5.1 System GMM Estimation

As advanced earlier, all preliminary tests for series stationarity and persistence, serial autocorrelation and instrument validity, indicate that the SYS GMM is the preferred estimator. *Appendix A.2.5.4* estimates the empirical model using various estimation methods: OLS, within-groups, DIFF and SYS GMM to examine if different estimators provide different outcomes. As demonstrated SYS GMM performs better in this framework.

The model specifications presented below treat as endogenous the lagged dependent variable, economic indicators and law enforcement variables. The instrument list starts from lags dated $t-3$, for the equations in levels. The findings are reported in Tables 2.1 through 2.5. Model alterations are presented alongside the preferred specification, which is reported in *column (3)*, to examine the consistency of the parameter estimates.

In all tables, *column (1)* estimates the lagged dependent variable along with only one economic indicator, the JSA per unemployed, and all three law enforcement variables. In *column (2)*, the baseline model is presented – IS pay and Gini coefficient are added to the model. *Column (3)*, our preferred specification, also includes young male population. Alternatively, *column (4)* incorporates an education variable in the model. *Column (5)* includes both. In *column (6)* the population density is added to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates.

All estimations point towards a highly significant effect of the lagged crime variable; signifying crime's persistence both over the short- and long-run, and also captures peer effects (Machin and Meghir, 2004). The coefficient of lagged dependent variable is higher for property crimes – burglary and thefts.

The estimation results presented in Tables 2.1, indicate that violence against the person is negatively affected by detection rates while showing a strongly significant positive effect on sentence length. The magnitude of both coefficients is persistent throughout all estimations. These findings imply that violent offenders are discouraged by the possibility of apprehension whereas longer spells of imprisonment lead to more violent crimes been committed. In fact, the model predicts that a 10% increase in detection rates, decreases violent crimes by, approximately, 2.7% and 6.6% in the short- and long-run, respectively. In other words, by detecting, on average, 5 more violent crimes, 400 and 978 less offences are to be committed in the short- and long-term, respectively. On the other hand, 10% longer sentences can increase violent crimes by more than 7.1% in the short-run, with the effect becoming even larger, around 17.4%, in the long-run. That is, 1 more year in prison leads to more than 1,000 more violent crimes been committed in the short-run and 2,500 more in the long-run.

The results reported in Table 2.2, show that sexual offenders are also likely to respond to the threat of apprehension. Again, this finding is consistent across all model specifications. By increasing detection rates by 10%, sexual offences are reduced by 2.3% (approximately equal to 30 cases) in the short-run whereas, in the long-run, the impact more than triples in size, 7.5% (approximately, 90 less sexual offences). As both violence against the person and sexual offences are more violent-oriented, economic indicators do not affect these two types of crime, as expected. This in line with the literature (Raphael and Winter-Ebmer, 2001; Levitt, 1996, 1997; Malby *et al*., 2012; Wu and Wu, 2012).

Table 2.1: Violence against the Person, Regression Estimates using System GMM, 2000/01-2011/12

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Violence,t-1	0.62***	0.59***	0.59***	0.59***	0.59***	0.60***	0.62***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.11)
rJSA per unemployed	0.03	0.00	0.00	−0.01	−0.01	0.00	0.00
	(0.05)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
rAv.Weekly IS		−0.71	−0.67	−0.72	−0.68	−0.71	−0.75
		(0.75)	(0.81)	(0.78)	(0.84)	(0.75)	(0.77)
Gini Coeff(x100)		−0.02	−0.02	0.00	−0.01	−0.02	−0.01
		(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Pop per Officer	0.09	−0.08	−0.09	−0.07	−0.08	−0.09	−0.03
	(0.21)	(0.25)	(0.24)	(0.24)	(0.24)	(0.28)	(0.31)
Violence Det.Rate	−0.27	−0.27 *	−0.27 *	−0.28 *	−0.28 *	−0.27 *	
	(0.18)	(0.15)	(0.14)	(0.16)	(0.15)	(0.14)	
Av.Violence Sent.Length	0.83**	0.72**	0.71***	0.74***	0.73***	0.72**	0.85**
	(0.35)	(0.27)	(0.25)	(0.27)	(0.25)	(0.27)	(0.35)
Violence Sent.Rate							−0.06
							(0.13)
Males,15-24			−0.07		−0.09		0.12
			(0.33)		(0.34)		(0.42)
Education				−0.18	−0.18		
				(0.14)	(0.14)		
Pop Density						0.00	
						(0.04)	
Obs	462	462	462	462	462	462	462
No of Instr	26	32	33	33	34	33	33
AR(1) p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.17	0.2	0.2	0.15	0.15	0.19	0.15
Sargan	0.85	0.86	0.85	0.92	0.92	0.86	0.67
Hansen	0.72	0.76	0.73	0.85	0.83	0.76	0.85
Diff-in-Hansen all	0.95	1.00	0.99	1.00	1.00	1.00	0.83
α	1.60	1.47	1.46	1.44	1.44	1.47	1.64
p-value	0.01	0.01	0.01	0.01	0.01	0.01	0.04
β_{JSA}	0.08	0.00	0.00	−0.03	−0.03	0.00	0.00
p-value	0.60	1.00	1.00	0.86	0.86	0.99	0.99
β_{ISpay}		−1.74	−1.65	−1.77	−1.67	−1.74	−1.99
p-value		0.33	0.39	0.34	0.40	0.33	0.29
β_{Gini}		−0.04	−0.04	−0.01	−0.01	−0.04	−0.02
p-value		0.49	0.50	0.90	0.87	0.53	0.81
$\gamma_{Pop.per.Off}$	0.23	−0.20	−0.21	−0.16	−0.19	−0.21	−0.07
p-value	0.68	0.74	0.72	0.77	0.75	0.75	0.93
$\gamma_{Det.Rate}$	−0.71	−0.67	−0.66	−0.68	−0.68	−0.67	
p-value	0.11	0.06	0.05	0.08	0.06	0.04	
$\gamma_{Sent.Length}$	2.16	1.76	1.74	1.81	1.80	1.77	2.23
p-value	0.04	0.03	0.03	0.03	0.02	0.03	0.10
$\gamma_{Sent.Rate}$							−0.15
p-value							0.62
δ_{Males}			−0.17		−0.21		0.32
p-value			0.84		0.80		0.77
δ_{Educ}				−0.44	−0.45		
p-value				0.18	0.18		
δ_{PopDen}						0.01	
p-value						0.94	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The equations are estimated using one-step system GMM. The reported standard errors are robust to heteroskedasticity. *Column (1)* estimates the lagged dependent variable with only 1 economic indicator, the JSA per unemployed, and all three law enforcement variables. *Column (2)* estimates the baseline model, by adding IS pay and the Gini coefficient. *Column (3)* presents the preferred model specification which also includes a variable capturing young male population. Alternatively, *column (4)* includes an education variable in the model. *Column (5)* includes both whereas *column (6)* includes the population density to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates. Also, for the *first-differenced* equations, the instrument list includes lags dated *t-3* to *t-4*; as there is serial autocorrelation of order 1 in the model. All variables are in natural logs, except for the Gini coefficient which is multiplied by 100.

Table 2.2: Sexual Offences, Regression Estimates using System GMM, 2000/01-2011/12

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sexual offences,t-1	0.66***	0.67***	0.70***	0.67***	0.70***	0.67***	0.63***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
rJSA per unemployed	0.02	0.04	0.04	0.04	0.04	0.03	0.06
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)
rAv.Weekly IS		0.29	0.37	0.33	0.41	0.34	0.36
		(0.48)	(0.50)	(0.48)	(0.50)	(0.48)	(0.52)
Gini Coeff(x100)		0.00	−0.01	0.00	0.00	0.00	−0.02
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Pop per Officer	−0.14	−0.14	−0.21	−0.1	−0.17	−0.22	−0.22
	(0.12)	(0.12)	(0.13)	(0.12)	(0.13)	(0.17)	(0.14)
Sexual Det.Rate	−0.36 ***	−0.24 **	−0.23 *	−0.26 **	−0.25 **	−0.22 *	
	(0.13)	(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	
Av.Sexual Sent.Length	0.19	0.03	0.03	0.04	0.04	0.02	−0.12
	(0.18)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
Sexual Sent.Rate							−0.29 ***
							(0.09)
Males,15-24			−0.22		−0.23		−0.05
			(0.28)		(0.28)		(0.29)
Education				−0.16	−0.14		
				(0.12)	(0.11)		
Pop Density						0.03	
						(0.03)	
Obs	462	462	462	462	462	462	462
No of Instr	26	32	33	33	34	33	33
AR(1) p-value	0.01	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.37	0.24	0.22	0.26	0.24	0.24	0.41
Sargan	0.10	0.07	0.09	0.05	0.07	0.07	0.10
Hansen	0.10	0.03	0.04	0.04	0.04	0.03	0.04
Diff-in-Hansen all	0.14	0.29	0.17	0.40	0.14	0.21	0.05
α	1.98	2.00	2.30	1.99	2.33	2.01	1.72
p-value	0.05	0.04	0.06	0.05	0.06	0.04	0.02
β_{JSA}	0.05	0.12	0.12	0.12	0.13	0.10	0.16
p-value	0.76	0.56	0.58	0.58	0.60	0.62	0.50
β_{ISpay}		0.88	1.22	0.99	1.37	1.04	0.98
p-value		0.53	0.45	0.48	0.42	0.46	0.47
β_{Gini}		−0.01	−0.02	0.00	−0.01	0.01	−0.06
p-value		0.76	0.63	0.99	0.81	0.88	0.20
$\gamma_{Pop.per.Off}$	−0.40	−0.42	−0.68	−0.29	−0.57	−0.65	−0.59
p-value	0.28	0.28	0.22	0.47	0.30	0.27	0.18
$\gamma_{Det.Rate}$	−1.08	−0.73	−0.75	−0.79	−0.82	−0.67	
p-value	0.07	0.08	0.09	0.08	0.08	0.10	
$\gamma_{Sent.Length}$	0.58	0.08	0.11	0.11	0.14	0.05	−0.34
p-value	0.24	0.83	0.79	0.75	0.71	0.88	0.30
$\gamma_{Sent.Rate}$							−0.79
p-value							0.00
δ_{Males}			−0.72		−0.77		−0.14
p-value			0.51		0.49		0.87
δ_{Educ}				−0.47	−0.47		
p-value				0.14	0.14		
δ_{PopDen}						0.09	
p-value						0.37	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The equations are estimated using one-step system GMM. The reported standard errors are robust to heteroskedasticity. *Column (1)* estimates the lagged dependent variable with only 1 economic indicator, the JSA per unemployed, and all three law enforcement variables. *Column (2)* estimates the baseline model, by adding IS pay and the Gini coefficient. *Column (3)* presents the preferred model specification which also includes a variable capturing young male population. Alternatively, *column (4)* includes an education variable in the model. *Column (5)* includes both whereas *column (6)* includes the population density to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates. Also, for the *first-differenced* equations, the instrument list includes lags dated *t-3* to *t-4*; as there is serial autocorrelation of order 1 in the model. All variables are in natural logs, except for the Gini coefficient which is multiplied by 100.

In contrast, the findings, presented in Table 2.3, indicate that economic incentives can affect robberies. The Gini coefficient, as expected, has a significantly positive effect on robberies. In the short-run, a 10% higher income inequality can potentially increase robberies by 0.9% whereas in the long-run the effect more than doubles in size to 2.4%. Although, in the short-run, only the model specification in *column (3)* predicts JSA benefits to be significantly negatively related to robbery rates, in the long run, most specifications (*columns 3-6*) indicate a significant relationship between the two. A 10% increase in JSA payments decreases robberies by 1.2% in the short-run and by 3.2% in the long-run. In other words, by increasing the weekly unemployment benefits amounts by a little more than £3, 11 less robberies are committed in the short-run and 29 in the long-run. IS pay is also shown to be negatively linked to robbery rates. Indicatively, by increasing weekly income benefits by, approximately, £7, this translates into 108 less robberies in the short-term and 283 in the long-term.

Further, the proportion of PFA population to police officers affects negatively the rate of robberies committed. Although there is some research supporting this negative effect between police officers and crime (Wills, 1983; Bradford, 2011), this is against our expectations. Thus, we consider this finding as counterintuitive and difficult to explain.

Finally, in accordance to the literature, the findings show that the proportion of young male individuals is positively linked to robbery rates. In fact, a 10% increase in male population aged between 15 to 24, increases robberies by 16.1% in the short-run, with the effect becoming more imminent in the long-run, 42%.

Table 2.3: Robbery, Regression Estimates using System GMM, 2000/01-2011/12

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robbery,t-1	0.69***	0.67***	0.62***	0.68***	0.64***	0.61***	0.72***
	(0.14)	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
rJSA per unemployed	−0.06	−0.10	−0.12 *	−0.10	−0.10	−0.08	−0.07
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)
rAv.Weekly IS		−0.78	−1.21 *	−0.70	−1.06 *	−0.85	−1.01 *
		(0.56)	(0.63)	(0.54)	(0.59)	(0.57)	(0.60)
Gini Coeff(x100)		0.07***	0.09**	0.07**	0.07*	0.05**	0.09**
		(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Pop per Officer	−0.57	−0.67 **	−0.52 *	−0.59 *	−0.44	−0.33	−0.60 **
	(0.40)	(0.33)	(0.30)	(0.32)	(0.28)	(0.33)	(0.26)
Robbery Det.Rate	−0.10	−0.18	−0.38	−0.23	−0.40 *	−0.21	
	(0.39)	(0.28)	(0.24)	(0.27)	(0.23)	(0.24)	
Av.Robbery Sent.Length	0.01	0.00	0.02	−0.01	0.00	−0.02	−0.15
	(0.29)	(0.24)	(0.25)	(0.24)	(0.25)	(0.22)	(0.24)
Robbery Sent.Rate							−0.17
							(0.19)
Males,15-24			1.61***		1.44**		0.96*
			(0.57)		(0.55)		(0.48)
Education				−0.17	−0.07		
				(0.21)	(0.18)		
Pop Density						−0.19 ***	
						(0.07)	
Obs	462	462	462	462	462	462	462
No of Instr	26	32	33	33	34	33	33
AR(1) p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.78	0.87	0.91	0.99	0.81	0.94	0.63
Sargan	0.06	0.23	0.16	0.11	0.07	0.41	0.06
Hansen	0.13	0.21	0.36	0.19	0.21	0.35	0.08
Diff-in-Hansen all	0.16	0.17	0.19	0.14	0.09	0.34	0.02
α	2.21	2.07	1.62	2.10	1.76	1.57	2.51
p-value	0.12	0.04	0.02	0.03	0.02	0.01	0.02
β_{JSA}	−0.19	−0.32	−0.32	−0.31	−0.29	−0.20	−0.26
p-value	0.22	0.02	0.03	0.03	0.05	0.07	0.12
β_{ISpay}		−2.40	−3.17	−2.16	−2.92	−2.19	−3.55
p-value		0.21	0.06	0.24	0.08	0.13	0.13
β_{Gini}		0.22	0.24	0.21	0.20	0.14	0.30
p-value		0.06	0.02	0.08	0.05	0.09	0.04
$\gamma_{Pop.per.Off}$	−1.84	−2.07	−1.36	−1.83	−1.22	−0.85	−2.12
p-value	0.07	0.01	0.04	0.01	0.07	0.29	0.02
$\gamma_{Det.Rate}$	−0.32	−0.54	−1.00	−0.72	−1.11	−0.53	
p-value	0.79	0.46	0.05	0.28	0.02	0.32	
$\gamma_{Sent.Length}$	0.05	0.01	0.04	−0.03	−0.01	−0.06	−0.54
p-value	0.96	0.99	0.95	0.97	0.99	0.92	0.53
$\gamma_{Sent.Rate}$							−0.60
p-value							0.28
δ_{Males}			4.20		3.97		3.38
p-value			0.00		0.00		0.02
δ_{Educ}				−0.53	−0.19		
p-value				0.40	0.69		
δ_{PopDen}						−0.50	
p-value						0.00	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The equations are estimated using one-step system GMM. The reported standard errors are robust to heteroskedasticity. *Column (1)* estimates the lagged dependent variable with only 1 economic indicator, the JSA per unemployed, and all three law enforcement variables. *Column (2)* estimates the baseline model, by adding IS pay and the Gini coefficient. *Column (3)* presents the preferred model specification which also includes a variable capturing young male population. Alternatively, *column (4)* includes an education variable in the model. *Column (5)* includes both whereas *column (6)* includes the population density to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates. Also, for the *first-differenced* equations, the instrument list includes lags dated *t-3* to *t-4*; as there is serial autocorrelation of order 1 in the model. All variables are in natural logs, except for the Gini coefficient which is multiplied by 100.

In addition, the estimations of Table 2.4 indicate that short-term increases of 10% in unemployment benefits can decrease burglaries by 0.7%. That is equal to, approximately, 100 fewer burglaries per year. Although the ratio of PFA residents to police officers and male youth is insignificant in the short run, they become significant in the long-run. A 10% increase, in the former, decreases burglaries by 8% whereas an increase, in the latter, increases burglaries by 14.9%. There seems to be no significant relation between burglaries and the other two economic indicators, IS payments and income inequality or, the law enforcement variables.

Further, as shown in Table 2.5, thefts are affected both by the level of unemployment benefits as well as the income inequality. Increases of 10% in JSA benefits lead to 1.2% fewer thefts. This translates into a reduction of more than 300 theft offences. On the other hand, higher levels of income inequality, increase the rate of incidents by 0.6%. That is, more than 150 cases. Both effects persist over the long-run and double in magnitude, the coefficients being 2.2% and 1.1%, respectively. These percentages correspond to 560 and 280 thefts. This finding is consistent across all model specifications. Also, young male population has a significantly positive impact on the number of thefts committed both in the short- (6.6%) and long-run (12.3%).

Table 2.4: Burglary, Regression Estimates using System GMM, 2000/01-2011/12

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Burglary,t-1	0.79***	0.73***	0.72***	0.73***	0.76***	0.69***	0.80***
	(0.11)	(0.13)	(0.18)	(0.14)	(0.16)	(0.13)	(0.10)
rJSA per unemployed	−0.07 **	−0.07 **	−0.07 **	−0.07 **	−0.07 *	−0.07 **	−0.07 *
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
rAv.Weekly IS		−0.17	−0.3	−0.15	−0.21	−0.26	−0.30
		(0.28)	(0.45)	(0.30)	(0.40)	(0.29)	(0.39)
Gini Coeff(x100)		0.01	0.01	0.01	0.01	0.00	0.02
		(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Pop per Officer	−0.22	−0.27	−0.22	−0.21	−0.15	−0.21	−0.18
	(0.14)	(0.22)	(0.22)	(0.20)	(0.19)	(0.24)	(0.15)
Burglary Det.Rate	−0.03	−0.14	−0.14	−0.13	−0.10	−0.15	
	(0.12)	(0.13)	(0.15)	(0.13)	(0.13)	(0.12)	
Av.Theft Sent.Length	−0.08	−0.07	−0.10	−0.09	−0.13	−0.09	−0.08
	(0.10)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Theft Sent.Rate							−0.02
							(0.13)
Males,15-24			0.42		0.37		0.34
			(0.39)		(0.35)		(0.28)
Education				−0.13	−0.08		
				(0.16)	(0.13)		
Pop Density						−0.03	
						(0.03)	
Obs	462	462	462	462	462	462	462
No of Instr	26	32	33	33	34	33	33
AR(1) p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.84	1.00	0.95	0.91	0.84	0.96	0.75
Sargan	0.03	0.02	0.02	0.02	0.02	0.02	0.06
Hansen	0.21	0.15	0.12	0.17	0.23	0.21	0.36
Diff-in-Hansen all	0.92	0.73	0.53	0.70	0.68	0.83	0.28
α	3.88	2.64	2.58	2.71	3.20	2.26	3.94
p-value	0.14	0.12	0.27	0.17	0.25	0.10	0.12
β_{JSA}	−0.32	−0.26	−0.25	−0.28	−0.29	−0.22	−0.36
p-value	0.15	0.08	0.14	0.07	0.14	0.08	0.21
β_{ISpay}		−0.62	−1.09	−0.55	−0.89	−0.86	−1.46
p-value		0.51	0.34	0.59	0.51	0.32	0.33
β_{Gini}		0.02	0.05	0.04	0.06	0.00	0.08
p-value		0.62	0.33	0.48	0.40	0.98	0.54
$\gamma_{Pop.per.Off}$	−1.09	−0.98	−0.80	−0.78	−0.64	−0.70	−0.89
p-value	0.04	0.04	0.08	0.08	0.22	0.26	0.12
$\gamma_{Det.Rate}$	−0.14	−0.51	−0.52	−0.47	−0.43	−0.48	
p-value	0.80	0.12	0.12	0.14	0.25	0.11	
$\gamma_{Sent.Length}$	−0.38	−0.25	−0.37	−0.34	−0.54	−0.29	−0.41
p-value	0.51	0.59	0.42	0.49	0.35	0.48	0.51
$\gamma_{Sent.Rate}$							−0.09
p-value							0.88
δ_{Males}			1.49		1.55		1.66
p-value			0.07		0.10		0.06
δ_{Educ}				−0.49	−0.34		
p-value				0.23	0.40		
δ_{PopDen}						−0.10	
p-value						0.36	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The equations are estimated using one-step system GMM. The reported standard errors are robust to heteroskedasticity. *Column (1)* estimates the lagged dependent variable with only 1 economic indicator, the JSA per unemployed, and all three law enforcement variables. *Column (2)* estimates the baseline model, by adding IS pay and the Gini coefficient. *Column (3)* presents the preferred model specification which also includes a variable capturing young male population. Alternatively, *column (4)* includes an education variable in the model. *Column (5)* includes both whereas *column (6)* includes the population density to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates. Also, for the *first-differenced* equations, the instrument list includes lags dated *t-3* to *t-4*; as there is serial autocorrelation of order 1 in the model. All variables are in natural logs, except for the Gini coefficient which is multiplied by 100.

Table 2.5: Thefts, Regression Estimates using System GMM, 2000/01-2011/12

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Thefts,t-1	0.52***	0.49***	0.46***	0.48***	0.49***	0.45***	0.33***
	(0.12)	(0.10)	(0.13)	(0.11)	(0.12)	(0.10)	(0.10)
rJSA per unemployed	−0.14 ***	−0.12 ***	−0.12 ***	−0.12 ***	−0.12 ***	−0.11 ***	−0.08 **
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
rAv.Weekly IS		0.31	0.06	0.36	0.18	0.22	−0.01
		(0.43)	(0.48)	(0.44)	(0.47)	(0.44)	(0.40)
Gini Coeff(x100)		0.05**	0.06**	0.06*	0.06**	0.04*	0.03**
		(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Pop per Officer	−0.29 *	−0.29	−0.2	−0.19	−0.11	−0.2	−0.12
	(0.16)	(0.20)	(0.20)	(0.15)	(0.16)	(0.25)	(0.21)
Theft Det.Rate	0.04	0.08	0.05	0.08	0.05	0.08	
	(0.09)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	
Av.Theft Sent.Length	−0.24 *	−0.01	−0.05	−0.03	−0.08	−0.04	−0.2
	(0.13)	(0.13)	(0.14)	(0.15)	(0.15)	(0.13)	(0.14)
Theft Sent.Rate							−0.14
							(0.10)
Males,15-24			0.66*		0.64*		0.87**
			(0.37)		(0.37)		(0.35)
Education				−0.22	−0.18		
				(0.21)	(0.19)		
Pop Density						−0.03	
						(0.04)	
Obs	462	462	462	462	462	462	462
No of Instr	26	32	33	33	34	33	33
AR(1) p-value	0.02	0.01	0.00	0.01	0.00	0.01	0.01
AR(2) p-value	0.89	0.40	0.37	0.33	0.34	0.41	0.38
Sargan	0.00	0.04	0.09	0.03	0.02	0.04	0.00
Hansen	0.49	0.70	0.82	0.78	0.76	0.73	0.34
Diff-in-Hansen all	0.48	0.75	0.88	0.80	0.78	0.81	0.79
α	1.07	0.96	0.87	0.94	0.97	0.81	0.49
p-value	0.04	0.01	0.05	0.02	0.04	0.02	0.03
β_{JSA}	−0.29	−0.24	−0.22	−0.24	−0.23	−0.21	−0.13
p-value	0.06	0.01	0.02	0.02	0.03	0.02	0.07
β_{ISpay}		0.61	0.12	0.70	0.35	0.40	−0.01
p-value		0.47	0.90	0.42	0.71	0.61	0.98
β_{Gini}		0.10	0.11	0.11	0.12	0.08	0.05
p-value		0.04	0.02	0.04	0.02	0.05	0.03
$\gamma_{Pop.per.Off}$	−0.60	−0.56	−0.37	−0.37	−0.22	−0.35	−0.18
p-value	0.08	0.12	0.32	0.16	0.48	0.42	0.57
$\gamma_{Det.Rate}$	0.09	0.15	0.08	0.16	0.10	0.14	
p-value	0.63	0.48	0.68	0.49	0.65	0.47	
$\gamma_{Sent.Length}$	−0.50	−0.02	−0.09	−0.07	−0.15	−0.08	−0.30
p-value	0.08	0.95	0.72	0.81	0.60	0.74	0.14
$\gamma_{Sent.Rate}$							−0.21
p-value							0.18
δ_{Males}			1.23		1.27		1.30
p-value			0.02		0.03		0.00
δ_{Educ}				−0.43	−0.35		
p-value				0.25	0.32		
δ_{PopDen}						−0.06	
p-value						0.44	

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The equations are estimated using one-step system GMM. The reported standard errors are robust to heteroskedasticity. *Column (1)* estimates the lagged dependent variable with only 1 economic indicator, the JSA per unemployed, and all three law enforcement variables. *Column (2)* estimates the baseline model, by adding IS pay and the Gini coefficient. *Column (3)* presents the preferred model specification which also includes a variable capturing young male population. Alternatively, *column (4)* includes an education variable in the model. *Column (5)* includes both whereas *column (6)* includes the population density to the baseline model. Finally, *column (7)* estimates the model using conviction rates instead of detection rates. Also, for the *first-differenced* equations, the instrument list includes lags dated *t-3* to *t-4*; as there is serial autocorrelation of order 1 in the model. All variables are in natural logs, except for the Gini coefficient which is multiplied by 100.

2.5.2 Discussion of Findings

For easier comparison and model interpretation, Table 2.6 presents a summary of the elasticities of the explanatory variables across all the categories of crime, for both the short- and long-run. The summary table displays the coefficients estimated using our preferred specification[97] – *column (3)* – from Tables 2.1 through 2.5.

Table 2.6: Summary of Short- and Long-Run Regression Estimates, System GMM

	(1) Violence		(2) Sexual		(3) Robbery		(4) Burglary		(5) Thefts	
Crime, *t-1*	0.59	***	0.70	***	0.62	***	0.72	***	0.48	***
rJSA per unemployed	0.00		0.04		-0.12	*	-0.07	**	-0.12	***
rAv. Weekly IS	-0.67		0.37		-1.21	*	-0.30		0.06	
Gini Coeff(x100)	-0.02		-0.01		0.09	**	0.01		0.06	***
Pop per Officer	-0.09		-0.21		-0.52	*	-0.22		-0.20	
Detection Rate	-0.27	*	-0.23	*	-0.38		-0.14		0.05	
Av. Sent. Length	0.71	***	0.03		0.02		-0.10		-0.05	
Males, 15-24	-0.07		-0.22		1.61	***	0.42		0.66	*
α	1.46	***	2.30	*	1.62	**	2.58		0.87	**
β_{JSA}	0.00		0.12		-0.32	**	-0.25		-0.22	**
β_{IS}	-1.65		1.22		-3.17	*	-1.09		0.12	
β_{Gini}	-0.04		-0.02		0.24	**	0.05		0.11	**
$\gamma_{Pop.per.Off}$	-0.21		-0.68		-1.36	**	-0.80	*	-0.37	
$\gamma_{Det.Rate}$	-0.66	**	-0.75	*	-1.00	**	-0.52		0.08	
$\gamma_{Sent.Length}$	1.74	**	0.11		0.04		-0.37		-0.09	
δ_{Males}	-0.17		-0.72		4.20	***	1.49	*	1.23	**

Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The table summarises the regression coefficients of *column (3)* across Tables 2.1 - 2.5. The upper part represents the elasticities during the short-run whereas the estimates below are the elasticities for the long-run.

In line with the literature, the findings indicate that violent crimes, in contrast to property crimes and robbery, are not reactive to changes in economic circumstances. This is unsurprising if we consider that violent crime is not usually financially motivated or at least, the majority is not committed for financial gain. Nevertheless, we acknowledge that economic distress can propel violence (Raphael and Winter-Ebmer, 2001). An individual level study might be more equipped to isolate and examine this relationship as it allows to control for other factors such as, earnings, family background, alcohol consumption etc. Rather, our

[97] This model specification is typical of that used by other scholars to estimate the effects of economic incentives on crime. Thus, any discrepancy between this paper and the literature cannot be explained by model specification.

findings indicate that violent crimes are responsive to higher probabilities of apprehension (Chalfin and McCrary, 2017) and longer sentences (Eher *et al*., 2016; Rydberg and Clark, 2016; Nagin *et al*., 2018). This suggests that, although a higher likelihood of apprehension discourages engagement in criminal activities; lengthier sentences, increase the rate of violent crimes. This suggests that the certainty rather than the severity of punishment is a more effective deterrent for violent offenders. Also, prison is a school for incarcerated, as it fosters peer relations allowing offenders to become more entrenched criminals (Branham, 1992). As violent offenders receive harsher sentences, they have more opportunities to learn from other incarcerated criminals.

Yet, property crime offenders seem to be unaffected by movements in law enforcement factors (Bradford, 2011; College of Policing, 2011). This finding is not surprising, considering the following. The magnitude and direction of the relationship between property crimes and police officers depends on police's efficiency in responding to these crimes (Willis, 1983). Nevertheless, the efficiency of police, at preventing and clearing-up offences, is not the same across all types of crime. Provided that the police resources are limited, and property crimes occur more frequently, while posing a lower threat to society, police's resources may be distributed towards most serious crimes. Thus, an insignificant coefficient might capture police's inefficiency to investigate property crimes.

Further, the detection rate[98] is used as a proxy for the probability of apprehension. Again, insignificance may reflect heavy workload. Provided that the number of officers is the same, more reports lead to less investigation time per case, effectively inducing lower probabilities of detection. Also, property crime offenders are more likely to receive a more lenient prison sentence than violent criminals, implying a smaller incapacitation effect due to a lower cost of incarceration. On the other hand, insignificance may simply suggest that variations on detection rates do not matter for property crime offenders. Finally, in line with previous empirical analyses, we find that young males are more likely to engage in robberies, burglaries (in the long-run) and thefts.

[98] In turn, the conviction rate, used in *column (7)*, depends on the probability of being detected and then, on the probability of being convicted.

In addition, as anticipated, property crimes, along with robberies, are responsive to shifts in economic indicators. Lower JSA and IS payments and higher levels of income inequality increase these financially motivated crimes. Further, in the long-run, all parameter estimates maintain their sign while the magnitude of the effect becomes stronger. This is a valuable finding as it suggests that by intervening and increasing benefit payments while keeping income inequality low, more *at-the-margin* individuals will be discouraged from committing property crimes. Most importantly, this negative effect on property crimes is not just contemporaneous but rather, it persists over time.

The literature, although more theoretical than empirical, gives support to our findings. Burdett *et al*. (2004) develop a job-search model of crime, unemployment and inequality. They suggest that increases in unemployment benefit replacement rate increases both unemployment and crime. Further, Engelhardt *et al*. (2008) build a search model, which theoretically assesses the effect of various labour market and crime policies, to examine the relationship between crimes and optimally determined employment contracts. They find that a more generous unemployment benefit scheme reduces the crime rate of the unemployed. However, the scheme’s impact on the employed is contingent upon job duration and prison sentences.

Empirical studies also reach similar conclusions. Machin and Marie (2006) assess, in a quasi-experimental setting, the effect of the 1996 JSA reform on crime in England and Wales. The authors support that there is a positive relation between crime rates and stricter eligibility criteria for unemployment benefits. Bindler (2017) exploits quasi-experimental variation in unemployment benefit duration induced by temporary policy changes during the U.S. Great Recession and finds that, *ceteris paribus*, extending benefit durations partially explains increased crime participation. Finally, although Fougère *et al*. (2009) find no relation between crime and long-term unemployment, in France, they report that there is a positive association between crime and not receiving unemployment benefit payments.

To the best of our knowledge, this is the first study making use of income subsidies to analyse their relationship with crime. Thus, a direct comparison with the existing literature is not possible. Nonetheless, other empirical studies use earnings of low-skilled workers to capture economic incentives of individuals who are more susceptible to engage in criminal activities. Unequivocally, these studies find that increases in the returns of low-wage earners have a negative effect on property crime (Wolpin, 1978; Grogger, 1998; Gould *et al*., 2002; Machin and Meghir, 2004). Further, higher income inequality has traditionally been associated with increases in crimes, particularly property crimes (Witt *et al.*, 1998, 1999; Wu and Wu, 2012; Han *et al*., 2013).

Furthermore, the findings indicate importance of estimating both the short- and long-run effects [of economic indicators on crime]. As discussed in *Section 2.2*, the work of Cantor and Land (1985) also stresses the importance of this distinction[99]. By isolating the exogenous effect of economic indicators on crime, we are able to capture the true size of the parameter estimates. The findings indicate that increases in the returns of disadvantaged groups have a negative effect on property crime during both periods.

2.6 Robustness Checks

2.6.1 Different JSA/Gini Coefficient Measures

The model is re-estimated using different variations of unemployment benefits and Gini coefficient. Instead of using the average JSA received per unemployed per annum, an average *weekly* JSA variable is constructed, following the same process as the IS pay variable. It is built at the PFA level. However, a limitation of using this variable is its availability. The data, published by Nomis, are only available at a specific point in time, for a particular week. Thus, for estimation purposes we assume that the number of recipients at that specific day are representative for the whole year.

In addition, the income inequality measure reported in this section is estimated using the *annual gross pay*[100] at the individual level, aggregated up to the PFA level. Up to this point,

[99] They support that unemployment causes two opposing effects: the motivation (positive, long-run) and the opportunity/guardianship (negative, short-run) effects. They argue that since these effects are realised in different points in time (this is disputed by other scholars, see *Section 2.2.1*), the net effect is ambiguous, and this also explains the mixed effects reported in the literature.

[100] Based on micro-level data, published in the *Annual Survey of Hours and Earnings*.

the Gini coefficient was estimated using *weekly basic* pay[101]. Gross pay captures both permanent and transitory earnings. Thus, to capture changes in gross earnings and examine its effect on crime, we re-estimate our preferred estimation using this inequality measure[102].

Table 2.7 reports estimates. The first column, for each type of crime, estimates the baseline model using the average *weekly* JSA and the Gini coefficient based on *basic pay*; whereas the second column utilises the *annual* JSA payments per unemployed and the Gini coefficient calculated on annual *gross pay*. Finally, the third column uses both the average *weekly* JSA and annual gross pay Gini coefficient. As shown, the findings support earlier results.

[101] Weekly basic wage is preferred, as changes in the permanent income are more likely to affect crime rates, than shifts in transitory income (Dahlberg and Gustavsson, 2008). Assuming that each individual's weekly basic wage is the main source of income; a loss (due to unemployment) or a reduction of that income is more likely to affect the incentives of the individual, and potentially motivate criminal engagement, than any other changes in the transitory income.
[102] The data also provide the *weekly gross* pay. Although, the estimations using Gini coefficient built on weekly gross pay are not shown here, the conclusions drawn are the same.

Table 2.7: Regression Estimates using other Economic Measures, 2000/01-2011/12

	Violence against person			Sexual Offences			Robbery			Burglary			Thefts		
	(1) wJSA	(2) gAGP	(3) JSA+gAGP	(4) wJSA	(5) gAGP	(6) JSA+gAGP	(7) wJSA	(8) gAGP	(9) JSA+gAGP	(10) wJSA	(11) gAGP	(12) JSA+gAGP	(13) wJSA	(14) gAGP	(15) JSA+gAGP
Crime,t-1	0.61***	0.61***	0.63***	0.68***	0.68***	0.65***	0.72***	0.61***	0.70***	0.86***	0.70***	0.84***	0.59***	0.48***	0.57***
	(0.09)	(0.09)	(0.10)	(0.11)	(0.11)	(0.11)	(0.10)	(0.12)	(0.12)	(0.09)	(0.14)	(0.09)	(0.15)	(0.12)	(0.14)
rJSA per unemployed		-0.01			0.03			-0.09			-0.06*			-0.09**	
		(0.07)			(0.06)			(0.07)			(0.03)			(0.04)	
rAv.Weekly JSA	0.11		0.18	-1.84*		-1.89**	-0.71		-1.20	-0.75		-0.93	-1.63		-1.41
	(1.48)		(1.55)	(1.04)		(0.93)	(1.20)		(1.30)	(0.68)		(0.66)	(1.17)		(1.01)
rAv.Weekly IS	-0.86	-0.73	-0.96	0.46	0.35	0.56	-0.79	-1.17*	-0.82	0.23	-0.32	0.21	0.78	0.27	0.87
	(0.85)	(0.72)	(0.86)	(0.47)	(0.47)	(0.47)	(0.60)	(0.62)	(0.54)	(0.41)	(0.39)	(0.41)	(0.67)	(0.39)	(0.60)
Gini Coeff(x100)	-0.03			0.00			0.06**			0.01			0.07**		
	(0.03)			(0.02)			(0.03)			(0.01)			(0.03)		
Gini Coeff(x100) -AGP		-0.01	-0.03		0.00	0.00		0.07***	0.06***		0.01	0.01		0.04*	0.04**
		(0.02)	(0.02)		(0.01)	(0.01)		(0.02)	(0.02)		(0.01)	(0.01)		(0.02)	(0.02)
Pop per Officer	-0.15	-0.12	-0.18	-0.23	-0.20	-0.20	-0.34	-0.46	-0.36	-0.07	-0.22	-0.08	-0.12	-0.11	-0.04
	(0.22)	(0.21)	(0.21)	(0.15)	(0.12)	(0.13)	(0.26)	(0.29)	(0.26)	(0.15)	(0.17)	(0.14)	(0.18)	(0.18)	(0.17)
Det.Rate	-0.36**	-0.29*	-0.38*	-0.28**	-0.18	-0.21	-0.39	-0.37	-0.32	-0.05	-0.16	-0.06	0.11	0.02	0.08
	(0.16)	(0.16)	(0.19)	(0.12)	(0.12)	(0.14)	(0.25)	(0.25)	(0.26)	(0.09)	(0.10)	(0.09)	(0.13)	(0.09)	(0.10)
Av.Sent.Length	0.70**	0.74**	0.80**	0.01	0.10	0.08	0.11	-0.07	0.02	0.00	-0.12	0.00	0.18	-0.08	0.10
	(0.27)	(0.29)	(0.35)	(0.16)	(0.13)	(0.18)	(0.25)	(0.25)	(0.24)	(0.13)	(0.11)	(0.12)	(0.23)	(0.13)	(0.20)
Males,15-24	-0.22	-0.14	-0.34	-0.22	-0.18	-0.19	0.98**	1.72***	1.16**	0.10	0.48	0.17	0.35	0.65**	0.43
	(0.35)	(0.38)	(0.45)	(0.28)	(0.29)	(0.29)	(0.48)	(0.62)	(0.52)	(0.25)	(0.36)	(0.25)	(0.38)	(0.30)	(0.32)
No of Instr	33	33	33	33	33	33	33	33	33	33	33	33	33	33	33
Sargan	0.38	0.87	0.53	0.14	0.11	0.12	0.01	0.11	0.01	0.00	0.02	0.00	0.01	0.03	0.00
Hansen	0.64	0.77	0.71	0.02	0.03	0.04	0.02	0.27	0.02	0.26	0.10	0.20	0.63	0.66	0.43
Diff-in-Hansen all	0.75	1.00	0.81	0.01	0.42	0.18	0.00	0.11	0.00	0.94	0.77	0.92	0.56	0.81	0.49

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) estimates the preferred model specification using the average weekly JSA (wJSA) and the Gini coefficient based on basic pay. *Column (2)* uses the annual JSA payments per unemployed whereas the Gini coefficient is estimated using annual gross pay (gAGP). Finally, *column (3)* uses both the average weekly JSA and the annual gross pay Gini coefficient.

2.6.2 Law Enforcement Variable Variations

Considering that law enforcement variables might not be endogenous, but in fact predetermined or even exogenous; the model is re-estimated to examine whether the estimation results vary. Table 2.8 reports the results for violence against the person and sexual offences while Table 2.9 summarises the estimations for robbery, burglary and thefts.

For ease of comparison, *column (1)* reproduces the estimates of *column (3)* from Tables 2.1 – 2.5 where all economic indicators and law enforcement variables are assumed to be endogenous. In *column (2)*, law enforcement variables are treated as predetermined and instrumented by 2 lags ($t-2$ and $t-3$) whereas in *column (3)* only 1 lag ($t-2$) is used as instrument. In *column (4)*, instead of controlling for their potential endogeneity by instrumenting contemporaneous values with own lags, the law enforcement variables enter the model in lagged form (Witt *et al*., 1999). *Column (5)* treats all three as exogenous. In all specifications, economic indicators are instrumented using lagged levels dated $t-3$ and $t-4$ for the difference equations.

As shown in Tables 2.8 and 2.9, for each type of crime, the results remain consistent with the previous findings. Violent and sexual offences are affected by detection rates and sentence lengths; whereas property crimes and robberies are influenced by economic factors. Higher benefits can lead to lower crime rates. However, higher levels of inequality increase the rates of crime. The findings are valid for both the short- and long-run.

Table 2.8: Regression Estimates using Law Enforcement as Predetermined or Exogenous Factors, *Violent Crimes*, 2000/01-2011/12

	Violence against Person					Sexual Offences				
	(1) ALL END(3-4)	(2) PRE-LV(2-3) EI(3-4)	(3) PRE(2-2) EI(3-4)	(4) LAG-iv(LV) EI(3 4)	(5) EXOG	(1) ALL END(3-4)	(2) PRE-LV(2-3) EI(3-4)	(3) PRE(2-2) EI(3-4)	(4) LAG-iv(LV) EI(3 4)	(5) EXOG
Crime,t-1	0.59***	0.61***	0.59***	0.56***	0.53***	0.70***	0.76***	0.88***	0.83***	0.76***
	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)	(0.11)	(0.13)	(0.12)	(0.15)	(0.13)
rJSA per unemployed	0.00	0.00	0.00	0.00	0.00	0.04	0.01	0.04	0.00	0.01
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.11)	(0.07)	(0.07)
rAv.Weekly IS	-0.67	-0.57	-0.34	-0.42	-0.45	0.37	-0.19	-0.5	-0.29	-0.31
	(0.81)	(0.70)	(0.56)	(0.51)	(0.54)	(0.49)	(0.55)	(0.54)	(0.70)	(0.55)
Gini Coeff(x100)	-0.02	0.00	0.01	0.02	0.01	-0.01	-0.01	-0.02	0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Pop per Officer	-0.09	-0.16	-0.16		-0.20*	-0.21	-0.20*	-0.06		-0.1
	(0.24)	(0.22)	(0.19)		(0.10)	(0.13)	(0.11)	(0.13)		(0.08)
Pop per Officer,t-1				-0.21*					-0.07	
				(0.11)					(0.10)	
Det.Rate	-0.27*	-0.18	-0.19**		-0.28***	-0.23*	-0.18	-0.25		-0.18**
	(0.14)	(0.14)	(0.10)		(0.08)	(0.11)	(0.11)	(0.22)		(0.07)
Det.Rate,t-1				-0.11					-0.01	
				-0.1					-0.06	
Av.Sent.Length	0.71***	0.57**	0.20		-0.03	0.03	0.03	-0.26		0.04
	(0.25)	(0.25)	(0.30)		(0.06)	(0.12)	(0.12)	(0.26)		(0.04)
Av.Sent.Length,t-1				0.00					-0.02	
				-0.06					-0.03	
Males,15-24	-0.07	-0.05	0.15	0.30*	0.23	-0.22	-0.14	0.07	0.01	0.02
	(0.33)	(0.31)	(0.31)	(0.15)	(0.14)	(0.28)	(0.22)	(0.25)	(0.14)	(0.14)
No of Instr	33	30	30	27	27	33	30	30	27	27
AR(1) p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.20	0.14	0.20	0.32	0.36	0.22	0.22	0.43	0.21	0.21
Sargan	0.90	0.89	0.10	0.20	0.22	0.13	0.31	0.48	0.20	0.18
Hansen	0.79	0.89	0.53	0.31	0.43	0.06	0.14	0.58	0.08	0.08
Diff-in-Hansen all	0.99	0.92	0.50	0.33	0.51	0.17	0.16	0.64	0.14	0.74

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Column (1) reproduces the estimates of *column (3)* from Tables 2.2 - 2.6; all economic indicators and law enforcement variables are assumed to be endogenous. *Column (2)* treats law enforcement variables as predetermined and instruments using lags dated *t-2* and *t-3* whereas *column (3)* uses only 1 lag (*t-2*). *Column (4)* controls for potential endogeneity by estimating the model using law enforcement variables in lagged form. *Column (5)* treats all three as exogenous. In all specifications, economic indicators are instrumented using lagged levels dated *t-3* and *t-4*, for the difference equations.

Table 2.9: Regression Estimates using Law Enforcement as Predetermined or Exogenous Factors, *Property Crimes*, 2000/01-2011/12

	Robbery					Burglary					Thefts				
	(1) ALL END(3-4)	(2) PRE-LV(2-3) EI(3-4)	(3) PRE(2-2) EI(3-4)	(4) LAG-iv(LV) EI(3 4)	(5) EXOG	(1) ALL END(3-4)	(2) PRE-LV(2-3) EI(3-4)	(3) PRE(2-2) EI(3-4)	(4) LAG-iv(LV) EI(3 4)	(5) EXOG	(1) ALL END(3-4)	(2) PRE-LV(2-3) EI(3-4)	(3) PRE(2-2) EI(3-4)	(4) LAG-iv(LV) EI(3 4)	(5) EXOG
Crime,t-1	0.62***	0.61***	0.58***	0.83***	0.54***	0.72***	0.59***	0.65***	0.80***	0.69***	0.46***	0.53***	0.45***	0.56***	0.48***
	(0.10)	(0.11)	(0.10)	(0.20)	(0.16)	(0.18)	(0.15)	(0.13)	(0.13)	(0.14)	(0.13)	(0.09)	(0.10)	(0.13)	(0.15)
rJSA per unemployed	-0.12*	-0.16**	-0.13*	-0.03	-0.20**	-0.07**	-0.09**	-0.06	-0.08**	-0.08**	-0.12***	-0.12***	-0.10**	-0.09*	-0.10**
	(0.07)	(0.07)	(0.08)	(0.06)	(0.09)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
rAv.Weekly IS	-1.21*	-2.05**	-1.22*	-1.31	-1.74*	-0.3	-0.98*	-0.67	-0.71	-0.72	0.06	0.11	-0.24	0.15	0.22
	(0.63)	(0.81)	(0.61)	(0.82)	(0.94)	(0.45)	(0.55)	(0.47)	(0.54)	(0.49)	(0.48)	(0.48)	(0.54)	(0.51)	(0.60)
Gini Coeff(x100)	0.09**	0.12***	0.05	0.08	0.08*	0.01	0.02	0.02	0.03	0.03	0.06**	0.05**	0.05*	0.05**	0.06**
	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Pop per Officer	-0.52*	-0.65	-0.29		-0.80**	-0.22	-0.35*	-0.21		-0.26**	-0.2	-0.11	0.05		-0.18
	(0.30)	(0.40)	(0.27)		(0.33)	(0.22)	(0.18)	(0.18)		(0.13)	(0.20)	(0.19)	(0.18)		(0.11)
Pop per Officer,t-1				-0.34					-0.20					-0.16*	
				(0.33)					(0.13)					(0.09)	
Det.Rate	-0.38	-0.29	-0.70***		-0.70**	-0.14	-0.27**	-0.27***		-0.15	0.05	0.04	0.01		-0.01
	(0.24)	(0.25)	(0.15)		(0.26)	(0.15)	(0.13)	(0.10)		(0.09)	(0.11)	(0.12)	(0.07)		(0.08)
Det.Rate,t-1				-0.14					-0.03					-0.01	
				-0.29					-0.08					-0.08	
Av.Sent.Length	0.02	-0.06	-0.10		-0.16	-0.1	-0.09	0.21		0.08	-0.05	-0.05	0.04		0.19*
	(0.25)	(0.28)	(0.36)		(0.11)	(0.11)	(0.13)	(0.29)		(0.09)	(0.14)	(0.16)	(0.29)		(0.10)
Av.Sent.Length,t-1				0.04					0.05					0.17**	
				-0.08					-0.07					-0.08	
Males,15-24	1.61***	1.85***	1.73**	0.77	1.59**	0.42	0.73	0.66*	0.42	0.56	0.66*	0.64*	0.99**	0.49*	0.59*
	(0.57)	(0.65)	(0.76)	(0.71)	(0.77)	(0.39)	(0.49)	(0.37)	(0.30)	(0.35)	(0.36)	(0.33)	(0.41)	(0.26)	(0.32)
No of Instr	33	30	30	27	27	33	30	30	27	27	33	30	30	27	27
AR(1) p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
AR(2) p-value	0.91	0.95	0.62	0.84	0.54	0.95	0.94	0.55	0.80	0.74	0.37	0.45	0.55	0.44	0.46
Sargan	0.22	0.36	0.08	0.01	0.38	0.03	0.58	0.35	0.42	0.53	0.13	0.31	0.47	0.42	0.58
Hansen	0.44	0.26	0.45	0.01	0.34	0.16	0.86	0.30	0.74	0.57	0.87	0.81	0.75	0.68	0.75
Diff-in-Hansen all	0.19	0.28	0.27	0.93	0.30	0.53	0.89	0.26	0.85	0.91	0.88	0.82	0.57	0.41	0.50

Notes:: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) reproduces the estimates of *column (3)* from Tables 2.2 - 2.6; all economic indicators and law enforcement variables are assumed to be endogenous. *Column (2)* treats law enforcement variables as predetermined and instruments using lags dated *t-2* and *t-3* whereas *column (3)* uses only 1 lag (*t-2*). *Column (4)* controls for potential endogeneity by estimating the model using law enforcement variables in lagged form. *Column (5)* treats all three as exogenous. In all specifications, economic indicators are instrumented using lagged levels dated *t-3* and *t-4*, for the difference equations.

2.7 Conclusions

This chapter uses a dynamic panel data model to explore the short- and long-run relationship between economic indicators and crime rates, by exploiting the bi-directional nature of economic and criminal justice factors and accounting for crime persistence. The findings indicate that crime persistence is a significant determinant for all types of crime and thus, should not be ignored in empirical studies.

A vast analytical literature uses unemployment rates when exploring the role of economic incentives on determining crime rates. However, this study indicates that the state of unemployment alone cannot motivate an individual to conduct a criminal act. As economic theory predicts, crime is a rational decision with the offenders deciding on whether to engage in legal or illegal activities based on the expected payoffs which are not fully captured by the unemployment rate.

Thus, it is argued that benefits paid towards disadvantaged population groups better capture the motivation of individuals under economic distress, i.e. people who are *at-the-margin* of offending. Three economic indicators are used in the analysis, these include the jobseeker's allowance (JSA) payments to the unemployed, the income support (IS) benefits received by low-income earners and finally, an income of inequality that we construct using individual level data. To the best of our knowledge, this is the first time that unemployment and income benefits are used to investigate the links between economic factors.

Benefit payments are made towards individuals who either are unemployed or in-need of income assistance. Arguably, these individuals are more likely to engage in criminal activities, especially property crimes (Hale, 1998) as they have no returns from legal activities, making crime engagement more tempting due to lower opportunity costs. In other words, the expected returns of offending might outweigh the expected legal payoff (i.e. benefits) received while being economically distressed. In effect, benefit payments can bridge the gap between these two expected payoffs; and thus, shift the incentives of *at-the-margin* individuals away from offending.

Further, this is the first study to exploit the relationship between economic incentives and crime, in England and Wales, using an income inequality matching the observational level of crime data. Till date, a national Gini coefficient or an inter-quantile range variable have been used to capture earnings inequality. The novel Gini coefficient is constructed using confidential micro-level data from the *Annual Survey of Hours and Earnings* (*ASHE*). To design this income inequality measure, basic weekly pay is used.

In line with literature, the results indicate that violent crimes are less likely to be affected by changes in economic incentives but rather, they are responsive to higher probabilities of apprehension (positively) and longer sentences (negatively). Moreover, in accordance with the literature, we find that young males are more likely to be involved in criminal acts, specifically in robberies, burglaries and thefts.

Nevertheless, the findings suggest that there is a significant negative link between economic indicators and property crime, both in the short- and the long-run. Increases in benefit payments lead to fewer property crimes, with the reductions being larger in size during the long-term. Specifically, 10% increases in unemployment benefits lead to lower robberies, burglaries and thefts of 1.2%, 0.7% and 1.2%, in the short-run, whereas the long-term effects are significantly larger: 3.2%, 2.5% and 2.2%, respectively. Similarly, we find that increases in income benefits are negatively linked to robbery rates. Higher levels of income inequality lead to higher rates of robberies and thefts – both in the short and long term.

From a policy perspective, these findings are particularly important as they uncover a dynamic relationship between economic indicators and property crime rates. The results suggest that contemporaneous small increases in benefit payments can have a considerable long-term negative effect on property crime. Thus, by intervening and increasing benefit payments while keeping income inequality low, more *at-the-margin* individuals will be discouraged from committing crimes. Further, the analysis provides strong indications about the pervasive relationship between economic indicators and crime. Strengthening law enforcement and enhancing the capacity of criminal justice system is not the only way to reduce crime, especially property crime.

Thus, by further understanding the effect of economic distress on crime, much may be gained, both in terms of policy development and crime prevention.

Appendix A.2

A.2.1 Sources and Description of Data

A.2.1.1 Data Sources

Appendix A.2.1.1: Description of Data Statistics

Data	Source	Published by	Available at	Description	Calculation
Dependent Variables					
Crime Rates	Police Recorded Crime Statistics	Home Office ONS	PFA	violent: violence against the person, sexual offences and robbery; property: burglary, theft and motor vehicle offences	# of crimes x 1,000 / PFA population
Economic Indicators					
Jobseeker's Allowance (JSA) per unemployed	*Benefit Expenditure and Caseload Tables*, Department for Work and Pensions	Nomis	LA	benefit paid to working-age individuals, not in full-time employment or work less than 16 hours a week	JSA expenditure / # of JSA recipients
Av. Weekly JSA	*Benefit Expenditure and Caseload Tables*, Department for Work and Pensions	Nomis	LA	average weekly unemployment benefit payments	total JSA weekly benefits / # of JSA recipients
Av. Weekly Income Support (IS)	*Benefit Expenditure and Caseload Tables*, Department for Work and Pensions	Nomis	LA	income benefits received by low-wage earners	total IS weekly benefits / # of IS claimants
Gini Coefficient	Annual Survey of Hours and Earnings (ASHE)	ONS	individual level data	an equality measure estimated by using basic weekly pay and annual gross pay	
Law Enforcement					
Population per Officer	Police Statistics	CIPFA	PFA	a ratio of PFA population to number of police officers; capturing the strength of law enforcement	PFA population / # of police officers
Detection Rates	Criminal Statistics, Home Office Statistical Bulletin	Home Office	PFA	available by type of offence (vehicle & other thefts are combined) a % measure of recorded offences being 'cleared-up' by the police; capturing the probability of apprehenssion	# of detections / # of recorded crimes
Conviction Rates	Justice Statistics Analytical Services	Ministry of Justice	PFA	available by type of violent offence, property crime convictions are not disaggregated a % of convicted criminals; captures the probability of conviction	# of convictions / # of recorded crimes
Av. Sentence Length	Justice Statistics Analytical Services	Ministry of Justice	PFA	by type of offence	custody sentence / months spent in custody
Demographics					
Males (15-24)	Mid-Year Population Estimates	Nomis	LA	% of male aged 15-24	# of males (15-25) / mid-year PFA estimates
Population Density	Police Statistics	CIPFA	PFA	resident population per hectare	PFA population x 1,000 / PFA area (in hectares)
Education	Labour Force Survey Annual Population Survey	Nomis	LA	% of resident population with NVQ4+ qualifications (National Vocational Qualifications)	individuals with NVQ4+ / PFA population

Notes: CIPFA stands for Chartered Institute of Public Finance and Accountancy. All variables included in the regressions are at the Police Force Area (PFA) level. They also enter the model in log form, except from the Gini coefficient which is multiplied by 100.

A.2.1.2 Jobseeker's Allowance (JSA)

Jobseeker's allowance (JSA) is a benefit paid to working-age individuals who are not in full-time employment or work less than 16 hours a week. Unemployed benefit recipients must be able to work and are actively seeking a job. The UK government offers two types of JSA: contribution- and income-based JSA. The former is non-means tested whereas the latter is means tested. The *contribution-based JSA* is received by individuals who have previously been working and paid enough national insurance contributions in the last two years. The benefits are received for up to 6 months, irrespective of having a partner. On the other hand, *income-based JSA* is paid towards individuals who are low income earners or have savings under £16,000. It is not necessary for the recipient to have paid any national insurance contributions prior to receiving the benefits, and payments can be made indefinitely as long as, on average, they work less than 16 hours per week. If recipients have a partner then, their partner must either be out of full-time employment or work for less than 24 hours a week. Individuals who receive JSA based on contributions might also be eligible for some income-based JSA if they are low income earners *and* have a partner, disability or they are carers to a person with a disability, or have housing costs, such as mortgage.

Annual JSA expenditures per local authority are available by the Department for Work and Pensions as part of the *Benefit Expenditure and Caseload Tables* publication, after the calendar year 2000/01. After deflating nominal values, the data are aggregated up to the PFA level by allocating LAs to corresponding police areas. Then, annual JSA expenditures are divided by the number of JSA recipients (again, at the PFA level), to obtain average annual JSA payments. The number of unemployed is obtain from *Nomis*[103].

[103] *Nomis* is an online tool run by the Office for National Statistics (ONS). It keeps updated records about UK's labour market statistics.

A.2.1.3 Income Support (IS)

In the UK, *Income Support (IS)* offers some relief to working-age low income earners. It is a means-tested benefit and entitlement is subjective to recipient's income and savings (less than £16,000). IS can be received on its own or on top of any other benefits or part-time income, in order for the individual to receive the basic amount the law says is needed to live on. However, it is targeted towards four specific groups of the population. The statistical categories are based on the claimant's primary reason for claiming benefit. This is done hierarchically, so a claimant can only appear in one group, which prevents double-counting. The ordering is: incapacity (due to illness or disability), lone parents, carers and other income related – mostly relating to people on Pension Credit[104]. Also, to be entitled to IS, the individual should not receive JSA[105] and although allowed to work (less than 16 hours per week), should not be in full-time employment.

To obtain the average income support benefits, two variables, available in *Nomis*, are used: the number of IS claimants and the average weekly benefits[106]. The data are available at the LA level thus, some adjustments are made. Before aggregating data to the PFA level, the total weekly benefits paid at the LA are estimated, by multiplying the average weekly benefits by the number of IS claimants. Then, the data are aggregated up to the PFA level. Finally, the total weekly benefits are divided by the number of claimants, to obtain average weekly earnings for each PFA.

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[104] Pension Credit is also an income-based benefit which consists of 2 parts: (1) *Guarantee Credit*, received by GB residents when claimants or their partners have reached the qualifying age for Pension Credit which is 66, and (2) *Savings Credit*, is an extra benefit received when individuals or their partner is 65 years old and over. For more information see, https://www.gov.uk/pension-credit/eligibility .

[105] Or recipients of Employment and Support Allowance (ESA) which is offered to ill or disabled individuals. For more information see, https://www.gov.uk/employment-support-allowance/overview .

[106] The data are published on a quarterly basis (February, May, August and November). The number of claimants for each quarter is measured on the last day of that quarter. For instance, if August 2010 is chosen, it shows the number of people on IS at 31st August 2016. It does not specify how many individuals receive IS in the year prior to that, just the number of people on the system at that specific date. Since, the IS is paid at the end of each week, the average weekly IS benefits, also available in Nomis, are estimated at these 4 specific points in time. To avoid seasonality, the same quarter is chosen for each year. For this analysis, February was chosen.

A.2.1.4 Gini Coefficient

To account for the limitations of national and inter-quantile measures of income inequality; individual level data, obtained from the *Annual Survey of Hours and Earnings (ASHE)*, are used to construct a Gini coefficient at the PFA level. ASHE is the most reliable and comprehensive source of information on wages and hours worked. The survey represents a 1% sample of the UK working population, approximately 140,000-185,000 individuals per year. The sample is drawn from HM Revenue and Customs Pay As You Earn (PAYE) records. Due to its large sample size and the earnings information being collected from employers and not from the employees themselves, the survey is considered to be more accurate than other surveys, such as the Labour Force Survey (LFS).

The dataset has information on each individual's work and home LA. The estimations presented make use of the work LA because, for many individuals the home LA was missing. Despite acknowledging the fact that an individual may live in a LA but work in another, since the income inequality is aggregated up to the PFA level, these two LAs should fall under the same PFA[107]. Also, the sample is restricted to include only LAs within England and Wales. Appendix A.2.2 provides a comprehensive list of LAs and to which PFA they belong to.

To design this income inequality measure, first, using work LAs, each individual has been given a PFA 'label'. This was done for all available years. Then, using the surveys' weights the individual *basic weekly pay* is weighted up to local authorities' level and then, to the respective PFAs. Again, this is done for all years, individually. Basic weekly earnings are used to estimate the Gini coefficient rather than the gross pay[108]. As discussed by Dahlberg and Gustavsson (2008), it is changes in permanent income – one's salary – that affect crimes the most, not shifts in transitory income. Thereafter, the *fastgini* command is implemented to obtain PFA income distributions. This is achieved by utilising a fast-optimised algorithm. The standard errors of this income inequality measure are also estimated. Although, the command allows us to approximate the Gini coefficient, the whole sample is used to obtain an exact measure of income inequality.

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[107] To show that this indeed the case, home LAs are used to construct the Gini coefficient and the regressions are re-estimated. The results indicate that there is no difference.

[108] Nevertheless, for robustness, a Gini coefficient using gross pay is also constructed and crime regressions are re-estimated. The estimation results are provided in Section 2.6.1.

A.2.2 LA to PFA Allocation

Appendix A.2.2.1: Local Authorities Districts (LAD) to Police Force Area (PFA)

1	***Avon and Somerset***
	Bath and North East Somerset
	Bristol, City of
	North Somerset
	South Gloucestershire
	Mendip
	Sedgemoor
	South Somerset
	Taunton Deane
	West Somerset
2	***Bedfordshire***
	Bedford
	Central Bedfordshire
	Luton
3	***Cambridgeshire***
	Peterborough
	Cambridge
	East Cambridgeshire
	Fenland
	Huntingdonshire
	South Cambridgeshire
4	***Cheshire***
	Cheshire East
	Cheshire West and Chester
	Halton
	Warrington
5	**Cleveland**
	Hartlepool
	Middlesbrough
	Redcar and Cleveland
	Stockton-on-Tees
6	**Cumbria**
	Allerdale
	Barrow-in-Furness
	Carlisle
	Copeland
	Eden
	South Lakeland
7	**Derbyshire**
	Derby
	Amber Valley
	Bolsover
	Chesterfield
	Derbyshire Dales
	Erewash
	High Peak
	North East Derbyshire
	South Derbyshire
8	**Devon & Cornwall**
	Cornwall
	Isles of Scilly
	Plymouth
	Torbay
	East Devon
	Exeter
	Mid Devon
	North Devon
	South Hams
	Teignbridge
	Torridge
	West Devon
9	**Dorset**
	Bournemouth
	Poole
	Christchurch
	East Dorset
	North Dorset
	Purbeck
	West Dorset
	Weymouth and Portland
10	**Durham**
	Darlington
	County Durham
11	**Dyfed-Powys**
	Powys
	Ceredigion
	Pembrokeshire
	Carmarthenshire
12	**Essex**
	Southend-on-Sea
	Thurrock
	Basildon
	Braintree
	Brentwood
	Castle Point
	Chelmsford
	Colchester
	Epping Forest
	Harlow
	Maldon
	Rochford
	Tendring
	Uttlesford
13	**Gloucestershire**
	Cheltenham
	Cotswold
	Forest of Dean
	Gloucester
	Stroud
	Tewkesbury
14	**Greater Manchester**
	Bolton
	Bury
	Manchester
	Oldham
	Rochdale
	Salford
	Stockport
	Tameside
	Trafford
	Wigan
15	**Gwent**
	Caerphilly
	Blaenau Gwent
	Torfaen
	Monmouthshire
	Newport
16	**Hampshire**
	Isle of Wight
	Portsmouth
	Southampton
	Basingstoke and Deane
	East Hampshire
	Eastleigh
	Fareham
	Gosport
	Hart
	Havant
	New Forest
	Rushmoor
	Test Valley
	Winchester
17	**Hertfordshire**
	Broxbourne
	Dacorum
	East Hertfordshire
	Hertsmere
	North Hertfordshire
	St Albans
	Stevenage
	Three Rivers
	Watford
	Welwyn Hatfield
18	**Humberside**
	East Riding of Yorkshire
	Kingston upon Hull, City of
	North East Lincolnshire
	North Lincolnshire
19	**Kent**
	Medway
	Ashford
	Canterbury
	Dartford
	Dover
	Gravesham
	Maidstone
	Sevenoaks
	Shepway
	Swale
	Thanet
	Tonbridge and Malling
	Tunbridge Wells
20	**Kent**
	Medway
	Ashford
	Canterbury
	Dartford
	Dover
	Gravesham
	Maidstone
	Sevenoaks
	Shepway
	Swale
	Thanet
	Tonbridge and Malling
	Tunbridge Wells
21	**Lancashire**
	Blackburn with Darwen
	Blackpool
	Burnley
	Chorley
	Fylde
	Hyndburn
	Lancaster
	Pendle
	Preston
	Ribble Valley
	Rossendale
	South Ribble
	West Lancashire
	Wyre
22	**Leicestershire**
	Leicester
	Rutland
	Blaby
	Charnwood
	Harborough
	Hinckley and Bosworth
	Melton
	North West Leicestershire
	Oadby and Wigston
23	**Lincolnshire**
	Boston
	East Lindsey
	Lincoln
	North Kesteven
	South Holland
	South Kesteven
	West Lindsey
24	**London, City of**
	City of London
25	**Merseyside**
	Knowsley
	Liverpool
	Sefton
	St. Helens
	Wirral
26	**Metropolitan Police**
	Camden
	Hackney
	Hammersmith and Fulham
	Haringey
	Islington
	Kensington and Chelsea
	Lambeth
	Lewisham
	Newham
	Southwark
	Tower Hamlets
	Wandsworth
	Westminster
	Barking and Dagenham
	Barnet
	Bexley
	Brent
	Bromley
	Croydon
	Ealing
	Enfield
	Greenwich
	Harrow
	Havering
	Hillingdon
	Hounslow
	Kingston upon Thames
	Merton
	Redbridge
	Richmond upon Thames
	Sutton
	Waltham Forest
27	**Norfolk**
	Breckland
	Broadland
	Great Yarmouth
	King's Lynn and West Norfolk
	North Norfolk
	Norwich
	South Norfolk
28	**North Wales**
	Anglesey
	Gwynedd
	Conwy
	Denbighshire
	Flintshire
	Wrexham
29	**North Yorkshire**
	York
	Craven
	Hambleton
	Harrogate
	Richmondshire
	Ryedale
	Scarborough
	Selby
30	**Northamptonshire**
	Corby
	Daventry
	East Northamptonshire
	Kettering
	Northampton
	South Northamptonshire
	Wellingborough
31	**Northumbria**
	Northumberland
	Gateshead
	Newcastle upon Tyne
	North Tyneside
	South Tyneside
	Sunderland
32	**Nottinghamshire**
	Nottingham
	Ashfield
	Bassetlaw
	Broxtowe
	Gedling
	Mansfield
	Newark and Sherwood
	Rushcliffe
33	**South Wales**
	Swansea
	Neath Port Talbot
	Bridgend
	The Vale of Glamorgan
	Cardiff
	Rhondda, Cynon, Taff
	Merthyr Tydfil
34	**South Yorkshire**
	Barnsley
	Doncaster
	Rotherham
	Sheffield
35	**Staffordshire**
	Stoke-on-Trent
	Cannock Chase
	East Staffordshire
	Lichfield
	Newcastle-under-Lyme
	South Staffordshire
	Stafford
	Staffordshire Moorlands
	Tamworth
36	**Suffolk**
	Babergh
	Forest Heath
	Ipswich
	Mid Suffolk
	St Edmundsbury
	Suffolk Coastal
	Waveney
37	**Surrey**
	Elmbridge
	Epsom and Ewell
	Guildford
	Mole Valley
	Reigate and Banstead
	Runnymede
	Spelthorne
	Surrey Heath
	Tandridge
	Waverley
	Woking
38	**Sussex**
	Brighton and Hove
	Eastbourne
	Hastings
	Lewes
	Rother
	Wealden
	Adur
	Arun
	Chichester
	Crawley
	Horsham
	Mid Sussex
	Worthing
39	**Thames Valley**
	Bracknell Forest
	Milton Keynes
	Reading
	Slough
	West Berkshire
	Windsor and Maidenhead
	Wokingham
	Aylesbury Vale
	Chiltern
	South Bucks
	Wycombe
	Cherwell
	Oxford
	South Oxfordshire
	Vale of White Horse
	West Oxfordshire
40	**Warwickshire**
	North Warwickshire
	Nuneaton and Bedworth
	Rugby
	Stratford-on-Avon
	Warwick
41	**West Mercia**
	Herefordshire, County of
	Shropshire
	Telford and Wrekin
	Bromsgrove
	Malvern Hills
	Redditch
	Worcester
	Wychavon
	Wyre Forest
42	**West Midlands**
	Birmingham
	Coventry
	Dudley
	Sandwell
	Solihull
	Walsall
	Wolverhampton
43	**West Yorkshire**
	Bradford
	Calderdale
	Kirklees
	Leeds
	Wakefield
44	**Wiltshire**
	Swindon
	Wiltshire

Notes: Local authority districts (LAD) refers to the 'district' level of local government in England and Wales. It includes non-metropolitan districts, metropolitan districts, unitary authorities and London boroughs in England; and Welsh unitary authorities. There are 43 police force areas (PFAs) in England and Wales, each covering one or more complete local authorities

A.2.3 Summary of England and Wales Literature

Appendix A.2.3.1: Summary Review of Economic of Crime Literature in the United Kingdom

Author(s)	Publication Year	Data Analysis	Aggregation Level	Time Frame	Estimation Method	Types of Crime	Dynamic Specification	Economic Indicators (EI) Used	EI Link to Crime	Controlling for EI Endogeneity	Law Enforcement (LE) Variables	LE Link to Crime	Controlling for LE Endogeneity	Findings on EI	Fndings on LE
Wolpin	1978	time-series	national	1894-1967	Simultaneous Equation Model (SEM)	larceny; burglary; robbery; auto theft; malicious and felonious wounding; all offences against the person; all offences		unemployment rate; real weekly wage in manufacturing for manual workers; GDP per capita	+ve -ve -ve		clearance rate; conviction rate; imprisonment rate; recognizance rate; fine rate; average sentence	-ve -ve -ve -ve -ve +ve		- Unemployment rate has a positive impact on non-violent property crime (burglary, larceny, auto theft, robbery); - Increases in weekly wages, lower non-violent property crimes and increase personal crimes; - GDP per capita is negatively linked to property crimes and positively to personal crimes	in general, all law enforcement variables are found to be negatively related to crimes, with the exception of average sentences which has a positive impact on crime
Willis	1983	cross-section	PFAs	1979	Simultaneous Equation Model (SEM)	violence against the person; sexual offences; theft		unemployment rate; mean income (incl. only for thefts); reteable property value (RV)	+ve -ve -ve (RV +ve and insignificant for thefts)		clearance rate; conviction rate; custodial sentence rate; police efficiency	-ve -ve -ve +ve		- Increases in unemployment is consistently linked to increases in all 3 types of crime - Increases in wages, lower the # of thefts - Higher reteable value translates into more targets of theft, while being negatively related to violent and sexual offences	clearence, conviction and custodial rates have a negativee link with all 3 types of crime police manpower efficiency coefficient is positve
Sampson and Wooldredge	1987	cross-section	individual level/ electoral wards	1982		*British Crime Survey -* **victimisation rates:** burglary; household theft; personal theft; personal larceny		unemployment rate	+ve		N/A			Unemployed are more likely to become victims of burglary and household and personal theft (for the latter: the risk of victimisation is captured by incidences in close proximity, 15-minute walk, to the victim's house)	
Field	1990	time-series	national	1950-1987	Simultaneous Equation Model (SEM)	**growth rates:** *violent crimes:* violence against the person; sexual offences; *property crimes:* burglary; (residential & non) theft; (from a person a shop, of a/from a vehicle) robbery; criminal damage; fraud		personal consumption/ unemployment rate/ unemployment benefits	-ve no effect +ve		clear-up rate; # of guilty or cautioned offenders; prison population; # of police officers	+ve +ve +ve mixed	X (but considers # of police officers as exogenous)	The estimates capture short-run effects. Property crimes are counter-cyclically related to business cycles. - Report short-run negative effects between personal consumption and crimes. No LR effects -No link between unemployment and crimes, although unemployment was not included in each regression - Unemployment benefits are included only for thefts from vehicle and violence against the person. A positive link is reported	clear-up rate, the # of offenders guilty or cautioned and the prison population are found to have a positive link to growth in all crimes; there is no deterred effect is inferred. the growth rate in police size was negative for theft of and from vehicles, other theft and sexual offences, but positive for violence against the person. Note: although the author tries to account for the reverse causality of LE variables, he highlights that the model may suffer from omitted variable bias
Hale and Sabbagh	1991	time-series	national	1949-1987	Error Correction Models (ECM)	total theft; theft by an employee; shoplifting; handling stolen goods; auto theft; burglary; robbery; violent crime	X	unemployment rate	+ve		N/A			There is a strong relation for 5 out of 8 crimes (no relationship for shoplifting, handling stolen goods and auto theft). - Evidence of motivation effect for property offences (theft, burglary, robbery), i.e. positive link between crime and unemployment. - Evidence of opportunity/guardniaship effect only evident on thefts, i.e. increases in unemployment, lower thefts	
Pyle and Deadman	1994	time-series	national	1946-1991	Error Correction Models (ECM)	**crime:** *property crimes:* burglary; theft; robbery		personal consumption/ GDP/ unemployment rate	-ve -ve +ve		conviction rate; # of police officers	-ve insignificant		Estimates capture long-run effects (the model allows LR relationships between variables to be incorporated into SR dynamic models). - LR relationships between all 3 economic indicators and crime are repored. - Increases in either GDP or personal consumption decrease property crimes whereas increases in unemployment rate have the opposite effect	increases in conviction rates are linked to less crimes; with the exception of burglary when unemployment rate is the economic indicator. The number of police officers is insignificant in most specifications, except for burglary and theft when including personal consumption as an economic variable.
Hale	1998	time-series	national	1946-1991	Error Correction Models (ECM)	*property crimes:* burglary; theft; robbery	X (when estimating *short-run* models)	consumer expenditure/ GDP/ unemployment rate	+ve no effect +ve (SR)		conviction rate; # of police officers	-ve -ve		- findings based in the long-run: burglary and theft are positively related to consumer expenditure, only. No relationship between any of the 3 economic indicators and robbery. Unemployment rate is not related to any of the crimes in the LR. - findings based in the short-run: personal expenditure and property crime are negatively related in the SR. Unemployment is positively linked to all 3 types of crime in the SR (but with none in the LR).	statistically significant but as the author stresses out it is highly dependent on the methodology used. when re-estimating the models using two-stage Engle Granger the estimates become insignificant.

Appendix A.2.3.1 *(cont'd)*: Summary Review of Economic of Crime Literature in the United Kingdom

Author(s)	Publication Year	Data Analysis	Aggregation Level	Time Frame	Estimation Method	Types of Crime	Dynamic Specification	Economic Indicators (EI) Used	EI Link to Crime	Controlling for EI Endogeneity	Law Enforcement (LE) Variables	LE Link to Crime	Controlling for LE Endogeneity	Findings on EI	Fndings on LE
Witt et al.	1998	panel	regional	1979-1993	OLS	burglary; theft from a vehicle; other theft; shoplifting; robbery		male unemployment rate; male earnings inequality (a ratio of 90th/10th decile of male gross weekly earnings)	+ve +ve		# of police employees	mixed		- Increases in unemployment and earnings inequality affects positively all 5 crimes (although changes in earnings inequality are insignificant for shoplifting) A 1% increase in unemployment, increases the number of thefts and violence by only 0.2 pp with no effect on sexual offences	weakly positive link between the number of police officers and burglary and theft from a vahicle. Its relation of shoplifting is negative; whereas for other theft is insingificant
Witt et al.	1999	panel	PFAs	1986-1996	First-Difference GMM	*property crimes:* vehicle; other theft; burglary and handling stolen goods	X	male unemployment rate; distribution (90th/10th decile) of FT manual male gross weekly earnings; car per capita	+ve +ve +ve		# of police officers per capita	-ve		- Higher unemployment rates lead to increases in all 4 types of crime; - Increases in wage inequality and in cars per capita impact positively property crime	a stronger police force, reduces property crime
Carmichael and Ward	2000	time-series	regional	1985-1995	OLS/ Fixed Effects/ Semi-Logs/ First-Differences	burglary; thefts; robbery; criminal damage; violence against the person; total crime		youth & adult male unemployment rate	+ve		clear-up rates; custodial rates; average sentence length (incl. only in total crime regressions)	-ve -ve insignificant		- A positive link between burglary and male youth (2.3%) and adult (4.4%) unemployment is reported; - Youth unemployment is positively linked to criminal damage (2.8-3%) and robbery (5-8%); - Theft (2%) is positively related to adult unemployment	Detection rates and crime are negatively linked, except for crimes committed agains the person; Prison sentences are also negatively linked to all crimes except for robberies; The severity of punishment is insignificant (tested only on total crime)
Carmichael and Ward	2001	panel	PFAs	1989-1996	OLS/ Semi-Logs/ First-Differences	burglary; thefts; robbery; fraud & forgery; violent crimes; criminal damage; total crime		youth & adult male unemployment rate	+ve		clear-up rates; custodial rates; average sentence length	-ve -ve insignificant		- A positive relationship between male unemployment rates is found, for both youth and adults, and property crime (burglary & thefts), fraud/forgery and total crime rates	Clear-up and custodial rates are negatively linked to most crimes; However, the link between average sentences and crime was insignificant and small
Machin and Meghir	2004	panel	PFAs	1975-1996	Within-Groups	**log odds ratios** *property crime:* crime against the property; (burglary & theft and handling) vehicle crime	X (as a robustness check controlling for LE/EI endogeneity)	25th percentile of the overall wage distribution/ 25th percentile of the retail trade wage distribution	-ve -ve		conviction rate	-ve	X	They find that there is a trade-off between crime and labour market incentives: - A 10% higher wages at the bottom of the distribution predict a 0.7 percentage point lower property crime rates - Increases in the direce economic return to crime, increase crime	Higher deterrence measures reduce criminal activity
Saridakis	2011	time-series	national	1960-2012	Vector Autoreggresive Model (VAR)	*violent crime rates:* total crime; homicide; rape; indecent assault on a female; aggravated assault		male unemployment rate; poverty rate (% of households below 60% median income)	+ve +ve (only for aggr. assault)		conviction rate; imprisonment rate	-ve -ve (only for aggr. assault)	X	- No LR causality between serious violent crimes, - Except for aggravated assault where increases in unemployment and poverty rates increase assaults	Increases in conviction and imprisonment rates lower the # of aggravated assaults
Wu and Wu	2012	panel	regional	2002-2007	Fixed Effects/ Random Effects	violence against the person; sexual offences; criminal damage; robbery; burglary; vehicle offences; other theft offences; fraud & forgery; drug-related crimes; other crimes		male unemployment rate; distribution of 10th/90th percentile of male wages	mixed +ve		santion detection rate	-ve		- Unemployment only significant for fraud (negatively), drug and other crimes - Wage inequality has a positive impact on economic-motivated' crimes, such as robbery, burglary, vehicle and thefts offences, fraud & forgery	Higher detection rates are significant and have a negative effect on most crimes (except for sexual offences, drug-related crimes and other crimes) and a positive impact on drug-related offences
Han et al.	2013	panel	PFAs	1992-2008	Forward Orthogonal Difference GMM	*violent crimes:* violence against the person; sexual offences; robbery; *property crimes:* burglary; theft & handling; fraud & forgery	X	unemployment rate; real average weekly earnings; Gini coefficient (national)	-ve +ve mixed		detection rate; prison population	+ve -ve	X	no consistent effect between economic variables and crimes, except with real earnings - Unemployment is negatively linked to burglaries, fraud/forgery and robberies - Increases in real earnings are linked to more crimes, except for robberies - Higher income inequality leads to more burglaries, thefts and robberies while being associated with less violence and sexual offences	All crimes are highly persistent (significant +ve lag); Increases in detection rates, decrease all types of crime whereas higher prison populations, lower burglaries and violent crimes

A.2.4 Summary Statistics

A.2.4.1 Descriptive Statistics

Appendix A.2.4.1.1: Descriptive Statistics

	Obs	Mean	Std.Dev.	Min	Max
Crime Rates					
Violence against the person	504	2.45	0.29	1.39	3.22
Sexual Offences	504	−0.10	0.25	−1.06	0.58
Robbery	504	−0.36	0.83	−3.04	2.01
Burglary	504	2.39	0.40	1.20	3.51
Thefts	504	2.99	0.23	2.16	3.76
Economic Indicators					
Real JSA per unemployed	504	7.41	0.30	6.63	9.38
Real Av.Weekly JSA	504	4.00	0.05	3.87	4.15
Real Av.Weekly IS	504	4.29	0.09	4.11	4.58
Gini Coeff(x100)	504	37.51	1.57	33.69	43.26
Law Enforcement					
Population per Officer	504	6.10	0.19	5.45	6.47
<u>Detection Rates</u>					
Violence	504	3.99	0.25	3.18	4.56
Sexual	504	3.61	0.32	2.94	4.56
Robbery	504	3.25	0.32	2.30	4.51
Burglary	504	2.59	0.27	1.77	3.66
Thefts	504	2.93	0.26	2.08	3.87
<u>Av.Sentence Length</u>					
Violence	504	2.95	0.16	2.37	3.40
Sexual	504	3.73	0.20	2.88	4.27
Robbery	504	3.56	0.18	2.80	4.19
Thefts	504	2.16	0.16	1.59	2.62
<u>Conviction Rates</u>					
Violence	504	1.48	0.36	0.59	2.68
Sexual	504	2.24	0.31	1.40	3.05
Robbery	504	2.57	0.47	1.05	4.14
Thefts	504	1.67	0.31	1.01	2.84
Demographics					
Males,15-24	504	1.84	0.09	1.63	2.02
Pop Density	504	5.62	0.94	2.94	7.73
Education	504	3.23	0.19	2.79	3.81

Notes: All variables are in natural logs, except Gini coefficient which is multiplied by 100. Sample period 2000/01-2011/12 for 42 PFA (excluding London).

A.2.4.2 Correlation and Multicollinearity Tests

Appendix A.2.4.2.1: Bivariate Correlation

	Thefts	JSA	ISpay	Gini	Pop/Off	Det.Rate	Av.Sent.Length	Males
Thefts	1							
Real JSA per unemployed	0.113**	1						
Real Av.Weekly IS	0.234***	−0.293***	1					
Gini Coeff(x100)	0.163***	−0.236***	0.121***	1				
Population per Officer	−0.344***	−0.271***	−0.381***	0.182***	1			
Thefts Det.Rate	−0.421***	0.197***	−0.138***	−0.448***	−0.021	1		
Av.Thefts Sent.Length	0.021	−0.018	−0.143***	−0.245***	0.090**	−0.037	1	
Males,15-24	0.268***	0.0316	0.267***	−0.216***	−0.558***	−0.053	0.072	1

Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All variables are in natural logs, except Gini coefficient which is multiplied by 100. Sample period 2000/01-2011/12 for 42 PFA (excluding London).

Appendix A.2.4.2.2: Multicollinearity (VIF) Test

	VIF	1/VIF
Thefts,t-1	1.55	0.65
Real JSA per unemployed	1.39	0.72
Real Av.Weekly IS	1.50	0.67
Gini Coeff(x100)	1.53	0.65
Population per Officer	2.06	0.49
Thefts Det.Rate	1.49	0.67
Av.Thefts Sent.Length	1.15	0.87
Males,15-24	1.56	0.64
Mean VIF	1.53	
N	462	

Notes: Sample period 2000/01-2011/12 for 42 PFA (excluding London).
All variables are in natural logs, except Gini coefficient which
is multiplied by 100.

A.2.5 Econometric Modelling

A.2.5.1 System GMM

Appendix A.1.5.1 describes, in detail the differences between SYS GMM and DIFF GMM estimators.

A.2.5.2 Tests for Series Persistence and Stationarity

SYS GMM is more efficient than DIFF GMM when the series is highly persistent and stationary (in differences). To test for series persistence, simple first-order autocorrelation models including year dummies[109] are estimated using all available lags. The test is also performed for all explanatory variables in the dataset – tables are available upon request.

Table A.2.5.2.1 shows that crime rates are fairly persistent across all estimators, ranging from 0.54 (violence against the person and robbery) to 0.88 (burglary). Also, the results indicate a serial correlation of order 1 and so, the instrument list should start from values dated $t-2$ and earlier. See *Appendix A.2.5.3* for a discussion of tests of serial correlation.

The second condition requires the dependent variable, in *differences*, to be stationarity. In other words, the *first-differences* of the explanatory variables should not be correlated with the PFA-specific effect, i.e. no unit root in differences. Correlation between regressors in *levels* and the PFA fixed effects is allowed, i.e. can have unit root in levels. To test for the series stationarity, the Levin-Lin-Chu panel-data unit root test[110] is implemented. As shown in *Table A.2.5.2.2* below, the series are stationary in *first-differences* and have a unit root in *levels*; satisfying the second additional assumption of SYS GMM.

The results of both tests indicate that both assumptions of high persistence and stationarity are satisfied. Thus, using SYS GMM would produce more efficient and consistent estimates than DIFF GMM.

[109] Accounting for heteroskedastic robust errors; allowing observations to be independent across states (clusters) but not necessarily within PFAs.
[110] The Im-Pesaran-Shin test is also used and confirms the results.

Table A.2.5.2.1: AR(1) Model Estimates, 2000/01-2011/12

	(1) OLS levels	(2) within groups	(3) one-step DIFF t-2	(4) one-step DIFF t-3	(5) one-step SYS t-2	(6) one-step SYS t-3	(7) two-step DIFF t-2	(8) two-step DIFF t-3	(9) two-step SYS t-2	(10) two-step SYS t-3
Violence,t-1	0.80***	0.60***	0.72***	0.56***	0.72***	0.54***	0.70***	0.57***	0.69***	0.52***
	(0.03)	(0.04)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.09)	(0.06)	(0.09)
AR(1) p-value	0.16	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.50	0.25	0.37	0.31	0.37	0.31	0.36	0.32	0.35	0.31
Sargan			0.01	0.18	0.01	0.06	0.01	0.18	0.01	0.06
Hansen			0.14	0.17	0.17	0.08	0.14	0.17	0.17	0.08
Diff-in-Hansen all					0.42	0.06			0.42	0.06
Sexual Offences,t-1	0.80***	0.51***	0.65***	0.59***	0.65***	0.58***	0.68***	0.60***	0.68***	0.60***
	(0.03)	(0.06)	(0.08)	(0.10)	(0.08)	(0.11)	(0.11)	(0.14)	(0.11)	(0.14)
AR(1) p-value	0.02	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.50	0.84	0.15	0.19	0.15	0.19	0.18	0.20	0.17	0.20
Sargan			0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01
Hansen			0.10	0.07	0.13	0.09	0.10	0.07	0.13	0.09
Diff-in-Hansen all					0.46	0.43			0.46	0.43
Robbery,t-1	0.97***	0.66***	0.73***	0.47***	0.86***	0.54***	0.78***	0.42**	0.90***	0.45**
	(0.01)	(0.06)	(0.10)	(0.16)	(0.09)	(0.17)	(0.14)	(0.17)	(0.13)	(0.18)
AR(1) p-value	0.22	0.81	0.00	0.02	0.00	0.01	0.00	0.05	0.00	0.05
AR(2) p-value	0.14	0.04	0.68	0.46	0.74	0.53	0.69	0.41	0.72	0.45
Sargan			0.00	0.05	0.00	0.04	0.00	0.05	0.00	0.04
Hansen			0.07	0.22	0.08	0.30	0.07	0.22	0.08	0.30
Diff-in-Hansen all					0.24	0.98			0.24	0.98
Burglary,t-1	0.94***	0.74***	0.95***	0.85***	0.99***	0.88***	0.95***	0.87***	1.05***	0.87***
	(0.01)	(0.04)	(0.09)	(0.10)	(0.09)	(0.08)	(0.12)	(0.13)	(0.12)	(0.11)
AR(1) p-value	0.27	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2) p-value	0.45	0.10	0.88	0.88	0.88	0.88	0.89	0.88	0.89	0.88
Sargan			0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
Hansen			0.11	0.06	0.05	0.09	0.11	0.06	0.05	0.09
Diff-in-Hansen all					0.05	0.53			0.05	0.53
Thefts,t-1	0.93***	0.61***	0.74***	0.54***	0.72***	0.55***	0.82***	0.56***	0.80***	0.58***
	(0.02)	(0.05)	(0.08)	(0.10)	(0.08)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)
AR(1) p-value	0.76	0.23	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.00
AR(2) p-value	0.38	0.42	0.95	0.78	0.94	0.79	0.94	0.80	0.95	0.82
Sargan			0.02	0.64	0.01	0.52	0.02	0.64	0.01	0.52
Hansen			0.03	0.58	0.06	0.60	0.03	0.58	0.06	0.60
Diff-in-Hansen all					0.82	0.39			0.82	0.39

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample period 2000/01-2011/12 for 42 PFA (excluding London). All variables are in natural logs.

All available lags are used as instruments to estimate a simple autoregressive model without controls: $crime_{PFA,t} = \alpha crime_{PFA,t-1} + \mu_{PFA} + \epsilon_{PFA,t}$

Table A.2.5.2.2: LLC Unit Root Tests for Series Stationarity, 2000/01- 2011/12

	(1) First Differences	(2) Levels
Crime Rates		
Violence against the person	0.00	0.00
Sexual Offences	0.00	0.00
Robbery	0.00	0.11
Burglary	0.00	0.00
Thefts	0.00	0.00
Economic Indicators		
Real JSA per unemployed	0.00	0.00
Real Av.Weekly JSA	0.00	0.00
Real Av.Weekly IS	0.00	0.02
Gini Coeff(x100)	0.00	0.00
Law Enforcement		
Population per Officer	0.08	1.00
Detection Rates		
Violence	0.00	0.00
Sexual	0.00	0.00
Robbery	0.00	0.00
Burglary	0.00	0.00
Thefts	0.00	0.00
Av.Sentence Length		
Violence	0.00	0.00
Sexual	0.00	0.00
Robbery	0.00	0.00
Thefts	0.00	0.00
Conviction Rates		
Violence	0.00	0.00
Sexual	0.00	0.01
Robbery	0.00	0.18
Thefts	0.00	1.00
Demographics		
Males,15-24	0.00	0.00
Pop Density	0.07	1.00
Education	0.00	0.00

Notes: All variables are in natural logs, except Gini coefficient which is multiplied by 100. Sample period 2000/01-2011/12 for 42 PFA (excluding London).

A.2.5.3 Specification Tests and Instrument Validity

The consistency of both GMM estimators depends on the instrument validity of lagged values of the explanatory variables. Inclusion of too many instruments can create biased estimates. This is known as instrument proliferation (Roodman, 2009a; 2009b).

As a rule of thumb, the number of instruments used should be less than the number of panels. Since 42 PFAs are included in this study, the total number of instruments used must be less than that. Further, to make sure that the lagged values included in the instruments list are valid, three specification tests are performed: Sargan/Hansen, difference-in-Hansen and AB autocorrelation tests (Arellano and Bond, 1991; Arellano and Bover, 1995 and Blundell and Bond, 2000). We explain each one in turn.

The *first* set of tests involves the *Sargan* and *Hansen J* test of overidentifying restrictions. The utility of these tests is twofold: indicating instrument validity and correct model specification. Both tests evaluate the *overall* validity of the instruments. Failure to reject the null hypothesis gives support to the model and thus, to the instruments used.

Also, both statistics range between 0 and 1. The Sargan test indicates a correct model specification if a low p-value, i.e. close to zero, is achieved. In contrast, the Hansen statistic, requires a high p-value to validate the GMM estimation results (Roodman, 2009a). Both statistics are reported after each estimation performed by DIFF and SYS GMM, since each test has its own pitfalls.

The Sargan statistic is not robust to heteroskedasticity or autocorrelation but it is robust to instrument proliferation whereas, the Hansen J statistic is robust to both but weakened by the inclusion of too many instruments. Hence, inclusion of too many instruments generates implausibly good p-values of 1.000 (Roodman, 2006, 2009a, 2009b). If the test reports p-values of 1 then the simplest and most effective way[111] to avoid the instrument proliferation issue is to limit the number of lags used as instruments.

The *second* test is the difference-in-Hansen test. It follows the same logic as the two above, but it is only conducted after using SYS GMM. As the moment conditions used by the DIFF GMM are only a strict subset of the instruments employed by the SYS GMM, we can test the validity of these additional moment conditions used in the level equation (Blundell and Bond, 2000). The null hypothesis denotes that only this subset of instruments is valid (Roodman, 2009a). However, similarly to the Hansen test, a high instrument count, weakens the test.

Finally, the Arellano-Bond (AB) serial correlation test is performed. The null hypothesis is that the error term, $\varepsilon_{PFA,t}$, is not serially correlated. The model specification is supported when failing to reject the null. In general, to determine if serial correlation of order l in *level equations* exists, need to search for autocorrelation of order $l+1$ in *differences*. As autocorrelation of order 1 is expected, if the test indicates a second-order serial correlation,

[111] For an extensive discussion of all the methods that can be used to avoid instrument proliferation, read Roodman (2009a).

the appropriateness of the proposed instruments is rejected and higher-order lags are required as instruments.

Accordingly, the AB autocorrelation test indicates which lag should be the first to be included in the instrument list. The tests performed after the simple AR (1) models indicate that, the errors are autocorrelated of order 1; rendering $crime_{PFA,t-2}$ a potentially invalid instrument. The results are presented in in *Table A.2.5.2.1* in *Appendix A.2.5.2*.

To avoid any endogeneity issues, the instrument set is restricted to lags dated $t-3$ and longer (Roodman, 2009b). Also, to avoid instrument proliferation, the number of instruments for each endogenous variable is restricted to two. That is, in period t, the endogenous variables in the first-differenced equations, are instrumented using *t-3* and *t-4*[112] *lags* in levels. Respectively, the instrument list for the equations in *levels* includes lags from *t-2* and longer. Also, as discussed above, instead of using all the available lags as instruments, the list is *collapsed*, i.e. restricted to make sure that it is less than the 42 – the number of panels (PFAs).

A.2.5.4 Comparing Estimators against SYS GMM

To determine the correct number of lags, to be included in the instrument list, as well as to examine if different estimators provide different outcomes; the preferred model specification is estimated using various estimation methods: OLS, within-groups, DIFF and SYS GMM. The last two make use of internal instruments to account for the possible endogeneity of the lagged dependent variable, the three economic indicators and law enforcement variables. Thus, we test instrument validity by estimating different specifications of the model.

[112] Also, as suggested by Roodman (2009a, 2009b), when estimating the model, the '*collapse*' command is employed.

As these do not represent our main empirical findings, we do not present tables for all five types of crime[113] rather, we compare estimated coefficients for thefts and discuss why SYS GMM performs better in this framework. Table A.2.5.4.1 presents the results.

All estimates are robust to heteroskedasticity, but not all are robust to autocorrelation[114]. Tests for first- and second-order serial correlation are reported and when applicable, Sargan/Hansen tests of overidentifying restrictions are also presented.

In *columns (1)* and *(2)* the model is estimated using OLS and within-groups estimators, respectively. Estimating a dynamic model causes endogeneity since, by construction, the lagged crime rate and the error term are correlated. The theory predicts that when the lagged dependent variable is positively correlated with the error term, the OLS regression biases the coefficient of interest upwards, close to unity, whereas the within-groups estimator's bias is downwards (see Roodman, 2009b).

The coefficient of lagged dependent variable, for both DIFF and SYS GMM, is expected to be within or close to these bounds. Hence, the range between the OLS and within-groups estimates provides a fair indication of the validity of the results obtained from theoretically superior estimators, such as DIFF and SYS GMM (Bond, 2002). As shown, the results, using OLS and within-groups, for the lagged dependent variable are between 0.87 and 0.60.

Columns (3), (4), (7) and *(8)* report the estimated results using the DIFF GMM in one- and two-step specifications. The two-step estimator controls for Windmeijer standard error bias. In period t, for every endogenous variable, in the first-differenced equations, lags dated $t-2$ and earlier are potentially valid instruments. Nonetheless, not all available lags are used, due to the limited dimension of the panel. The instrument count is reported after each estimation. For *columns (3)* and *(7)*, three lags, in levels (instrumenting first-differenced equations), are included, starting from $t-2$[115], whereas *columns (4)* and *(8)* use two lags, in levels, starting from $t-3$[116].

[113] Tables for other four crimes are available upon request.
[114] As shown in *Table 2.1*, DIFF and SYS GMM variants, starting from lag $t-2$, are not robust to serial correlation since there is first-order serial autocorrelation.
[115] Instrument endogenous variables using lagged logs of that variable dated $t-2$ to $t-4$.
[116] The instrument list includes only two lags for each endogenous variable, dated $t-3$ to $t-4$.

Table A.2.5.4.1: Regression Estimates using various Regressors, 2000/01-2011/12

	(1) OLS levels	(2) within groups	(3) 1step DIFF, t-2	(4) 1step DIFF, t-3	(5) 1step SYS, t-2	(6) 1step SYS, t-3	(7) 2step DIFF, t-2	(8) 2step DIFF, t-3	(9) 2step SYS, t-2	(10) 2step SYS, t-3
Thefts,t-1	0.87***	0.60***	0.56***	0.38***	0.58***	0.46***	0.61***	0.43***	0.62***	0.47***
	(0.02)	(0.06)	(0.08)	(0.11)	(0.07)	(0.12)	(0.11)	(0.14)	(0.08)	(0.11)
rJSA per unemployed	−0.03	−0.04 *	−0.06 **	−0.09 ***	−0.07 ***	−0.12 ***	−0.07 *	−0.09 ***	−0.09 ***	−0.09 ***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
rAv.Weekly IS	0.26**	−0.04	−0.07	0.10	−0.39	0.06	−0.51	0.12	−0.51	0.09
	(0.11)	(0.24)	(0.49)	(0.70)	(0.36)	(0.46)	(0.47)	(0.74)	(0.36)	(0.48)
Gini Coeff(x100)	0.00	0.00	0.00	0.02	0.01	0.06**	0.00	0.01	0.01	0.04**
	0.00	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)
Pop per Officer	0.00	0.05	0.41	−0.15	0.07	−0.20	0.52	−0.23	0.14	−0.15
	(0.03)	(0.18)	(0.52)	(0.74)	(0.14)	(0.20)	(0.59)	(0.71)	(0.17)	(0.21)
Theft Det.Rate	−0.08 ***	−0.09 ***	−0.15 **	−0.13	−0.06	0.05	−0.16 **	−0.11	−0.08	−0.01
	(0.02)	(0.03)	(0.06)	(0.12)	(0.05)	(0.11)	(0.08)	(0.13)	(0.06)	(0.09)
Av.Theft Sent.Length	0.01	−0.04	−0.19	−0.13	−0.19 *	−0.05	−0.18	−0.14	−0.21 **	−0.03
	(0.02)	(0.03)	(0.14)	(0.13)	(0.11)	(0.13)	(0.18)	(0.16)	(0.10)	(0.13)
Males,15-24	0.06	−0.04	−0.72	−0.68	0.74**	0.66*	−0.37	−0.88 *	0.66*	0.68*
	(0.05)	(0.22)	(0.49)	(0.55)	(0.33)	(0.35)	(0.55)	(0.47)	(0.39)	(0.35)
Constant	−0.27	1.82*			1.94	0.00			2.48	0.50
	(0.68)	(1.02)			(1.77)	(.)			(1.65)	(2.40)
No of Instr			32	25	40	33	32	25	40	33
AR(1) p-value	0.25	0.05	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01
AR(2) p-value	0.63	0.63	0.37	0.62	0.99	0.37	0.39	0.78	0.73	0.45
Sargan			0.01	0.07	0.02	0.09	0.01	0.07	0.02	0.09
Hansen			0.25	0.45	0.66	0.82	0.25	0.45	0.66	0.82
Diff-in-Hansen all					0.90	0.88			0.90	0.88
α	6.75	1.52	1.25	0.61	1.41	0.87	1.57	0.75	1.60	0.87
p-value	0.00	0.00	0.00	0.03	0.00	0.04	0.03	0.07	0.00	0.02
β_{JSA}	−0.22	−0.09	−0.13	−0.15	−0.18	−0.22	−0.17	−0.16	−0.22	−0.17
p-value	0.31	0.08	0.03	0.04	0.00	0.02	0.09	0.05	0.00	0.04
β_{ISpay}	2.05	−0.11	−0.16	0.16	−0.93	0.12	−1.31	0.22	−1.32	0.17
p-value	0.03	0.86	0.88	0.89	0.25	0.89	0.30	0.87	0.13	0.85
$\beta_{Gini(x100)}$	−0.03	−0.01	−0.01	0.04	0.03	0.11	0.00	0.02	0.02	0.07
p-value	0.21	0.65	0.88	0.29	0.34	0.01	0.97	0.70	0.47	0.02
$\gamma_{Pop.per.Off}$	0.02	0.12	0.92	−0.24	0.16	−0.37	1.34	−0.40	0.36	−0.29
p-value	0.93	0.79	0.43	0.84	0.65	0.30	0.38	0.76	0.42	0.46
$\gamma_{Det.Rate}$	−0.58	−0.23	−0.35	−0.21	−0.16	0.08	−0.40	−0.20	−0.22	−0.03
p-value	0.00	0.00	0.02	0.25	0.18	0.67	0.07	0.33	0.16	0.88
$\gamma_{Sent.Length}$	0.08	−0.10	−0.43	−0.21	−0.45	−0.09	−0.47	−0.24	−0.56	−0.06
p-value	0.61	0.15	0.17	0.32	0.06	0.71	0.29	0.42	0.01	0.79
δ_{Males}	0.44	−0.11	−1.62	−1.09	1.78	1.23	−0.95	−1.53	1.73	1.26
p-value	0.23	0.84	0.15	0.26	0.01	0.02	0.51	0.12	0.04	0.03

Notes: Standard errors in parentheses; Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All variables are in natural logs, except the Gini coefficient which is multiplied by 100. All equations include a full set of set of PFA specific effects and yearly dummies. Sample period 2000/01-2011/12 for 42 PFAs. The reported standard errors are robust to heteroskedasticity. *Columns (1)* and *(2)* estimate the model using OLS and within-groups estimators, respectively. *Columns (3), (4), (7)* and *(8)* report the estimated results using the difference GMM in one- and two-step specifications. Respectively, in *columns (5), (6), (9)* and *(10)* the model is estimated using system GMM in one- and two-step variations. Instruments, for the difference equations, in *columns (4), (6), (8) (10)* include lags from *t-3* to *t-4*. Instruments, for the difference equations, in *columns (3), (5), (7)* and *(9)* include lags from *t-2* to *t-4*.

Respectively, in *columns (5), (6), (9)* and *(10)* the model is estimated using SYS GMM in one- and two-step variations. In *columns (5)* and *(9)*, the endogenous regressors in the first-differenced equations are instrumented using the second to fourth lags ($t-2$ to $t-4$) [of these variables]. *In addition*, the equations in levels are instrumented using the lag-1 of the endogenous variables in first-differences. Finally, *columns (6)* and *(10)* include lag-2 differences for the equations in levels *in addition to* lags in levels dated $t-3$ to $t-4$ for the first-differenced equations.

The AB tests for autocorrelation indicate that there is serial correlation of order 1. Therefore, the estimations in *columns (3), (5), (7)* and *(9)* using instruments from $t-2$ are invalid since, $crime_{PFA,t-2}$ is correlated with error term, $e_{PFA,t-1}$. Thus, longer lags are required for the model to be correctly specified. Accordingly, *columns (4), (6), (8)* and *(10)* include a valid instrument list.

Comparing the Hansen statistic for both the DIFF GMM and SYS GMM, in *columns (4)* and *(6)*, as well as their two-step variants in *columns (8)* and *(10)*, it is evident that the SYS GMM performs better. The Hansen statistic is higher and closer to unity when SYS GMM is used, indicating that the model is correctly specified, and the instrument set is valid. Also, the difference-in-Hansen statistic which specifically tests for the validity of the first-differenced instruments, is close to unity (0.88). This suggests, the *additional instruments* used by the SYS GMM are integral when estimating the model. Since all the necessary assumptions outlined by Blundell and Bond (1998) are met, the SYS GMM estimator allows us to obtain consistent and efficient parameter estimates. Thus, it is our preferred estimator.

Further, Table A.2.5.4.1 illustrates that irrespective of the estimator used; the coefficient estimates have the same sign across all estimators, but they differ in magnitude and significance. Specifically, the jobseeker's allowance benefits variable is significantly negatively correlated with thefts across all estimates except the OLS. The magnitude is larger in size, and the level of significance is stronger when SYS GMM is used. As expected, the parameter estimates suggest that 10% higher unemployment benefits are linked with lower thefts (-1.2%). For individuals *at-the-margin*, e.g. people whose expected returns from illegal activities are only marginally exceeding their legal expected returns, even a slight increase in the level of benefits can pivot crime engagement. The magnitude of this negative effect becomes even larger in the long-run: a 10% increase in JSA leads to 2.2% reduction in theft. This indicates that increases in unemployment benefits not only have a contemporaneous negative effect but, in fact, it becomes more prevalent during the long-run. Moreover, as expected, thefts and income inequality have a positive relationship both over the short- and long-run; with the magnitudes being higher in the latter. Also, in line with the literature, a larger young male population is positively linked to thefts.

Chapter 3

Fraud Solvability Matrix: Identifying Factors that Forecast Case Clearance

Abstract

This study builds a predictive model which identifies solvability and case-limiting factors of fraud and computer misuse crimes by utilising preliminary investigative information from cases referred to Warwickshire Police (WWP) and West Mercia Police (WMP) between 2013-2015. The dataset is randomly split into equally sized samples; the *developmental* and the *validation*. The former sample is used to identify prevalent factors and build the predictive model, which is then tested on the validation sample to obtain external validity. This is the first study that empirically identifies fraud solvability and case-limiting indicators while developing a solvability model that increases investigatory efficiency by addressing the implicit resource constraint. Given the high correlation of solvability with a named suspect, factors which can affect solvability in the absence of a named suspect are also considered. We find that certain variables are more likely to serve as viable investigative leads, when no suspect is identified by the victim. After estimating the predictive model, we evaluate the various cut-off points to minimise the trade-off between incorrect filling and false case allocation. The empirical analysis suggests that the overall predictive accuracy of the model is 91.35%; with correct fraud allocation and case filing amounting to 87.45% and 95.41%, respectively. The findings indicate that local forces can increase solvability when adopting statistical allocation models that capitalise on information collected during preliminary investigation.

Keywords: fraud; cyber; solvability; investigation; predictive model

Glossary G.3

The following list of abbreviations, used in Chapter 3, is expanded below.

AF	Action Fraud
CSEW	Crime Survey of England and Wales
FFA	Financial Fraud Action UK
HMIC	Her Majesty's Inspectorate of Constabulary
ICT	Information and Communications Technology
LR	Likelihood Ratio Test
MG11	Method of, or Magistrates' Guidance form 11, i.e. Witness Statement Form
MO	Modus Operandi, i.e. Method of Operation Report
NFIB	National Fraud Intelligence Bureau
ONS	Office for National Statistics
PFA	Police Force Area
VRM	Vehicle Registration Mark
WMP	West Mercia Police
WWP	Warwickshire Police

Other useful terminology for Chapter 3.

Advance fee payments	Fraudsters require victims to make advance or upfront payments for goods, services and/or financial gains which are never materialised.
Call-for-service Fraud	Frauds that a reported to the police and require immediate action either due to the victim being vulnerable or the offence is taking place at the time of reporting.
Computer Misuse Crime	It covers any unauthorised access to computer material, this is not limited to a desktop or laptop computers. Rather, it includes any device that has an operating system connected to the internet, such as smart TVS, game consoles etc.
Cyber-dependent crime	Crimes that are only committed via a computer, computer network or other ICT.
Cyber-enabled crime	Traditional crimes that are committed at a larger scale with the use of ICT. Unlike cyber-dependent crimes, they can be committed without the cyber element.
Fraud	A fraud occurs when a person deceitfully and deliberately deludes a victim for own private gain, either in terms of property or money, or when the victim experiences loss or risk of loss. It includes computer misuse crimes.
NFIB Fraud	Frauds directly reported to Action Fraud.
Non-investment fraud	It includes various types of fraud such as, online shopping, door to door sales and ticket fraud.

3.1 Introduction

Fraud consists of a diverse range of criminal, civil and regulatory offences and poses a large-scale threat for both victims and local forces (Button *et al*., 2016). Fraudsters dishonestly and deliberately exploit victim's negligence, ignorance or candidness for their own private benefit (Fraud Review, 2006). Although fraud does not constitute a new type of criminality, fraudsters, in response to an ever-changing world, which has become more digital-dependent, have evolved rapidly. The technological advances and the rise of people depending, storing and sharing personal details online, not only allowed the development of new techniques to commit traditional fraud, but also generated new types of fraud, notably, computer misuse fraud and cybercrime offences (ONS, 2018). This is unsurprising when considering that the internet provides offenders with a wide-ranging opportunity to obtain the data being stored online, to use for their own personal gain while devising the tools to remain unseen (HMIC, 2015).

Over the years, the size of the problem has been overlooked, despite annual estimates suggesting the UK economy suffers fraud losses of £190 billion[117] (UKFCMC, 2017). In 2016, the financial banking sector alone suffered losses amounting to approximately £768.8 million with banks preventing another £1.38 billion (FFA UK, 2017). The *Crime Survey of England and Wales (CSEW)* indicates that incidents of fraud account for 46% of the total CSEW crime while fraud victims account for 42% of all individuals being victimised (ONS, 2017). In fact, the *Office for National Statistics (ONS)* estimates that an individual is more likely to fall victim to fraud or computer misuse than any other crime (Action Fraud, 2018). Individuals are 10 times more likely to be victimised by fraud or cybercrime than by theft, and 35 times more likely than to be a victim of robbery (ONS, 2017). Further, CSEW finds that, between mid-2016 and mid-2017, adults aged 16 and over experienced approximately 3.3 million fraud incidents with 57% of these incidents being computer misused crimes.

[117] This is the total estimated amount of *overall* fraud.

Despite the huge economic implications of fraud and the heightened efforts of government and authorities to understand fraud better[118], especially in recent years, empirical research is almost non-existent in this area[119]. Although fraud has the lowest clearance rate among all types of crime, there is limited evidence on factors affecting solvability of fraud let alone research on predictive fraud solvability models.

This chapter aims to expand our knowledge on fraud solvability factors while developing a novel predictive case solvability model for fraud. As we point out, in *Sections 3.3.1* and *3.3.2*, the distinctive features of fraud and cybercrime[120] make this analysis unique. Although there are solvability models which are built using a similar statistical methodology as the one we employ[121] for other types of crime, to the best of our knowledge this study represents the *only* in-depth empirical analysis of fraud, in England and Wales.

More specifically, the study aims to answer four research questions. The *first* is identifying the determinants which indicate solvability of fraud offences and financially motivated cyber-dependent crime. To that extent, continuous and categorical variables are tested using t- and chi-squared tests, respectively, while also estimating effective size estimates and calculating factor prevalence.

Further, it is proved that a named suspect is one of the strongest solvability factors and thus, the *second* research question investigates whether, case solvability is possible in the absence of suspect information. That is, we identify other viable lines of enquiry that lead to case solvability, when the suspect is unknown.

The *third* one asks whether a logistic model can correctly predict case clearance by utilising

[118] The Fraud Review (2006) identified the police's lack of understanding of what constituted fraud while highlighting that fraud, in all of its forms, does not respect police boundaries. Therefore, the need of centralisation of fraud recording was apparent (HMIC, 2015). Effectively, as of 2013, the Action Fraud (AF)[118] represents the national centre of reporting for fraud offences (ONS, 2017; 2018).

[119] Identification of solvability and case-limiting factors for violent and property crimes – such as burglary, vehicle and robbery – have been examined in the literature, but not fraud. To our knowledge, no other empirical work has examined potential determinants of fraud, let alone solvability factors.

[120] For a detailed description of the offences constituting fraud see Appendix A.3.1.3. Cybercrime falls under the umbrella, of the more generic term, fraud.

[121] For instance, Olphin (2015) uses a similar approach to build a solvability model for non-domestic violent crime in West Midlands Police whereas Olphin *et al.* (2017) develop an empirical model that examines solvability of burglary offences in Norfolk Police. For a comprehensive review of the literature, see Section 3.2.

solvability[122] and case-limiting factors[123]. The model identifies, based on a cut-off value, whether the case is solvable or not. This is determined by assigning a *score*, formulated by summing identified factors that are present in each case, to individual cases. The score is then compared to a cut-off value. If the case's score is at least equal to the cut-off point, cases are allocated whereas cases are filed when the score is lower than the chosen cut-off value. Thus, this type of analysis can potentially allow local forces to make effective use of their resources while maximising solvability. The *fourt*h research question asks whether the solvability model developed is externally valid. Thus, we address the validity of the model by externally testing its predictive capabilities using a randomly assigned validation sample.

To determine the optimal cut-off point[124], a trade-off between two types of errors is considered. That is, two types of errors are generated when deciding whether to allocate or file a case, based on a threshold value: (i) cases are incorrectly allocated, i.e. they are allocated when they should have been filed; and (ii) cases are incorrectly filed when they should have been allocated for further investigation. Trying to minimise one type of error; causes an increase in the other. For instance, by increasing allocative efficiency, more cases will be incorrectly filed. Nevertheless, it is important to note that there are no formal test procedures which identify the optimal cut-off point. Thus, we experiment with different cut-offs on an ad-hoc basis.

Despite local forces implicitly using solvability predictors, there is no empirical evidence to back these up and neither are these tested to obtain external validity. Rather, these factors are, primarily, based on officer judgment and therefore, are highly subjective. Accordingly, the predictive model is proposed as a rigorous basis to screen frauds by focusing on more solvable cases and hence, allowing the release of limited resources.

To build the model, data from Warwickshire Police (WWP) and West Mercia Police (WMP) are used. The model exploits information obtained from the stages of initial investigation[125]

[122] Presence or absence of factors that lead to case solvability.
[123] Case-limiting factors are the ones where their presence or absence leads to the case being filed.
[124] Section 3.5.2 discusses in detail the empirical procedure followed to determine a cut-off value that minimises both types of errors.
[125] Initial investigation phase refers to the first stages of reporting where information about the offence is gathered. According to College of Policing, the phase of initial investigation is concluded when the investigator obtains victim's account and any potential witnesses are identified while submitting all intelligence gathered. More information can be found here:

to predict clearance. The dataset consists of automatically recorded indicators, such as time of offence and victim details, as well as factors identified using the original police reports. The latter category combines filed (MO) reports in free-text and investigation logs.

The empirical findings[126] indicate that case-limiting factors include: banking and computer misuse fraud, phone scams and individual frauds; whether victim has suspicions as to who the offender is but cannot name the suspect, suspect personally attending the place of offence and finally, when cash is the payment method. On the other hand, the analysis identifies the following variables as solvability factors: fraud call-for-service[127]; offence being part of a series; corporate employee fraud; repeated victimisation; suspect is known; suspect's physical description, VRM details or CCTV footage is available and finally, when offence location is known.

All aforementioned factors have *individually* been identified to be associated with solvability. However, the study acknowledges that although, in isolation, some factors may be insignificant, when 'co-existing' with other indicators, they may be *jointly* significant. Numerous variable compilations are tested[128] to examine whether that is true. Indeed, the results identify four interaction terms as solvability factors. These include, cases where the victim completes an MG11 form *and* evidence is available; suspect's phone number is known, *and* the call provider has confirmed the details of the suspect; the police was able to seize items from the scene *and* the victim has lost funds; and finally, cases where the payment method is through a bank transfer *and* the suspect's name is known. We believe that this is the first work that assesses the impact of compilation variables on solvability.

Overall, the model correctly classifies 91.35% of the sampled cases. Specifically, the percentage of correctly allocated cases is equal to 87.45% whereas correctly filed cases amount to 95.41%. These findings indicate the model's precision and consistency. The

https://www.app.college.police.uk/app-content/investigations/investigation-process/ .

[126] The case-limiting and solvability factors presented here include only the predictors that have been identified as statistically significant in the estimated logistic regression.

[127] As AF is the central point of contact, any fraud offence should be reported to AF. However, as explained in Section 3.3.1, if the victim is considered to be vulnerable or the offence is taking place at the moment of reporting, the local force can take action. This is known as call-for-service.

[128] The same procedure is followed as with individual significant factors. That is, we create pairwise combinations of individually insignificant factors and then conduct chi-squared tests, and calculate effective size and factor prevalence.

performance of the model is also tested on a separate dataset of equal size, providing external validity. Specifically, based on the chosen cut-off point, we find that the overall accuracy of the model is 89%, with 85% an 93% of the cases being correctly allocated and filed, respectively. Although, not directly comparable with other solvability models developed on other types of crime, the predictive capability of our model is one of the highest reported in the literature.

The rest of the chapter is structured as follows. *Section 3.2* presents an overview of the literature on solvability models used in other types of crime. In *Section 3.3*, the fraud reporting process is described, followed by a description of the dataset and a presentation of the descriptive analysis. Further, *Section 3.4* introduces tests for solvability and case-limiting factor identification while explaining the development of the predictive model. *Section 3.5* presents the empirical findings; which are followed by a robustness check measuring the model's accuracy using a randomly assigned sample. *Section 3.6* discusses possible policy implications and data limitations. Finally, *Section 3.7* concludes.

3.2 Literature Review

As stated above, this is a novel study that empirically assesses investigatory factors associated with fraud solvability. Therefore, there is no prior empirical research on solvability models of fraud, *per se*, that we can refer to, or compare our findings against. However, there is existing literature that identifies solvability factors for other crime types. Therefore, the methodologies and the research design of solvability models, in general, are discussed and their findings are presented. Emphasis is given on the model specifications and estimation methods used; allowing for identification of potential methodological gaps in the literature.

The national fraud outcome rate[129] is, just, around 7%; which is the lowest rate of outcome assigned to offences among all types of crime recorded (Home Office, 2017). Considering that fraud is heavily under-reported[130] – more than any other type of fraud – a high clearance rate may encourage more reporting. That is, higher solvability signals police effectiveness (Cordner, 1989; Litwin, 2004) which in turn, can encourage reporting as the public's trust toward police will be restored (Regoeczi *et al*., 2000; Tankebe, 2008; Tyler and Fagan, 2008) while boosting police officer's morale (Riedel and Jarvis, 1998). Additionally, higher detection can stimulate incapacitation and deterrence effects (Von Hirsch *et al*., 1999; Levitt, 2004; Jansson, 2005).

Perhaps unsurprisingly, a named suspect has been found to be the single most significant solvability factor (Isaacs, 1967; Greenwood, 1970; Brandl and Frank, 1994; Olphin, 2015). Isaacs (1967) finds that 86% of the cases with a suspect being named are cleared, whereas if the offender is unknown, 88% of cases remain unsolved. Greenwood (1970) studies the association of property crimes with solvability and finds that suspect identity information is linked to higher arrest rates. This association is stronger even when comparing cases where only suspect's description was available, or evidence has been collected. This is consistent across various studies and types of offences (Eck, 1979, 1983; Coupe and Griffiths, 1996; Burrows *et al*., 2005; Eitle *et al*., 2005; Peterson *et al*., 2010; Olphin, 2015). The opposite is also found to be true. That is, incidents between strangers have a lower probability of detection (Snyder, 1999; D'Alessio and Stolzenberg, 2003).

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[129] Outcomes assigned to offences. Since 2013, Home Office introduced an outcome framework to replace the then recording system which narrowly accounted only for detections. Section 3.3.3.1 explains this in more detail.

[130] Indicatively, in 2016/17, CSEW indicated that approximately 5 million incidents of fraud and computer misuse have been experienced by the responders. The police recorded data, for the same period, amounted to just 653,468 cases. This suggests that only 17% of incidents of fraud come up to police's attention. Nevertheless, it important to stress out that most victims experiencing bank and credit industry fraud are encouraged by their banks to contact them first than the police. Also, the two sources vary in their coverage. CSEW covers a broader range of frauds, including attempted and successful occurrences; with or without monetary loss. It also captures low-harm cases; which are unlikely to be reported to the police. On the other hand, police data include incidents reported to AF and focus on more serious fraud – at least serious enough that the victim will consider it important to report it to the police. Further, it is useful to note that CSEW only started recording fraud and computer misuse in the year ending September 2016. So prior comparisons are unable. For more information see, https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/june2017#main-points ; *Tables 1a* and *2*.

Further, the RAND Criminal Investigation Study (1979) assessed how detectives allocate their time while examining the importance of different investigative activities on police effectiveness. The study finds that 44% of solvable cases have identified an offender during the reporting process and shows that follow-up investigation has only a minimal effect on detection. The author argues that much of detective’s time is wasted on administrative work undertaken for cases that have a low probability of clearance. More specifically, the study stresses that it is the circumstances of crime – i.e. factors which are readily available – that lead to clearance, not follow-up investigatory efforts. Other researchers agree and assert that the most useful and indicative information, in terms of solvability, is collected during the preliminary stages of investigation (Greenwood and Petersiua, 1975; Brandl and Frank, 1994; Coupe and Griffiths, 1996; Weisburd and Eck, 2004).

However, the RAND study has been criticised as misleading (Sherman, 2003) due to its extremely small sample size – only 10 cases of aggravated assault were used, all of which have been cleared during preliminary investigation. Telep and Weisburd (2011) support that, still, there is insufficient information on the performance of detectives and their workload and thus, assessing their investigative value is at least crude.

Eck (1983) has extended the work undertaken by the RAND study – which supports the *circumstance-result* hypothesis as he calls it – and combines it with the work of Folk (1971) – who argued that, irrespective of investigative leads, *detective’s effort* is more important. Eck supports that, in fact, there are three types of cases and called this the *triage hypothesis*. The first group involves cases where little effort is required for clearance. The second group contains cases where viable investigative leads exist and the cases are potentially solvable, provided effective investigation. And finally, the third group includes cases which will never be solved, at least not by devoting a reasonable amount of effort and resources. The study focuses on burglary and robbery offences. The results indicate that identified predictive factors, collected during initial investigation, are associated with arrest, but this is also true for detective’s follow-up actions. Essentially, Eck supports that a large number of cases is solvable when effective investigation techniques are followed, provided there are viable investigative links. Although, critics argue that sometimes it is difficult to determine which case falls into which group, Eck’s work is significant as it acknowledges that investigative efficiency can be achieved by identifying different characteristics (factors present) in solved and unsolved cases.

Based on that premise, Paine (2012) uses chi-squared tests to compare different characteristics between detected and undetected burglary and attempt-burglary offences. This enables solvability factor identification. The study finds 14 predictors, 12 of which are argued to have over 80% predictive accuracy. However, this study has a few pitfalls. First, it only examines the effectiveness of *individual* factors on clearance and discards the possibility of a *combination* of factors leading to detection. Second, due to its large sample, the author is restricted to include only electronically recorded information which prevents close examination of each case. Finally, the study is just a descriptive analysis where no predictive model is developed. Other studies have identified various solvability factors including: presence of witness (Paine, 2012); CCTV footage and implementation of proactive policing methods (Robb *et al*., 2015).

Further, although not directly relevant to fraud, many homicide papers develop multivariate models to identify factors that are linked to solvability. Usually, homicide clearance is used as the dependent variable and the identified predictors as the independent regressors while the model is estimated using a logistic regression (Mouzos and Muller; Alderden and Lavery, 2007; Ousey and Lee, 2010). Multivariate models are useful since not only do they allow for the inclusion of multiple variables to predict possible outcomes – in this case, case solvability – but they also allow for more detailed 'what-if' scenarios. For instance, the outcome of a case depends on a range of factors that are simultaneously present, not just one. The better the quality of the data, the more accurate the predictive power of the model.

Nevertheless, the aforementioned studies test the effectiveness of the model on the dataset used to develop the model on and not on separate data. Thus, there is no external validity. Even for burglary crimes, which are exhaustively studied in the literature, the empirical research fails to develop and test predictive models using large-scale datasets and examine their validity.

To our best knowledge, only two other studies (Olphin, 2015; Olphin *et al*., 2017) test the validity of the model using a randomly assigned sample. To build a solvability model, we follow a similar statistical methodology as the two papers above. Olphin (2015) examines predictive clearance factors for non-domestic violent offences by exploiting a large-scale dataset from West Midlands Police. The overall effectiveness of the model is estimated to be around 67%. Specifically, the model correctly allocates 69% of the cases whereas it correctly files 65% of the reported offences. On the other hand, Olphin *et al*. (2017) builds a solvability model for burglary in Norfolk with an estimated overall accuracy of 56%. Depending on the cut-off used, the designed model correctly allocates and files 87% and 52% of reported burglaries, respectively.

In general, what all these studies try to capture is that, solvability factor identification is possible – across all types of crime – and given the scarce police resources, neglecting to use these for guidance and more effective case allocation will result in lower clearances.

Also, when developed correctly, statistical modelling can be more precise in case classification than an experienced investigator (Kahneman and Egan, 2011). The Association of Chief Police Officers (ACPO, 1989) acknowledges that, and therefore, encourages the use of a system which objectively assesses the nature of the offence and the presence of solvability factors to allocate investigative resources on cases which are more likely to be solved. Although formal screening is a reality in many forces (BBC, 2013), it is mainly based on officer's experience, subjective perceptions, mandatory offences, media coverage and what the public perceives as important (Gill *et al*., 1996; Robinson and Tilley, 2009).

However, even if formal screening is not in place, the officers informally decide which cases to investigate based on which crimes they view as more solvable (Brandl and Frank, 1994; Coupe and Griffiths, 1996). Nonetheless, this may result in inconsistencies across local forces since these decisions are not based on a unified and coordinated approach (Coupe and Griffiths, 1996).

Greenberg *et al*. (1973) utilise information gathered from primary investigation and create a case screening model using 2000 burglaries; where 6 solvability factors are identified. Afterwards, the model is tested on a different dataset, of only 500 cases, with each factor being weighted using its own predictive probability. The model's accuracy is estimated to be between 67% and 92%. In a later study, Eck (1979), replicates the analysis of Greenberg *et al*. (1973) and finds that 85% of the cases can be correctly classified.

Further, Eck (1983) examines investigation of burglary and robbery in relation to case clearance. He finds that 6% and 9% of cases are incorrectly filed and allocated, respectively. This translates into victims being let down and resources being wasted. However, as the author argues, this it to a lesser degree than if no crime screening mechanism is implemented.

Olphin (2015) tests the predictive model developed in the study against the existing West Midlands Police allocation mechanism and finds that, the designed model increases efficiency by 11.62%. Even so, the author finds that the screening model’s accuracy is, only, around 67% – which is relatively low. Although, predictive models are usually expected to perform better than that; the findings provide evidence to the argument that police forces do not efficiently use the scarce investigative resources and if, statistical allocation models are adopted, efficiency can be increased.

To sum up, the above findings reinforce the usage of applicative methods to prioritise allocation of scarce police resources. By directing investigative efforts towards cases that are more likely to be solved, more effective investigation is allowed; which leads to higher solvability. In effect, this ensures not wasting resources and effort on cases that are unlikely to be solved.

3.3 Data Description

3.3.1 Fraud Reporting

Fraud, in all its forms has a particular feature: it disregards police force boundaries, both within the UK and internationally (HMIC, 2015). Thus, due to its versatile nature and its ever-growing severity, a more clustered and nationally consistent approach was deemed necessary. As a result, Action Fraud (AF) was established. It represents a national and central point of reporting and recording of all fraud and financially motivated cybercrime. Since the implementation of AF, the way in which fraud is reported and thereafter recorded has changed (Home Office, 2017).

Previously, fraud offences were directly reported to local police forces whereas now, AF provides an online reporting tool and has a dedicated call centre to record fraud, nationally. Unless the fraud is a *call-for-service*, in which case the local authority takes immediate action, the victim must report the fraud via the online portal. A call-for-service requires certain criteria to be met. These are: victim is vulnerable or at risk[131]; offenders are arrested by police; victim calls police to report fraud *and* the offender is currently committing or has recently committed (at the time of the call) fraud and finally, in cases where the offender is suspected to be residing within the force's jurisdiction area[132]. If local forces take on a case as a call-for-service, AF is notified.

If none of these conditions apply the fraud must be directly reported to AF. The National Fraud Intelligence Bureau (NFIB) reviews the reports[133] and is responsible for allocating cases to the local forces. The forces are advised about which cases are to be investigated further. The NFIB's scoring matrix analyses the fraud reports and "*identifies key information supplied in a report, as well as searching for any matching data within the system in existing reports*" (Home Office, 2017). If viable investigative leads are identified, the NFIB distributes the case to the most appropriate local force for further investigation.

It is important to highlight that AF is simply a reporting centre, it is not responsible for fraud investigation. Still, that authority remains with the law enforcement agencies. Furthermore,

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[131] According to Warwickshire and West Mercia's guidelines, vulnerability is defined with respect to victim's circumstances and/or age. An adult at risk is one that suffers from mental or physical disabilities, illness, or any other condition or circumstance rendering them either permanently, or temporarily incapable of caring and/or protecting themselves against exploitation or unable to demonstrate capacity to decide while requiring care and support.

[132] A 'local suspect' is where there are possible lines of enquiry about who the offender might be. That is, police can or could potentially identify the offender with the information being provided or in cases where police have enough details to arrest a suspect. This 'locality' condition is put in place to ensure that fraud victims are treated the same way, by the police, as victims of any other type of crime where local viable investigative leads exist, and an investigation is undertaken immediately.

[133] NFIB uses a database, called the *Know Fraud* system to analyse the information gathered as well as to establish links and patterns in offending. Reports are distinguished based on whether there is a realistic prospect of solvability or not.

on a monthly basis, local forces are also informed about cases without any investigative leads but which are committed against victims in their jurisdiction. This is for the police forces to have a good indication of the fraud levels within their area. Nevertheless, these cases are kept in the dataset, if new information comes to light, either from the victim or by matching information across different cases and viable lines of enquiry are believed to exist then, the most appropriate force is notified. Further, AF receives information reports. These are cases which are not classified as a crime but still implicate fraudulent activity. These are also forwarded to the local agencies. Figure A.3.1.1[134], in the Appendix, graphically displays the recording process of fraud.

3.3.2 Types of Fraud

As explained in the section above, frauds are self-reported to AF via its online tool. Victims are asked about the type of fraud that they have experienced before submitting the final report in order to be redirected to the appropriate section of the website. Although, this information is available in our dataset, most cases have empty entries. For cases with a type of fraud attached to them, unless the full police report is read, we are unable to know if this is indeed the fraud that victims have experienced.

Thus, we re-allocate cases using the correct NFIB Fraud classifications[135]. This process was extremely time-consuming as it was not possible to automate it. However, this allows us to include types of fraud in our model specification while also creating a variable that captures whether victims have correctly identified the type of fraud they have experienced. The former allows us to test whether specific types of fraud are more likely to be solved than others whereas the latter permits us to test if incorrect classification leads to insolvability. *Appendix A.3.1.1* discusses in detail the various lines of enquiry that different types of fraud generate. If more than one types of fraud apply to each case, as per NFIB counting rules, the most serious offence is recorded.

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[134] The flow chart is published by Home Office (2017).
[135] Table 3.1 provides the complete list.

Table 3.1 provides a detailed description of the NFIB types of fraud been committed during the period of study within the WWP and WMP Constabularies. As shown, the most frequent type of fraud – or at least, more likely to be reported – is non-investment fraud, followed by banking frauds, advance fee payments and computer misuse frauds.

3.3.3 Dataset

3.3.3.1 Outcome Variable

To determine which cases have been detected and which have been filed as undetected, the outcome variable is used. In 2013/14, the Home Office revised its framework for recorded crime outcomes by taking a more victim-oriented approach. Previously, a detection framework was followed instead. The new outcome framework advances the way crime is dealt with by the police, by providing a broader range of possible outcomes to resolve a case than the formerly available sanction detection categorisation. Under this framework, each case has an attached outcome to it (Home Office, 2014). *Appendix A.3.2* discusses other possible case clearance factors used in the literature.

Figure 3.1 presents the outcomes of fraud cases examined in this study. As shown, most cases are resolved with the suspect being charged or summoned. The fraud outcome rate is only 25%, in our dataset suggesting that there is a lot of room for improvement. Figures 3.2-A1 and 3.2-A2 illustrate solvability by type of offence; Figure 3.2-A2 present confidence intervals for each detection rate. As demonstrated, for more prevalent types of fraud, the confidence intervals are smaller. Both figures confirm that the probability of detection is low. This is evident across all types of fraud that are available in the dataset, with computer misuse fraud having the lowest outcome rate among all of them.

Table 3.1: Types of Fraud

NFIB Code	NFIB Fraud Name	Count
NFIB1	**Advance Fee Payments**	**519**
NFIB1A	419 Advance Fee Faud	2
NFIB1B	Lottery Scam	7
NFIB1C	Counterfeit Cashiers Cheques	3
NFIB1D	Dating Scams	23
NFIB1E	Fraud Recovery	7
NFIB1F	Inheritance Fraud	2
NFIB1G	Rental Fraud	72
NFIB1H	Other Advance Fee Frauds	361
NFIB1J	Lender Loan Fraud	44
NFIB2	**Financial Investments**	**36**
NFIB2A	Share Sales or Boiler Room Fraud	8
NFIB2B	Pyramid or Ponzi Schemes	1
NFIB2C	Prime Bank Guarantees	
NFIB2D	Time Share and Holiday Club Fraud	4
NFIB2E	Other Financial Investment	23
NFIB3	**Non Investment Fraud**	**1490**
NFIB3A	Online Shopping and Auctions	505
NFIB3B	Consumer Phone Fraud	1
NFIB3C	Door to Door Sales and Bogus Tradesmen	240
NFIB3D	Other Consumer Non Investment Fraud	80
NFIB3E	Computer Software Service Fraud	157
NFIB3F	Ticket Fraud	83
NFIB3G	Retail Fraud (not NFIB3A or NFIB5A)	430
NFIB4A	Charity Fraud	48
NFIB4B	Fraudulent Applications for Grants from Charities or Lottery Fund Organ	5
NFIB5	**Banking and Credit Industry Fraud**	**680**
NFIB5A	Cheque, Plastic Card and Online Bank Accounts (not PSP)	572
NFIB5B	Application Fraud (excl. Mortgages)	71
NFIB5C	Mortgage Related Fraud	2
NFIB5D	Mandate Fraud	29
NFIB5E	Dishonestly Retaining a Wrongful Credit	8
NFIB6A	Insurance Related Fraud	23
NFIB6B	Insurance Broker Fraud	7
NFIB7	Telecom Industry Fraud (Misuse of Contracts)	43
NFIB8A	Corporate Employee Fraud	81
NFIB8B	Corporate Procurement Fraud	1
NFIB9	Business Trading Fraud	
NFIB10	False Accounting	
NFIB11	Bankruptcy and Insolvency	
NFIB12	Passport Application Fraud	2
NFIB13	Department of Works and Pensions (DWP) Fraud	1
NFIB14	Fraudulent Applications for Grants from Government Organisations	3
NFIB15	HM Revenue and Customs Fraud (HMRC)	1
NFIB16	**Pension Fraud**	**37**
NFIB16A	Pension Fraud committed by Pensioners	1
NFIB16B	Pension Fraud committed on Pensioners	
NFIB16C	Pension Liberation Fraud	36
NFIB17	Other Regulatory Fraud	
NFIB18	Fraud by Failing to Disclose Information	10
NFIB19	Abuse of Position of Trust	49
NFIB20A	DVLA Driver Licence Application Fraud	2
NFIB90	Other Fraud (not covered elsewhere)	75
NFIB50	**Computer Misuse Crime**	**237**
NFIB51A	Denial of Service Attack	
NFIB51B	Denial of Service Attack Extortion	
NFIB50A	Computer Viruses/Malware/Spyware	6
NFIB52A	Hacking-Server	3
NFIB52B	Hacking-Personal	166
NFIB52C	Hacking-Social Media and E-mail	71
NFIB52D	Computer Hacking & PBX/Dial Through	1
NFIB52E	Hacking (Extortion)	2

Figure 3.1: Outcome Method

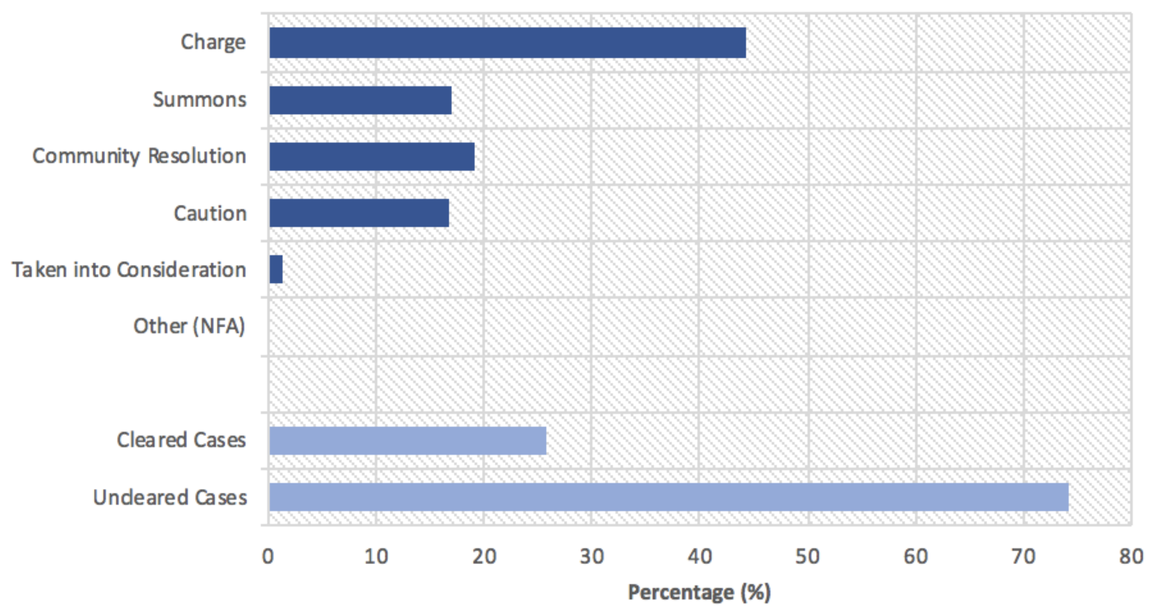
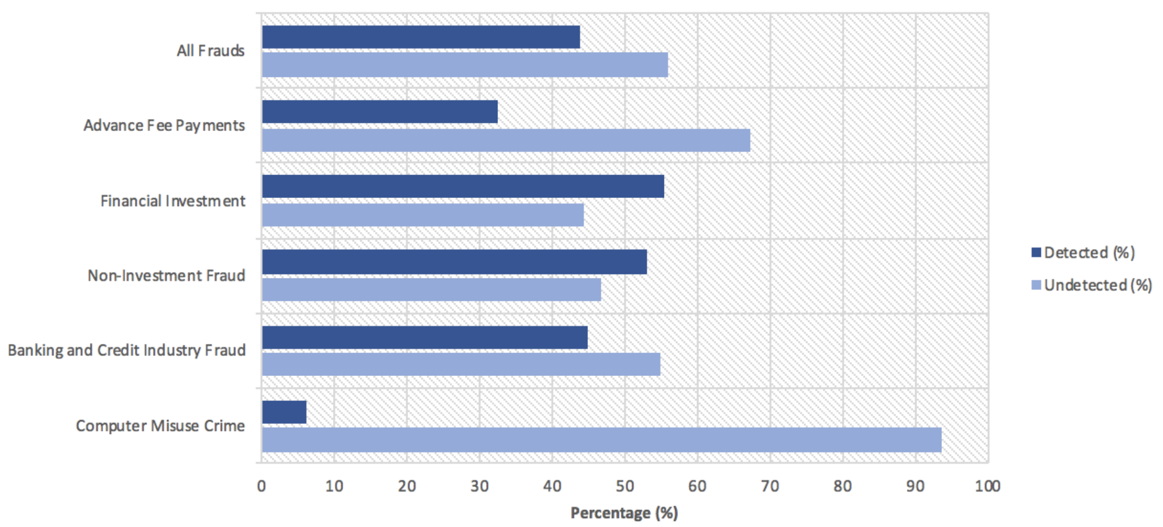
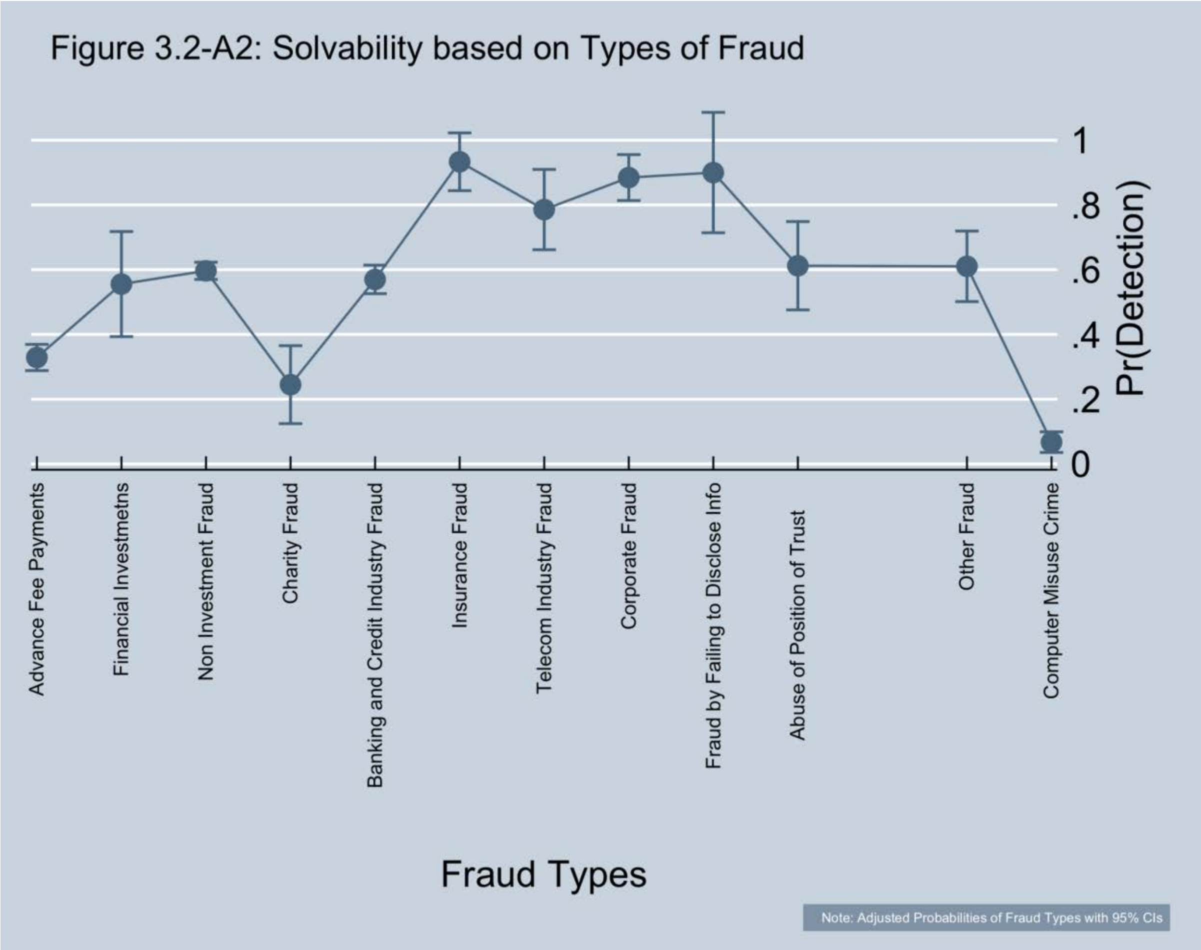


Figure 3.2-A1: Solvability by Type of Offence





3.3.3.2 Data Sources and Variables Examined

The dataset comprises of all reported fraud offences in WWP and WMP between January 2013 and December 2015. These are used to build an empirical model that predicts case solvability by evaluating information gathered in the first stages of investigation. The end date has been carefully chosen to allow enough time for the investigation process to take its course and thus, for the cases to be cleared. This was of incremental importance since we did not want to sacrifice any of the model's accuracy, which heavily depends on the outcome of the cases. The dataset includes all frauds reported either directly to the PFA or cases allocated by AF to the two PFAs. In total, 4012 cases[136] have been documented, both detected and undetected.

[136] This is the total number of cases during the period of study. However, cases with no information been recorded, or cases were no specific intend victim is identified are excluded. As explained later in Section 3.3, for a case to be recorded as fraud, Home Office counting rules require a specific intend victim, if that is not able to be established, the case is only recorded for information purposes and no further investigatory steps are taken. Also, cases were people report that a bank account has been opened in their name without their knowledge or

We acknowledge that data accuracy is a fundamental principle to obtain true estimates. The only tangible way to evaluate incident reporting quality is by reading reports, which assess WWP and WMP's strategy for securing correct crime records, as prepared by HMIC[137]. In a 2015 report, WMP is described as having "*good processes for initial investigation and subsequent allocation of crimes for further investigation. The force has a crime allocation policy that directs which resources should be allocated to investigate; taking into account the nature of the offence and the needs of the victim*" (HMIC, 2016a). WWP is presented as a force that "*has effective, well-established arrangements to collect, share and act on partner information to prevent crime*" (HMIC, 2016b). These reports give us confidence about the information collected and incident reports being drafted.

Also, as advanced earlier, the process of reporting and investigating fraud is different and more complex than for any other type of crime. Therefore, it is possible that local forces receive AF referrals, not because the victim lives in the area, but because it is believed that the offender resides within their jurisdiction – i.e. in WWP and WMP area. This does not affect the analysis in any way as we develop a solvability model using the intelligence data collected during the primary investigation. These are either collected by the two PFAs, when there is a call-for-service, or forwarded by the AF[138].

The dataset consists of a combination of electronically automated variables, officer free-text fields (MOs) and investigation plan scripts. The former category involves variables downloaded directly from WWP and WMP systems. These variables provide incident-specific information such as custody records, and other personal information about the victim and suspect – if they are indications as to who the offender is –, MOs, offence location, interest indicators, warnings and other markers. Although desirable, obtaining data on workload of officers was not possible. Nevertheless, these automated variables are included in the analysis with ease. Consistent with the literature (Litwin, 2004; Puckett and Lundman, 2003;

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permission and/or false information has been used are excluded. According to Home Office fraud counting rules this does not constitute a fraud per se. Fraud should only be recorded if there is evidence suggesting that the account was opened to purposely commit fraud or if there is any usage on the account (Home Office, 2018).

[137] The full name is Her Majesty's Inspectorate of Constabulary and Fire & Rescue Services (HMICFRS). It is an independent criminal justice inspectorate organisation that assesses the effectiveness and efficiency of police forces and fire & rescue services.

[138] If it is deemed that the case has viable investigative leads, the allocated detective adds comments in the investigation log, explains the procedure followed and the information gathered.

Riedel and Boulahanis, 2007), dummy variables are created for categorical variables, such as location.

On the other hand, free-text fields and investigation plans are coded manually for each case in the sample. By coding these scripts, additional potential solvability factors are examined. To build a solvability model that correctly classifies fraud, it is important to have as much detail as possible, especially due to each case being inherently unique.

Interestingly, the most useful information uncovered during preliminary investigation is not recorded electronically by WWP and WMP Constabularies rather, police officers write detailed free-text memos about how fraud was conducted while also preparing an investigation plan. The latter provides details about the crime scene, any observations made, if there are witnesses, physical description of suspect, bank account details, or any other personal detail which might reveal the offender's identity, whether CCTV footage is available, evidence gathered, and items seized, whether resources need to be distributed while also updating any outstanding actions. Coding this information provides insightful information about how the fraud was committed.

As these are free-text fields, officers are not obliged to record information in a specific format or detail. Further, automating the process was deemed impossible. For instance, consider an incident where the detective writes in the investigation log that 'no CCTV' footage is available at the scene, but CCTV footage can be obtained from nearby shops. A search for 'no CCTV' will not provide the correct number of cases where CCTV is not available. Therefore, considerable time was spent coding these factors.

As explained in *Section 3.4.1*, after performing various tests to determine which variables have little explanatory power in terms of detection or which are highly correlated with other indicators, the initial list of potential factors is curtailed to 48 variables which are then included in a statistical model to predict solvability.

3.3.3.3 Developmental and Validation Samples

To build the solvability model and examine its predictive capabilities, the sample is randomly split into two groups. To do that, each case is given a unique reference number. Random allocation ensures that there is no sample selection bias (Heckman, 1979) while also securing external validity. As it allows to build the model on one, the *developmental* sample, and afterwards test its predictive powers and accuracy on the second group, the *validation* sample. Additionally, by having two samples, we avoid overfitting the model.

Nevertheless, to ensure the accuracy of the model, it is paramount that the two samples are equivalent in terms of both detection and types of fraud. Table 3.2 demonstrates that this is indeed the case.

Table 3.2: Comparison between Developmental and Validation Samples by Type of Offence and Outcome

	Developmental Sample		**Validation Sample**	
	Detected	*Undetected*	*Detected*	*Undetected*
Advance Fee Payments	82	174	88	175
Financial Investmetns	9	5	11	11
Non Investment Fraud	399	361	394	336
Charity Fraud	6	19	6	17
Fraudulent Applications for Grants from Charities	1	0	0	4
Banking and Credit Industry Fraud	151	201	155	173
Insurance Related Fraud	11	2	10	0
Insurance Broker Fraud	3	0	4	0
Telecom Industry Fraud (Misuse of Contracts)	17	4	16	6
Corporate Employee Fraud	32	3	40	6
Corporate Procurement Fraud	0	0	1	0
Business Trading Fraud	0	0	0	0
False Accounting	0	0	0	0
Bankruptcy and Insolvency	0	0	0	0
Passport Application Fraud	1	0	1	0
Department of Works and Pensions (DWP) Fraud	0	0	1	0
Fraudulent Applications for Grants from Government	2	0	1	0
HM Revenue and Customs Fraud (HMRC)	0	1	0	0
Pension Fraud	0	12	1	24
Other Regulatory Fraud	0	0	0	0
Fraud by Failing to Disclose Information	6	1	3	0
Abuse of Position of Trust	20	12	10	7
DVLA Driver Licence Application Fraud	1	0	1	0
Other Fraud (not covered elsewhere)	23	9	22	21
Computer Misuse Crime	8	130	7	92
Total	**772**	**934**	**772**	**872**

3.3.4 Descriptive Analysis

This section presents the findings from the descriptive analysis. First, victim and offender characteristics are discussed and then, incident and fraud attributes are examined.

3.3.4.1 Victim Characteristics

As shown in Figure 3.3-A, both genders are as likely to experience fraud but, cases where the victim is female are less likely to be detected. Also, the descriptive statistics showcase that the younger the victim, the higher the probability for case clearance. To put that into perspective, cases where the victim is 35 years old or younger are twice as likely to be solved than cases involving victims aged 66 and over. This is also demonstrated in Figure 3.3-B1 and Figure 3.3-B2. In the latter one, the probability of solvability is broken down by victim's sex and age group while providing 95% confidence intervals. Further, Figure 3.3-B2 confirms that male victims have higher levels of detection.

Figure 3.3-C illustrates the four types of fraud that victims are most likely to experience[139], based on victim's gender and age. When not accounting for the age difference among victims, as depicted in the last section of the graph, both sexes seem to be vulnerable to non-investment fraud; advance fee payments; banking and credit industry fraud and computer misuse crime; in that order. However, when taking into consideration the age of the victim, we can see that older individuals are more likely to become victims of advance fee payments. For the remaining age groups, the order does not change from the general conclusions.

Nevertheless, it is evident that, across all age groups (except 66+), males have only a higher probability of becoming victims of non-investment fraud which accounts to 40% of the overall fraud been reported by men. In fact, males become victims of non-investment fraud

[139] CSEW experimental statistics on fraud and computer misuse also indicate that individuals are more likely to be victimised by these four frauds (*Table E5*). Also, CSEW identifies these four types as the most likely to be reported to police by victims (*Table E7*). More information can be found in the ONS website which publishes national estimates on fraud and cybercrime; https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/crimeinenglandandwalesexperimentaltables .

1.25 times more than women. Interestingly, although not depicted in the graph, males are also 1.6 times more likely than women to experience financial investment fraud.

However, women experience a higher likelihood of victimisation for all remaining types of fraud, across all age groups. Advance fee payments account for 22% of the overall fraud being committed and 60% of these cases are against women. In general, women are 1.5 times more likely to experience advance fee payment fraud than men. In addition, 16% of fraud reports involve banking and credit industry fraud – at least, cases been reported to the police and not directly to victim's bank. Also, 56% of the time, banking frauds are against women. Further, women experience higher probabilities of, or at least are more likely to report[140], computer misuse fraud.

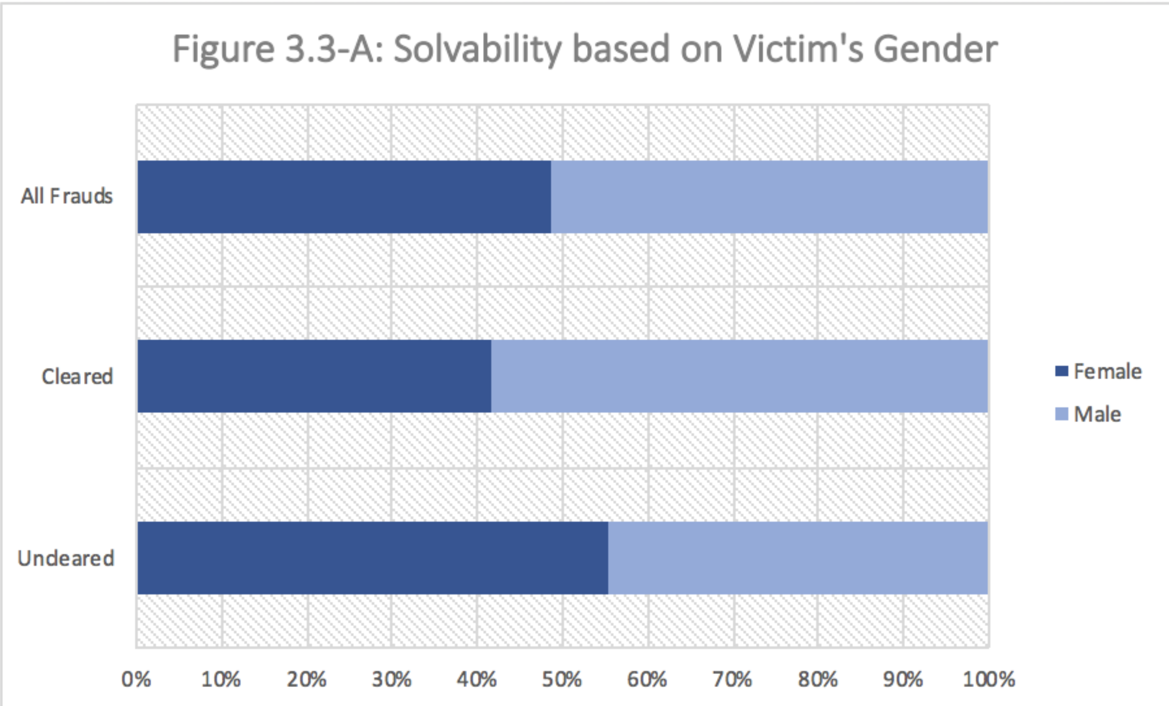
In total, computer misuse fraud accounts for 10% of the overall recorded fraud. Nevertheless, this percentage includes only *cyber-dependent* crimes, such as hacking. The percentage might turn out to be a lot higher than that if *cyber-enabled* crimes are also considered. Cyber-dependent offences are crimes which "*can only be committed via a computer, computer network or other form of information and communications technology (ICT)*" (NCA, 2016). On the other hand, cyber-enabled crimes are traditional crimes which are conducted in a larger scale when ICT is used. Unlike, cyber-dependent crimes, cyber-enabled crimes can be committed without its cyber-element[141].

As per NFIB counting rules, if more than one offence is committed, only the most serious crime is recorded. For example, if an offender hacks into the personal email of the victim and steals banking details, which are then used by the suspect, the fraud recorded will be banking and credit card industry fraud. However, this case can be characterised as a *cyber-enabled* fraud. Therefore, accounting for all cases in the dataset with a cyber-element attached to them, we find that the percentage of cyber-fraud amounts to 39%.

Additionally, although, in 75% of the cases victims are present during offence taking place (including phone scams), only 13% of individuals realise victimisation while it is happening.

[140] Computer misuse fraud is one of the most underreported crimes at the moment. Comparatively, 2016 estimates from the *Crime Survey of England and Wales (CSEW)* indicate that adults aged 16 and over have experienced 5.4 million incidents of fraud and computer misuse (ONS, 2017).
[141] For instance, ticket fraud where the victim buys tickets that are never supplied or turn out to be forged.

Half of the victims comply with the offender once before reporting the fraud to the police whereas 14% of the victims comply more than once, in many cases, for years. Further, in cases where victim's personal information has been extracted (including name, home address, bank details), 1 out 3 victims provide this information themselves. Interestingly, in cases where offender asks specifically for victim's bank details – most likely, by impersonating victim's bank – 7 out of 10 individuals disclose their bank and/or credit card details. Even more alarming, in cases where offender asks victim to pay or transfer funds, 93% of the time the victim does so.



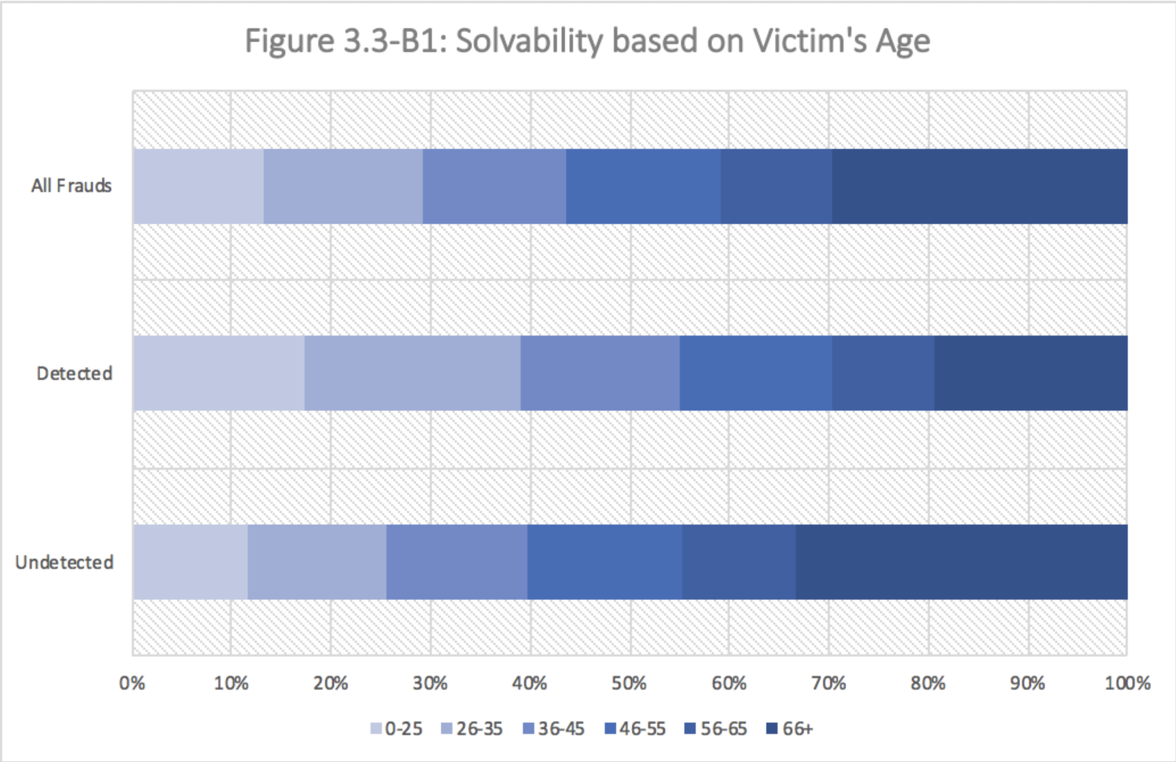
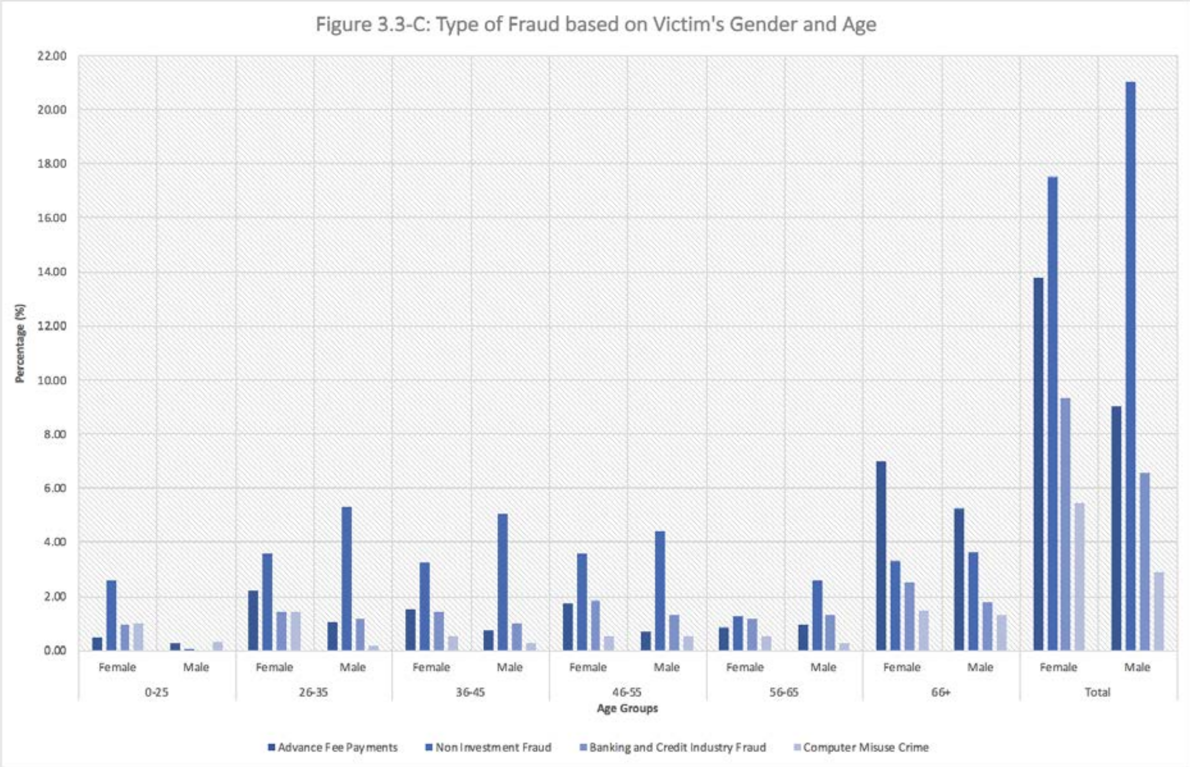


Figure 3.3-B1: Solvability based on Victim's Age
All Frauds
Detected
Undetected
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%
0-25 26-35 36-45 46-55 56-65 66+


Figure 3.3-B2: Fraud Solvability based on Victim's Age and Gender
.5
.4
.3
.2
.1
Pr(Detection)
0-25 26-35 36-45 46-55 56-65 66+
Age Groups
Victim's Gender
Female
Male
Note: Adjusted Probabilities of Age Groups with 95% CIs

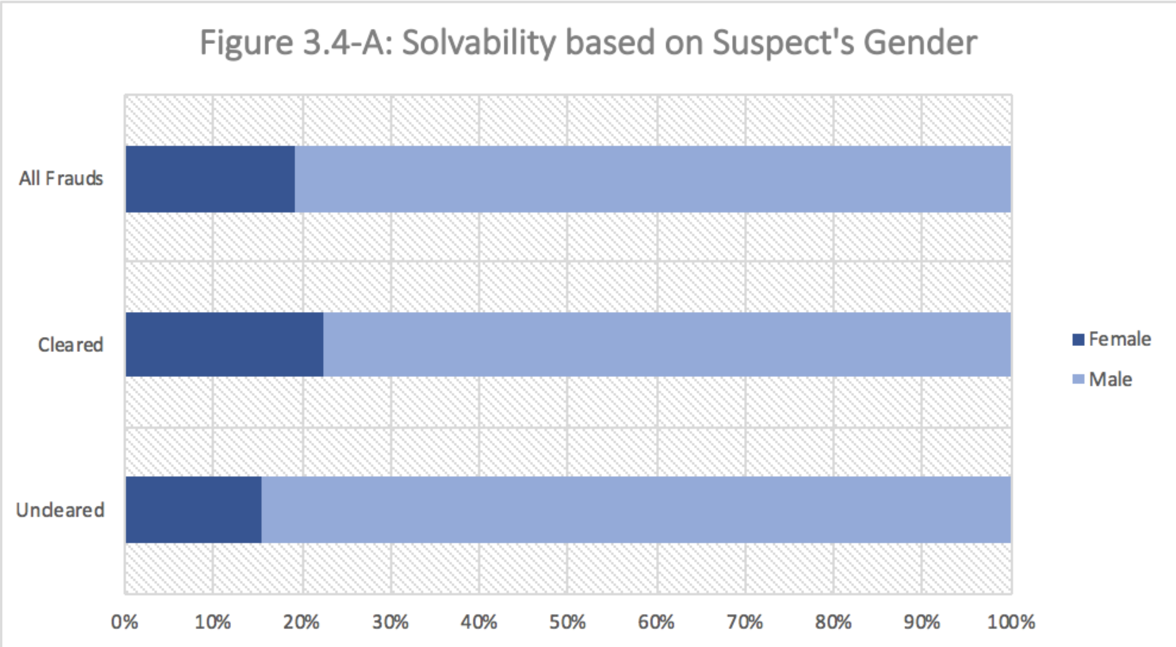


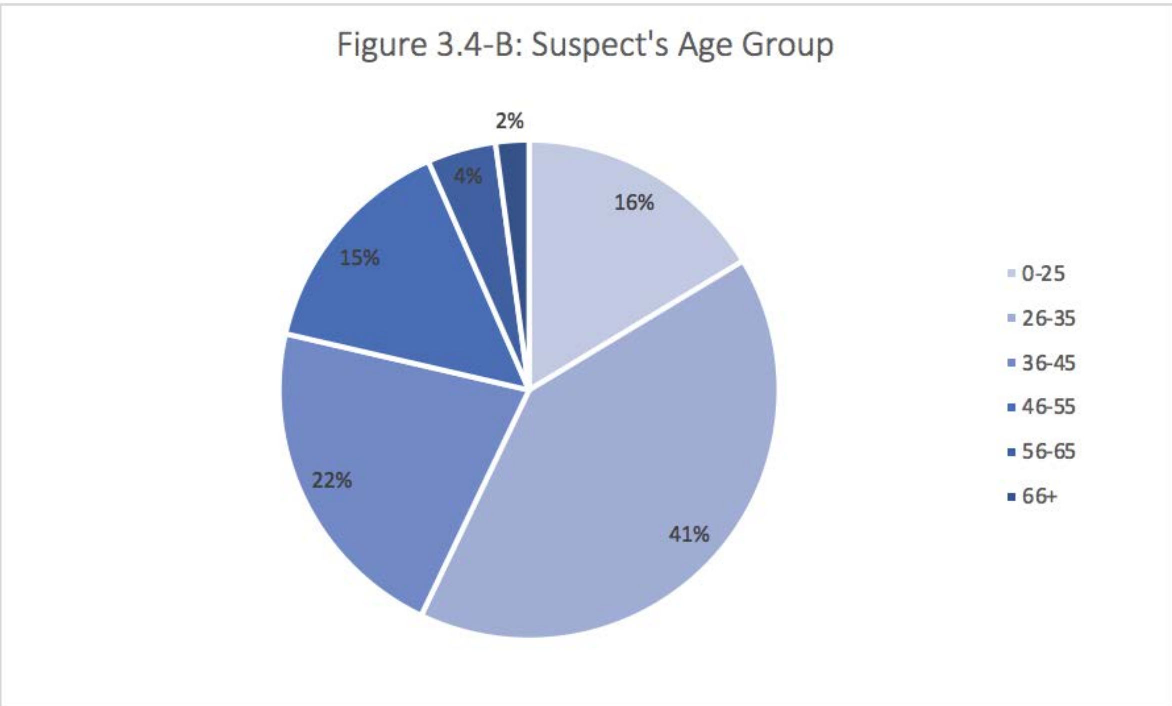
3.3.4.2 Suspect Characteristics

Figures 3.4-A and 3.4-B demonstrate that young males are more likely to commit crimes. This finding is consistent with the literature (Freeman, 1992). The descriptive analysis indicates that males are 4 times more likely to engage in fraud than females. For male offenders, Figures 3.4-C1 confirms the findings of *Section 3.3.4.1*. In particular, male offenders are more likely to engage in non-investment, advance fee payments, banking and credit industry fraud and computer misuse crime – and in that order. On the other hand, female offenders commit more banking and credit card frauds.

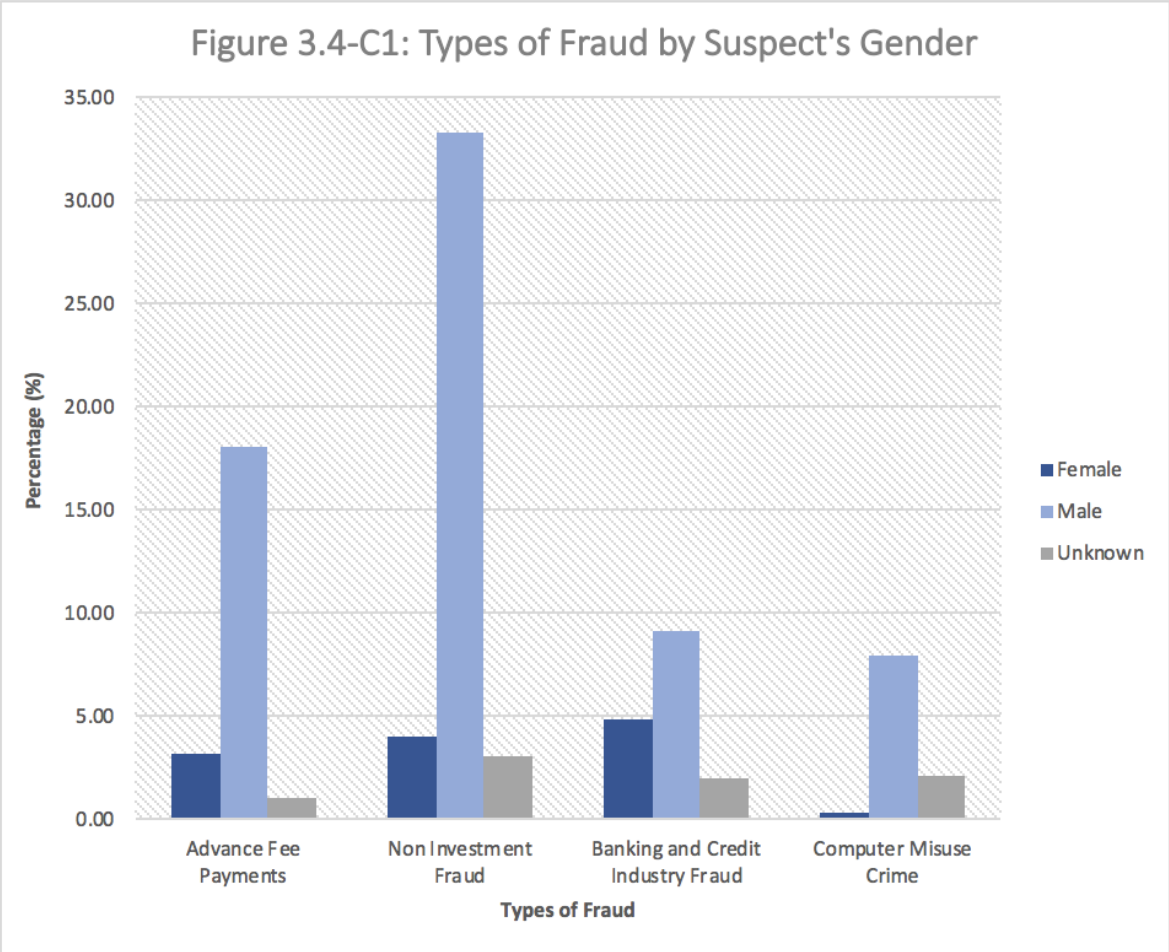
Figure 3.4-C2 examines the type of fraud based on suspect's age. The estimations are limited to detected cases, where this information is known. As shown, non-investment and banking fraud are the most prevalent types of fraud, across all age groups. However, since the estimates are only based on detected cases, we must acknowledge that, although being among the most popular types of fraud; cases of non-investment and banking frauds have also the highest probability of detection. This is in-line with the solvability outcomes presented in Figure 3.2-A1.

In addition, prevalence tests indicate that fraudsters are more interested in deceiving victims and securing funds than obtaining victim's banking details. Specifically, offenders are 4.7 times more likely to ask victims to transfer funds than requiring their personal banking information.

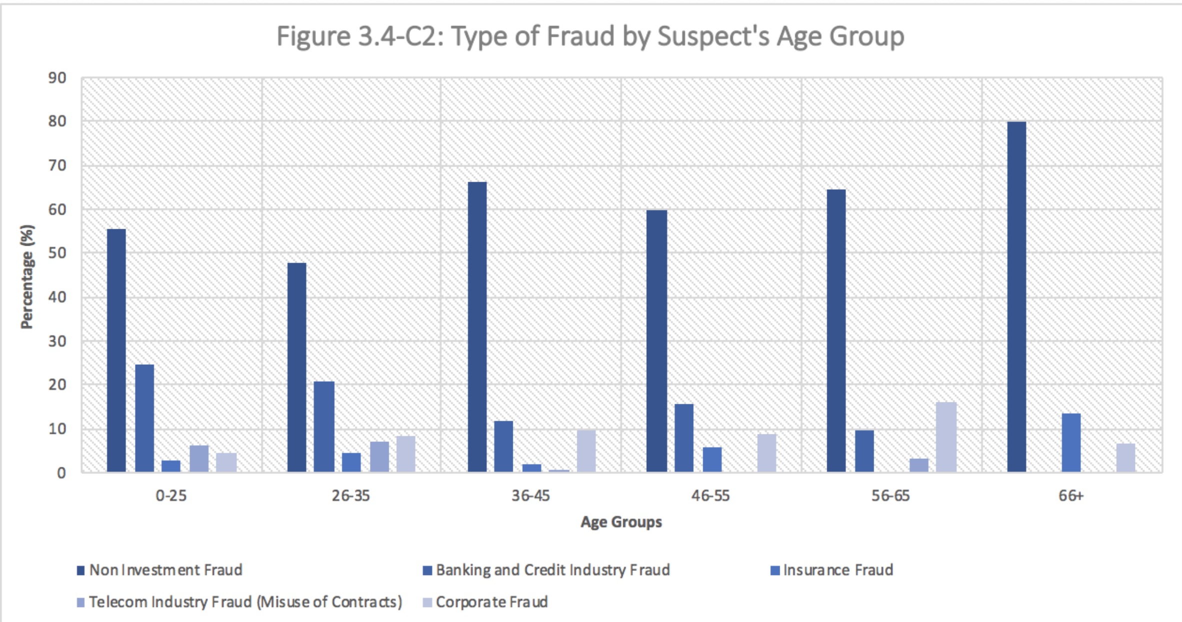




Notes: Percentages based only on detected cases.



Notes : The percentage probabilities are based on the total number of frauds available in the dataset. Using victim's (or reporting person's) decription of suspect, we are able to include both detected and undetected cases to compare the most committed types of fraud between the two sexes.



Notes : Percentages based only on detected cases.

3.3.4.3 Incident and Fraud Characteristics

Tables 3.3 – 3.5 assess the importance of various incident characteristics. Table 3.3 compares case clearance based on the number of victims and offenders involved. In the majority of cases, there is only one offender. Cases involving only one victim and one offender have a higher probability of detection, about 29% of these cases are solved whereas only 0.64% of cases involving multiple victims and offenders are cleared. Table 3.3 also showcases that victims and police have different perceptions as to how many suspects are involved. Only in 25% of the cases, victims report that there might be multiple suspects involved whereas after police investigation, multiple offenders are identified in 42 cases out of 100.

Further, Table 3.4, indicates that 77% of the time, cases are cleared because the offender has a custody record whereas Table 3.5 illustrates that in 28% of the cases being reported, the victim identifies potential suspects, 47% of which are cleared. In general, if the victim knows who the suspect might be, the probability of detection is 60%. Interestingly, in 4 out of 10 cases, where suspect is known, the victim and the suspect are related either through a business or personal relationship.

In addition, the descriptive analysis indicates that when a fraud is committed, 84% of the time the victim ends up losing money. Figures 3.5-A and 3.5-B illustrate the cost of fraud by outcome and by type of fraud, respectively. As shown, the cost of detected and undetected cases is approximately the same with the total cost adding up to £18 million[142]. This is a staggering amount, considering that only 2 PFAs are included in the analysis and it is just over a 2-year period. As demonstrated in Figure 3.5-B, the most lucrative fraud is banking and credit industry fraud with an approximate cost of £5 million; financial investment and advance fee payments fraud follow. The costs of banking fraud are probably even higher, if we consider that financial institutions encourage customers to report cheque, card or online banking fraud directly to them and not to the police (Home Office, 2018).

[142] Comparatively, between April 2014 and March 2015, the total losses reported to Action Fraud amounted to £3.5bn (HMIC, 2015).

The above findings amplify the need for a more comprehensive and coordinated approach when investigating fraud offences. This is explored in the following sections.

Table 3.3: Percentage of Incidents with respect to Number of Victims/Offenders

	One offender		**Multiple Offenders**	
	One Victim	Multiple Victims	One Victim	Multiple Victims
As identified:				
By Victim	**65.44**	**7.93**	**25.00**	**1.63**
Detected	29.76	4.03	2.40	0.51
Undetected	35.68	3.90	22.60	1.11
From Police Investigation	**47.90**	**5.96**	**42.54**	**3.60**
Detected	28.82	3.90	3.34	0.64
Undetected	19.08	2.06	39.19	2.96

Table 3.4: Custody Record of Victim and Offender

	Yes			**No**		
	Total	*Detected*	*Undected*	*Total*	*Detected*	*Undected*
Victim	**9.38**	**2.51**	**6.87**	**89.26**	**23.12**	**66.29**
Female	6.35	1.62	4.73	92.26	21.77	70.50
Male	12.76	3.51	9.25	86.22	5.55	61.54
Offender	**77.94**	**77.22**	**0.43**	**22.06**	**21.63**	**0.72**
Female	67.28	66.82	0.46	32.72	32.26	0.46
Male	82.74	81.91	0.42	17.26	16.84	0.83

Table 3.5: Relationship between Victim and Offender

	Female			**Male**		
	Total	*Detected*	*Undetected*	*Total*	*Detected*	*Undetected*
Prevalence Rates:						
Unknown Suspect	**71.97**	53.90	81.20	**70.89**	51.24	83.98
Known Suspect	**28.03**	46.10	18.80	**29.11**	48.76	16.02
Suspect and Victim are Related	*12.70*	*15.85*	*11.08*	*9.07*	*11.46*	*7.49*
Outcome Rates subject to factor being present:						
Unknown Suspect	**873**	25.32	74.68	**789**	28.90	71.10
Known Suspect	**340**	55.59	44.41	**324**	66.98	33.02
Suspect and Victim are Related	*154*	*42.21*	*57.79*	*101*	*50.50*	*49.50*

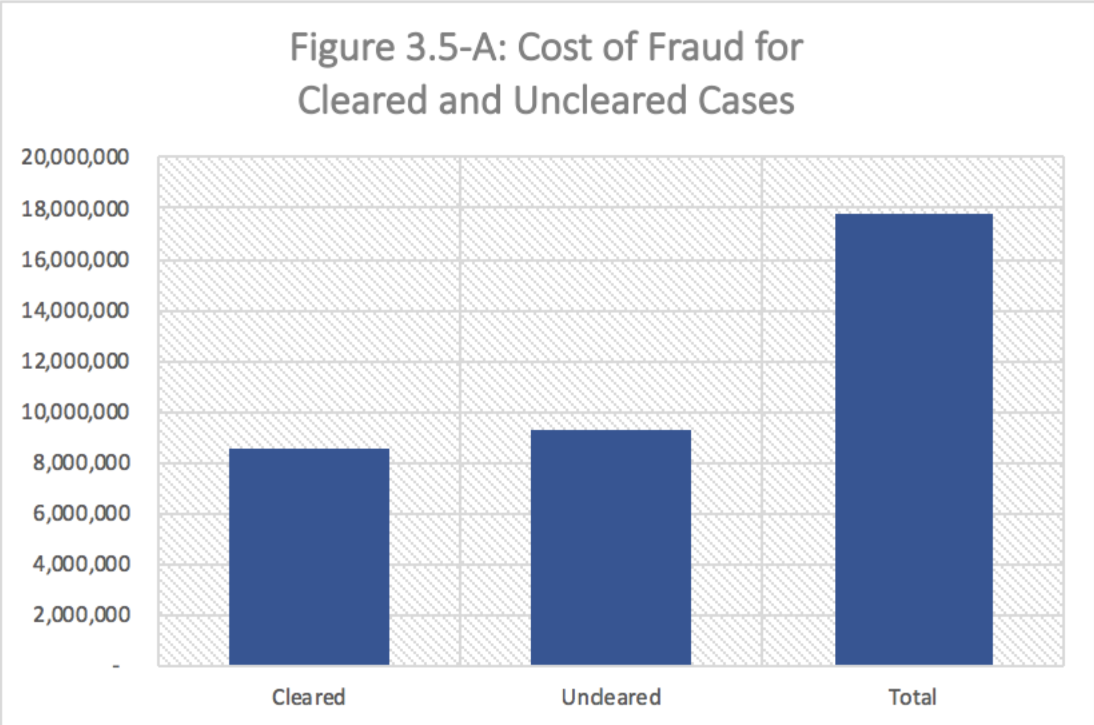


Figure 3.5-A: Cost of Fraud for Cleared and Uncleared Cases
20,000,000
18,000,000
16,000,000
14,000,000
12,000,000
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
-
Cleared
Uncleared
Total

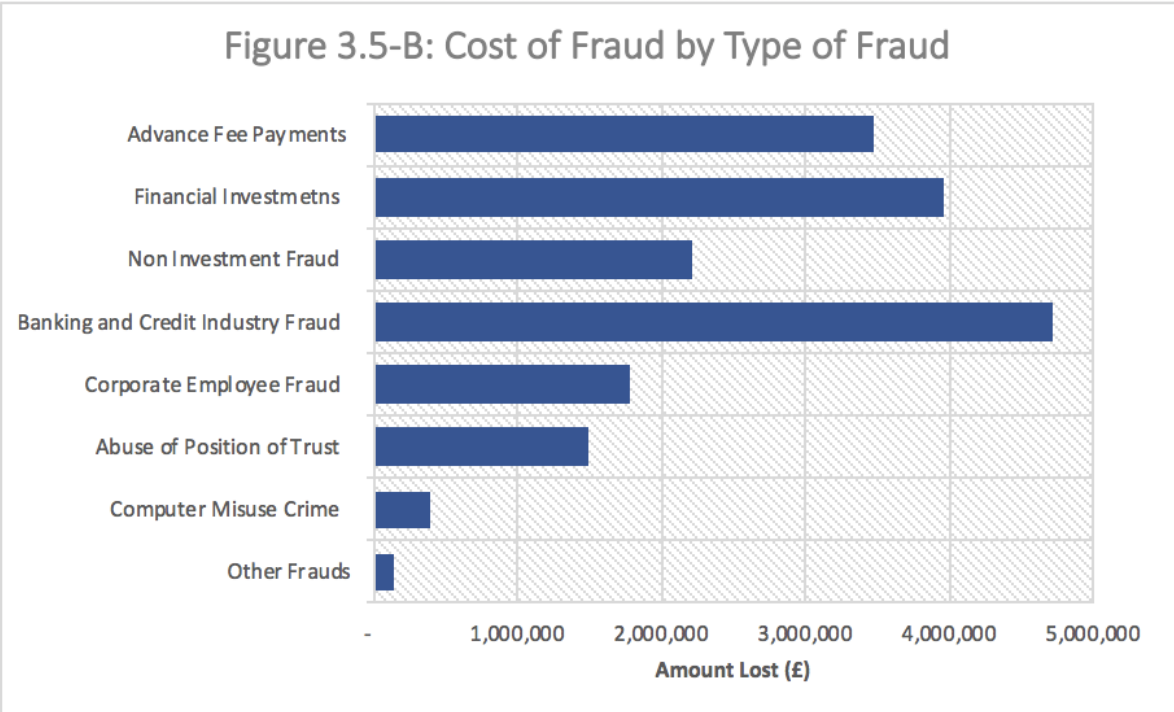


Figure 3.5-B: Cost of Fraud by Type of Fraud
Advance Fee Payments
Financial Investmetns
Non Investment Fraud
Banking and Credit Industry Fraud
Corporate Employee Fraud
Abuse of Position of Trust
Computer Misuse Crime
Other Frauds
-
1,000,000
2,000,000
3,000,000
4,000,000
5,000,000
Amount Lost (£)

3.4 Methodology and Empirical Analysis

As there is no previous examination of fraud solvability, before developing a predictive model and testing its forecasting capabilities on a validation sample, the study first focuses on the identification of investigatory factors that signify clearance.

Specifically, this study aims to answer the following research questions:

- **i.** Which factors indicate solvability of fraud offences and financially motivated cybercrimes?
- **ii.** Which factors affect solvability in the absence of a named suspect?
- **iii.** Can the developed model, encompassing solvability and case-limiting factors as identified in this study, correctly predict case clearance?
- **iv.** Is the developed model externally valid?

It should be noted that there is no record of mandatory investigation. That is, none of the cases is highlighted as high profile, or receiving lots of media attention, or having a major financial impact. Therefore, all cases, whether NFIB referrals or call-for-service, are equally likely to be allocated to an officer for further investigation, given there is an investigative lead.

Although, there are many variables in the dataset capturing what information is known about the suspect, a more generic variable capturing whether there is *any* known level of intelligence about the suspect, ranging from physical descriptions to names, is created. Further, variables capturing whether a witness was present at the time of offence are created. If not, other variables capturing whether third parties can be contacted to obtain information about the suspect are also considered. These factors are divided into two 'groups': *known* and *can be known*. If more information can be obtained either by a witness or a third party, the officer notes that down either in a free-text field or investigation log. However, in some cases it is not clear if the police officer has taken the deposition from the witness or whether third parties have been contacted. Therefore, for these cases a variable is created, capturing whether witness and third parties *can* be contacted whereas for cases clearly stating that the information *has* already been confirmed by the witness/third parties, we generate another variable. A VRM variable records if there are any vehicle details that can be of help in the investigation. A variable capturing the availability of CCTV footage is also considered.

3.4.1 Factor Identification

To answer the first research question, three tests are performed. For the first test, investigatory factors are *individually* tested to examine how each one differs between solved and unsolved cases. Continuous variables, such as victim's age and days between record created and fraud first committed, are tested using t-test whereas chi-squared tests are used for categorical factors[143]. Afterwards, the effective size is estimated to assess the impact that each factor independently exerts on case solvability. This test ensures that the factor's magnitude is considered. In other words, it tests whether the difference between solved and unsolved cases is large enough to be of practical importance. Finally, the prevalence of each variable within the sample is estimated. This test simply estimates the percentage of cases having that factor present.

All significant factors, as determined by the three tests, are subsequently tested for correlation and multicollinearity before forming our logistic regression. All tests presented are performed on the *developmental sample*[144].

3.4.1.1 T-tests and Chi-square Tests

The findings from the t-tests[145], presented in Table 3.6, demonstrate that all continuous variables considered are significant, apart from the variable capturing the days between last and first time of offending. Nevertheless, only age and the variable capturing the days elapsed between first offence and recording are considered in the analysis moving forward because, as shown in *Appendix A.3.3*, this is the only continuous variable – apart from age – that has entries for all cases in the sample.

[143] For continuous variables, we use t-tests as the chi-squared test tests whether there is no association between two categorical values.
[144] Before estimating the predictive model on the *validation sample*, the tests are re-estimated. The results are available upon request.
[145] The t-tests which simply examine whether the sample mean differs from the hypothesised mean. The t-statistic can be smaller (negative) or larger (positive) than the hypothesised value. However, as we are doing a two-sided test, its sign makes no difference.

Table 3.6: Results of t-tests for Continuous Variables

	obs	mean	std.dev	min	max	t-stat	p-value
Age	3,852	51.21	20.90	13	102	12.92	0.00
Days between Recording and Fraud First Committed	4,012	167.46	469.31	0	6670	-2.19	0.03
Days between Recording and Fraud Last Committed	2,787	64.13	211.79	-18	4431	-2.42	0.02
Days beetwen Last and First Time Fraud Committed	2,787	147.92	435.13	0	6600	-0.28	0.78

For presentation purposes, the results from chi-square tests are broken-down into groups. The chi-square statistic tests the hypothesis of no association between two categorical variables. A small p-value indicates a significant correlation between the tested variables. It also allows identification of solvability and case-limiting factors. If the p-value of the chi-square test is significant and the named factor has a higher percentage in cleared than unsolved cases, then it is considered as a solvability factor. Likewise, negative indicators imply case-limiting factors.

Factors Directly Downloaded from WWP and WMP Systems

Figure 3.6-A displays the results of chi-squared tests of directly downloadable factors from the WWP and WMP systems. All variables, except correct type of fraud, action and interest markers[146] are statistically significant. Unsurprisingly, variables identifying suspect's characteristics – such as custody record, body description, ethnicity, or nationality – serve as solvability factors. Also, if fraud is directly reported to the police instead of AF or fraud is part of a series or linked to another crime, then the case is more likely to be solved.

[146] Appendix 3.2 contain lists of location, interest and warning markers that are used to generate these dummy variables.

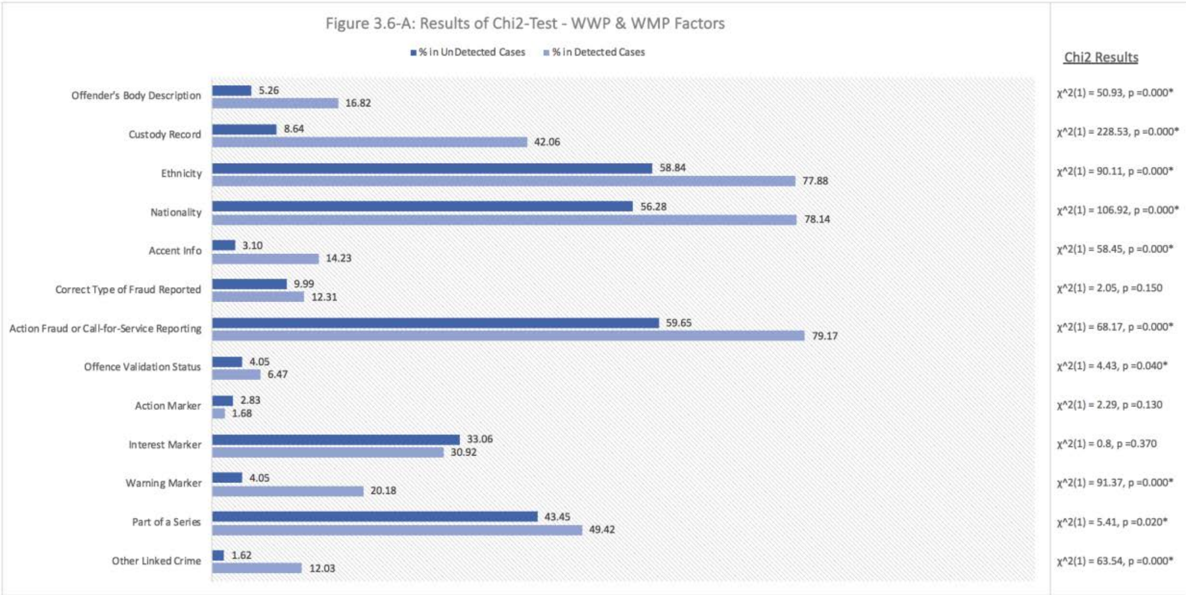


Figure 3.6-A: Results of Chi2-Test - WWP & WMP Factors

Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

Types of Fraud as a Factor

The test is also performed on different types of fraud that are present in the sample. As shown in Figure 3.6-B, only six types of fraud are significant. The tests indicate that when advance fee payments, banking and credit industry, and computer misuse fraud is committed, the case is less probable to be cleared whereas solvability of telecom industry and corporate employee fraud is more likely.

Advance fee payment frauds include offences such as lottery and dating scams. The likelihood of the victim knowing the offender is minimal and, usually, the suspect asks for the money to be transferred using MoneyGram or Western Union making the transaction practically untraceable.

Most banking frauds involve cheque, card and online bank accounts being defrauded. On average, the number of days between the first-time fraud is committed and a record being created is 158. This is not surprising since cases are individually analysed by AF and this takes time. An offence reported to AF takes, at least, 30 days to be processed before forwarded to a force for further investigation. This delay bestows a unique opportunity to the fraudster to generate a complex money trail frequently, involving bank accounts outside the force's jurisdiction, to accumulate on funds obtained dishonestly. Inherently, the investigation of banking and industry frauds becomes cumbersome.

Moreover, the ratio of detected to undetected cases for computer misuse fraud, which mainly includes hacking of personal accounts, is the smallest among the types of fraud being studied. This is anticipated given that police have yet to establish a response strategy or form risk assessments for this type of incidents (HM Government, 2014). Digital crime still is an unchartered territory for the police for the time being.

HM Government (2014) and Home Office (2015) reports showcase that forces do not have a wider understanding of cybercrime, the way it is committed or, who is more susceptible to victimisation. Police staff lacks adequate training which not only restricts them from recognising digital crime, but also restricts police from implementing preventive plans and investigatory tactics[147]. The nature of cybercrime does not make the situation any easier. The internet gives the ability to the offenders to hide their tracks by providing online anonymity. Interestingly, by reading the police reports and the victim's account, it was evident that, in most cases, it is with the victim's help that cybercrimes are enabled either by downloading malware or viruses into own computer without realising it or, by the offender deceivingly obtaining victim's consent to remotely control their computer. Nevertheless, it is highly likely that offenders are not even residing in the same jurisdiction as the victim or even within the same country, making the investigation even more difficult.

On the other hand, the chi-squared tests indicate that telecom industry and corporate employee fraud are more likely to be detected. This makes sense since telecom frauds are usually committed in a shop, where individuals obtain phone contracts by false representation. The fraud is witnessed by the employees who can provide a description of the suspect and the offence is, most likely, captured in CCTV. Also, corporate employee fraud has a positive indication as offender is probably known. Accordingly, investigation becomes more straight forward when there is a lead suspect while making it is easier for the police to get hold of incriminating evidence.

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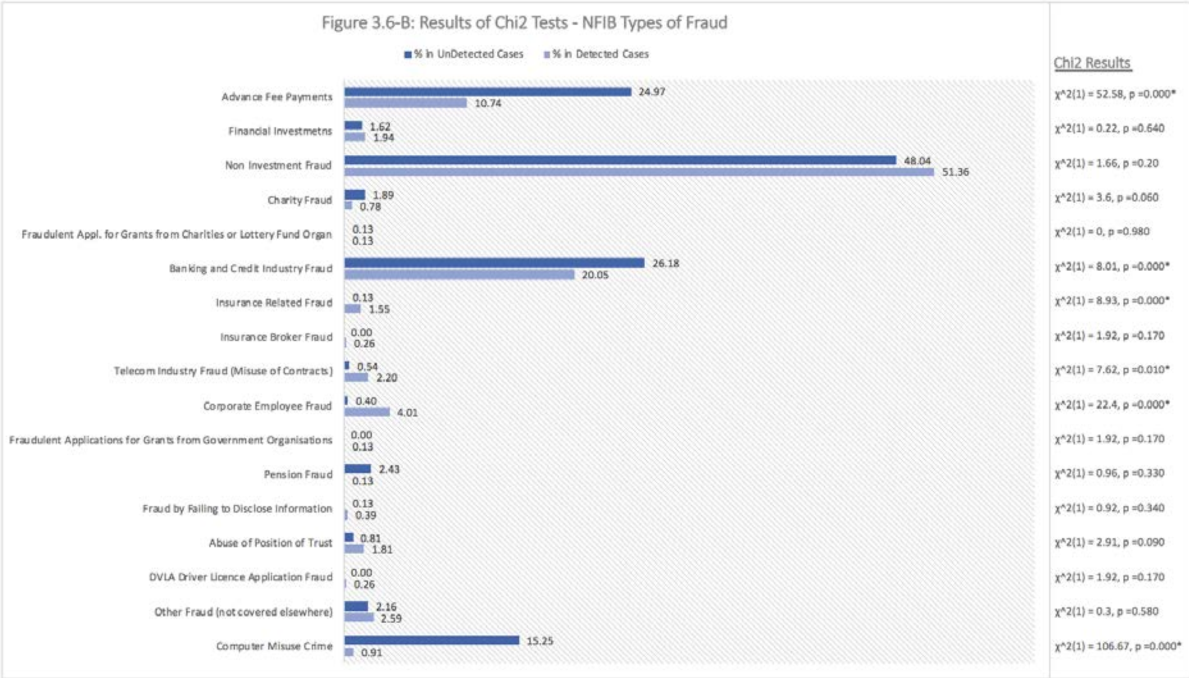
[147] The Home Office (2015, p.30-33) report provides detailed arguments as to why appropriate training is crucial to effectively tackle cybercrime.



Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

Victim Information

Figure 3.6-C presents the information, collected from the MOs and investigation logs, relating to the victim. Only two solvability factors have been identified: victim compliance with the offender (once) and been victimised before. The case limiting factors identified are: there is only one victim, victim refusing to make an official complaint, victim being present during offence, complying with the offender more than once, victim being vulnerable or old and finally, when the honesty of the victim is question.

All results seem to be self-explanatory, except perhaps for the negative indication of the variable capturing whether the victim was present during the offence taking place. However, this also applies to numerous cases where the offence takes place over the phone. In such cases, the victim has no idea about who the offender is, what he/she looks like, nor does the victim have any other information relating to the fraudster. The only possible lead is the offender's phone number but in most cases, the call is made using a withheld number. Respectively, it is not surprising that the 'presence' of the victim in the scene does not help the investigation process in any way[148].

[148] Also, further tests indicate that this factor is insignificant and thus, not included in the predictive model developed.

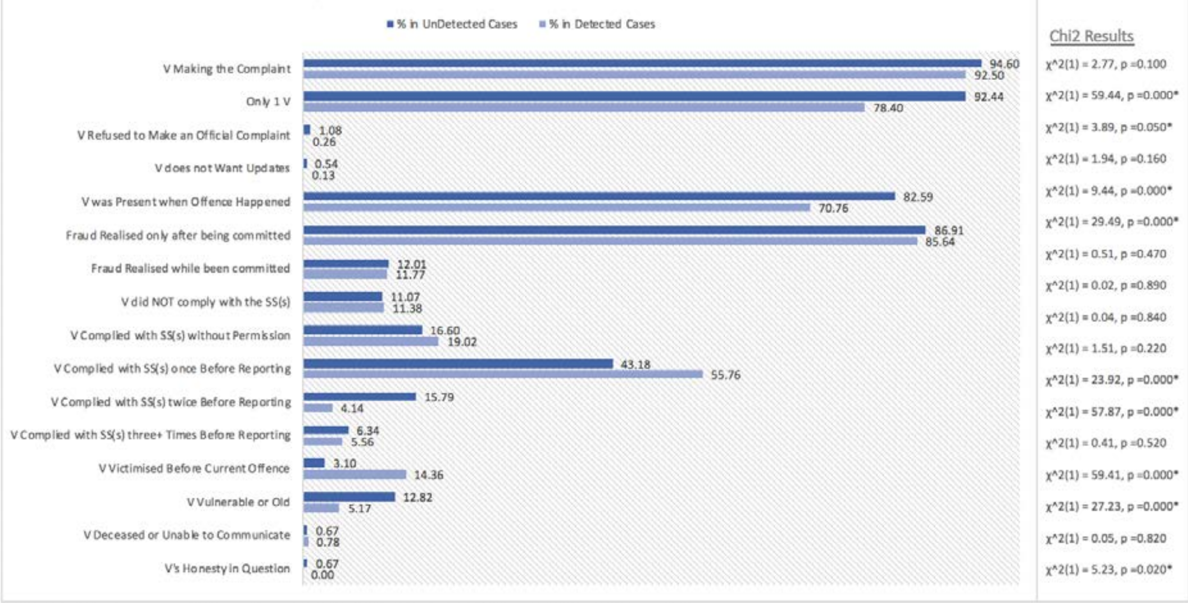


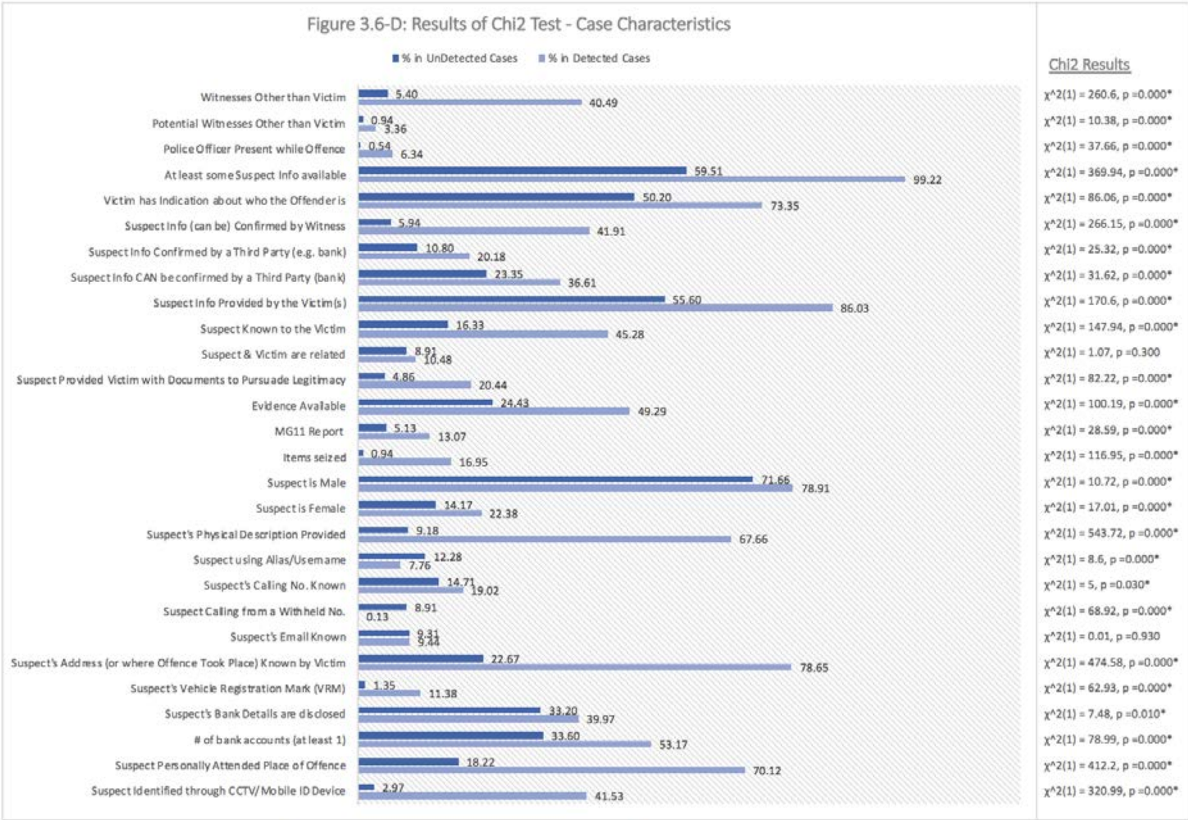
Figure 3.6-C: Results of Chi2 Tests - Victim Information

Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

Case Characteristics

The most interesting finding from Figure 3.6-D is that, the more information available, the more likely is the case to be solved. Only variables capturing the relationship between the suspect and victim, and if suspect's email address is known are found to be insignificant. Although the former variable may seem odd to be insignificant, considering that the parties involved are usually family members, it is possible in later stages of the investigation, they may choose to resolve the issue without involving the police any further. Unfortunately, this cannot be known with certainty since the police reports do not always explicitly mention the reasons as to why the case has been filed.

All remaining factors are significant and have a positive indication, except for when the suspect is using an alias or calling from a withheld number, which the test classifies as case-limiting factors. The solvability factors identified are: witness present; police officer at the scene; suspect information provided either by the victim, witness or by a third party such as a bank; suspect is known to the victim; evidence collected from the scene – including documents handed over by offender to persuade for legitimacy; other items seized; victim completing a MG11 report; suspect's gender is known; physical description; suspect's phone number known; offence location is known; suspect personally attending the location; VRM details; suspect bank account details and CCTV footage.



Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * Indicates significance of 5%.

Reason for Fraud

Furthermore, useful investigative leads can be collected by understanding suspect's intentions. Is the suspect after the personal details of the victim or prefers to deceive victim to transfer money into own account? In the second scenario, the bank details of the suspect are known so the police can ask the offender's bank to disclose the information of the suspect, such as name, registered address or phone number. The findings, displayed in Figure 3.6-E, demonstrate that if victims comply with suspect, the less likely the offence to be solved. That is true irrespective of whether victims disclose their own personal account details or transfer money directly into the offender's account. This is due to the suspect being able to immediately use victim's details to extract funds or generate a money trail that it is really difficult to put a stop to. As discussed earlier, this is especially evident when considering how long it usually takes for the police to allocate the case to an officer.

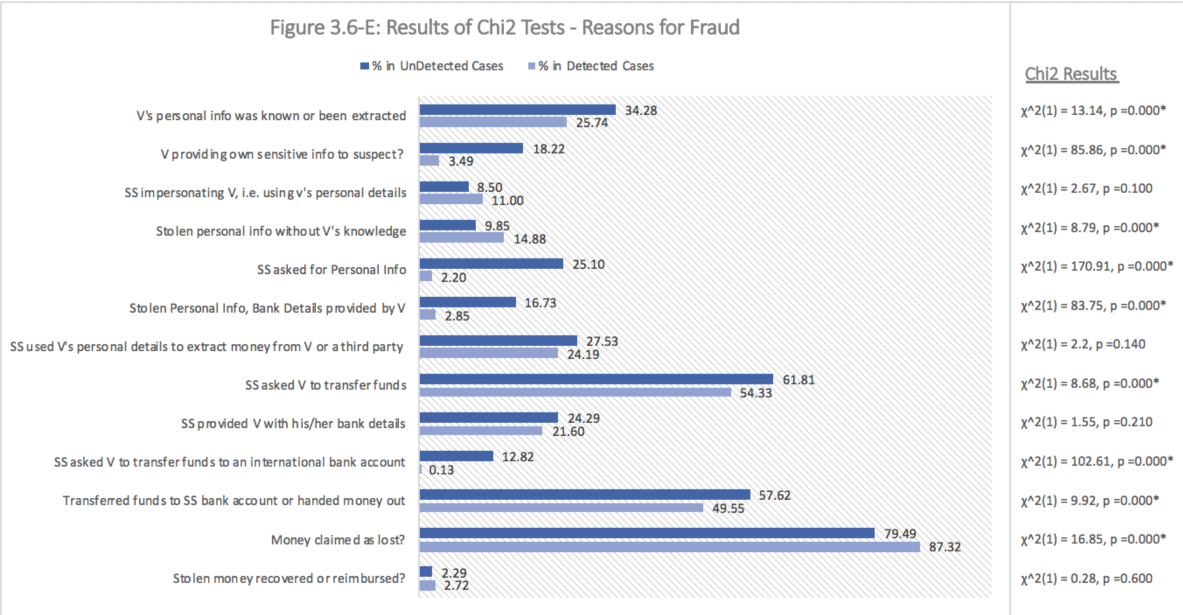


Figure 3.6-E: Results of Chi2 Tests - Reasons for Fraud

Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

Payment Methods

Figure 3.6-F demonstrates the various payment methods that are used to facilitate fraud and examines which ones contribute in the identification of the suspect. Use of bank cards, in shops and cash points as well as use of cheques are more prevalent in detected cases. Paying in cash also has a positive indication. As we found this odd, we examined the cases where cash is the preferred method of payment. Most cases involved petrol stations and retail frauds. In both cases, it is possible that the offence has been witnessed by someone so there is a physical description of the suspect as well as CCTV footage. Furthermore, the tests indicate that when online banking or online payment services such as, PayPal, are used or funds are transferred using MoneyGram or Western Union, it is less probable that the case will be cleared.

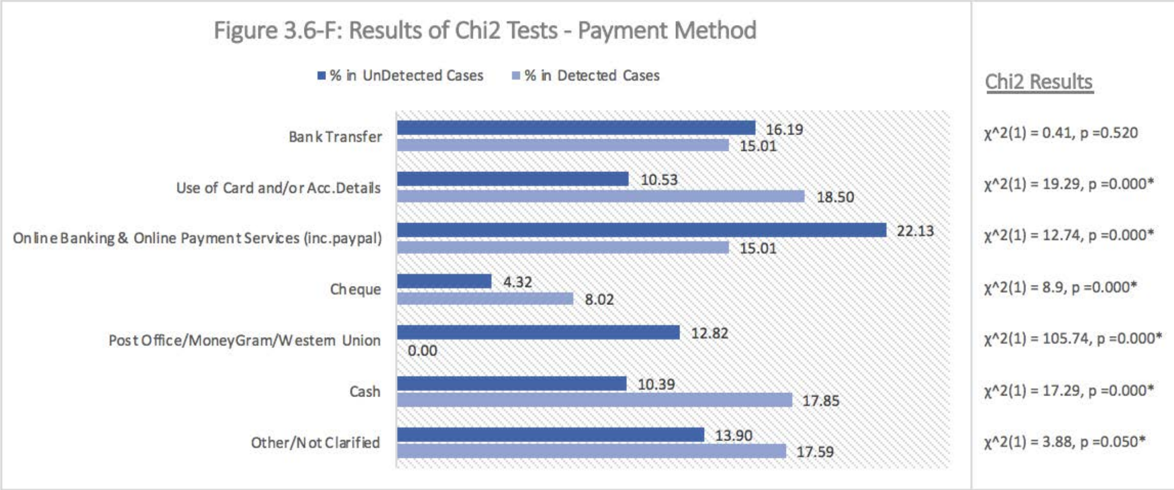


Figure 3.6-F: Results of Chi2 Tests - Payment Method

Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

Method of Contact

Figure 3.6-G demonstrates that, in isolation, any method of contact apart from personally meeting the suspect, incommodes fraud investigation. This is to be expected since the victim has no idea who the offender is[149] and there are no witnesses. Therefore, any information relating to the suspect's identity need to be requested and collected from third parties.

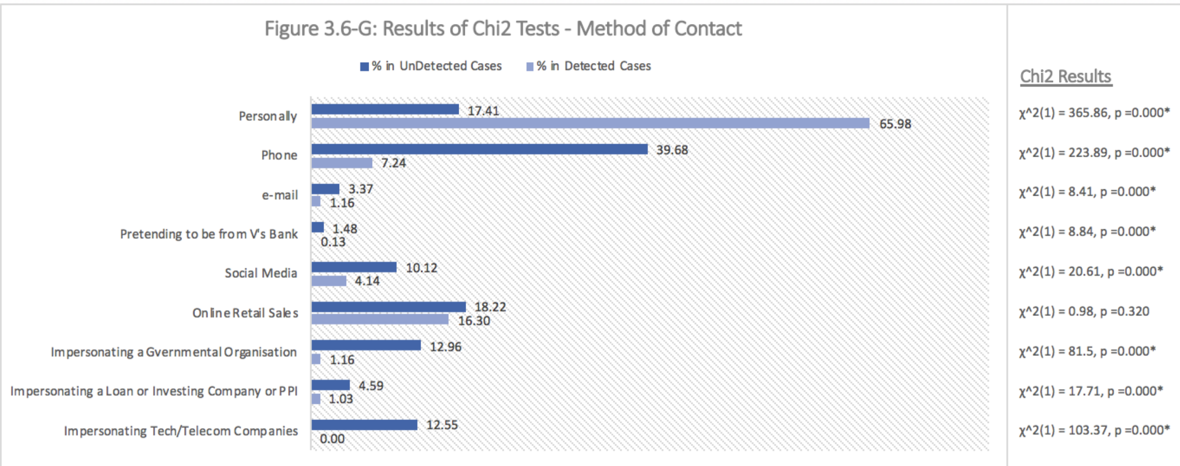


Figure 3.6-G: Results of Chi2 Tests - Method of Contact

Notes: The estimates are represent the prevelance of the factor in detected and undetected cases. * indicates significance of 5%.

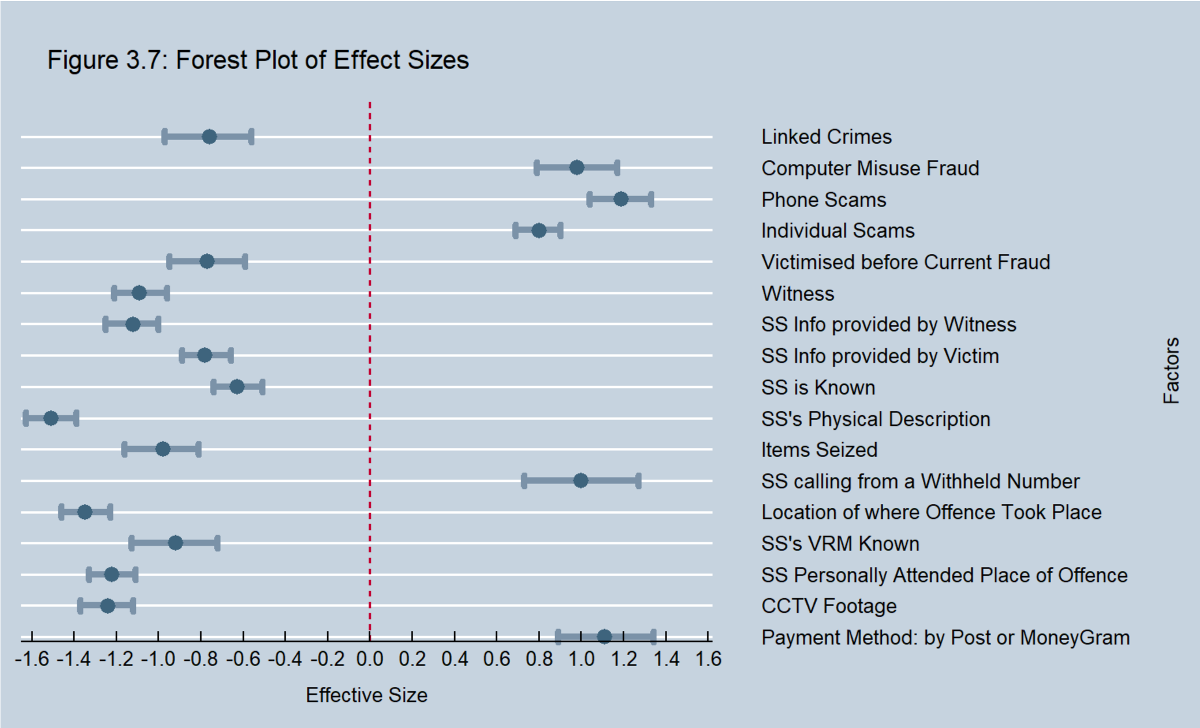
[149] Unless there is an online retail sale; in which case the victim may have an indication as to who the offender is; but the fraudster can always use an alias name or the account of a third person; e.g. by hacking.

3.4.1.2 Effective Size Estimates

In addition to statistical significance, it is important to account for the magnitude of the relationship between detected and undetected cases. In other words, just because a factor is statistically significant, it does not necessarily mean that the difference between the two outcomes, solved and unsolved, is large enough to be of practical importance. To that extent, an effect size analysis is performed.

The Hedge's G statistic is estimated for each factor in our sample. It captures the difference between two means, expressed in standard deviations units. The larger the difference, the stronger the relationship between the examined factor and solvability. A negative statistic indicates that in the absence of that factor, the likelihood of solving the case decreases. Likewise, a positive estimated difference in means indicates that factor presence has a positive impact on unsolvability. Typically, an effect size of 0.8, either negative or positive, is considered as a large effect size (Cohen, 1988). For instance, an effect size of 0.9 indicates that means of detected and undetected cases differ by a standard deviation of 0.9. Figure 3.7 presents, in a forest plot, – including lower and upper 95 percent confidence intervals – factors with an effect size of 0.8 and larger.

The solvability factors identified are: fraud being linked to another crime, prior victimisation, if there is a witness, and who is able to provide information about the suspect, if there any suspect information available, physical description of the suspect, whether items have been seized, offender's VRM details are available, CCTV footage, offence location is known, suspect personally attending offence location and where the method of contact is face-to-face. On the other hand, case-limiting factors include: suspect calling from a withheld number, or when the method of contact for fraud to committed is through a phone call and when victims transfer funds into suspect's account via post office, MoneyGram or Western Union. *Appendix A.3.4* presents the effective size estimates for all factors being considered.



Factor prevalence is also tested in an effort to identify other solvability factors with low sample predominance which could, potentially, be used more often during investigation. It is estimated as the percentage of cases having that factor present. Prevalence is estimated for each factor identified as significant, in the previous two tests, as well as for variables believed to capture information not picked up by other factors and thus, have intrinsic value in the analysis. The test aims to capture factors which are highly predictive of case solvability but they may not be used frequently. Nevertheless, the tests do not classify any other solvability factors which are not already been identified by earlier tests. Appendix A.3.5 presents the results.

3.4.2 Case Clearance without Suspect Information

From the above factor-identification tests, it is evident that *suspect information* has consistently been one of the main predictors of solvability. This is also in-line with the existing literature studying solvability models for other types of crime (Brandl and Frank, 1994; Burrows *et al.*, 2005; Tilley *et al.*, 2007). Thus, it is interesting to examine, in the absence of suspect information, if the factors affecting solvability change conditional on there being no suspect. In other words, we want to analyse whether previously insignificant factors are now significant or if case-limiting variables are transformed into solvability factors and vice versa.

We believe this is useful as in many cases of fraud the victim has no indication as to who the offender might be. Thus, upon reporting the fraud, the police have to identify other viable lines of enquiry to determine if investigation should progress or if the case should be filed instead.

To assess this, the sample is restricted to include only cases *without* suspect information. Then, the above three tests[150] are re-estimated using all available factors in the sample to answer the second research question posed in this study.

Indeed, as shown in Figures 8-A and 8-B, four factors are identified as more prevalent in cleared than unsolved cases whereas previously, in the presence of suspect information, they were insignificant and identified as case-limiting factors. The variables are: suspect providing victim with bank account details, victim's bank being contacted as soon as the fraud is realised, if the victim paid via a bank transfer and whether the method of contact between offender and victim was through online shopping websites.

All four indicate that, when the victim cannot provide adequate information on the suspect, third parties such as banks, online retailers (e.g. eBay, amazon) can be contacted to ask for information relating to the suspect. This information, probably, has to do with the name of the offender and registered or delivery address provided when the suspect opened up his/her bank or online account.

Therefore, in the absence of suspect information, the solvability predictors may differ. This not only emphasises the importance of acknowledging that suspect information may conceal other important determinants that need to be considered in the analysis; but it also demonstrates the urgency to create multivariate models rather than examining the association of each *individual* factor with case solvability. All four variables are considered as potential predictors for the multivariate regression model developed in *Section 3.4.3*.

[150] Chi-squared tests, effective size and factor prevalence.

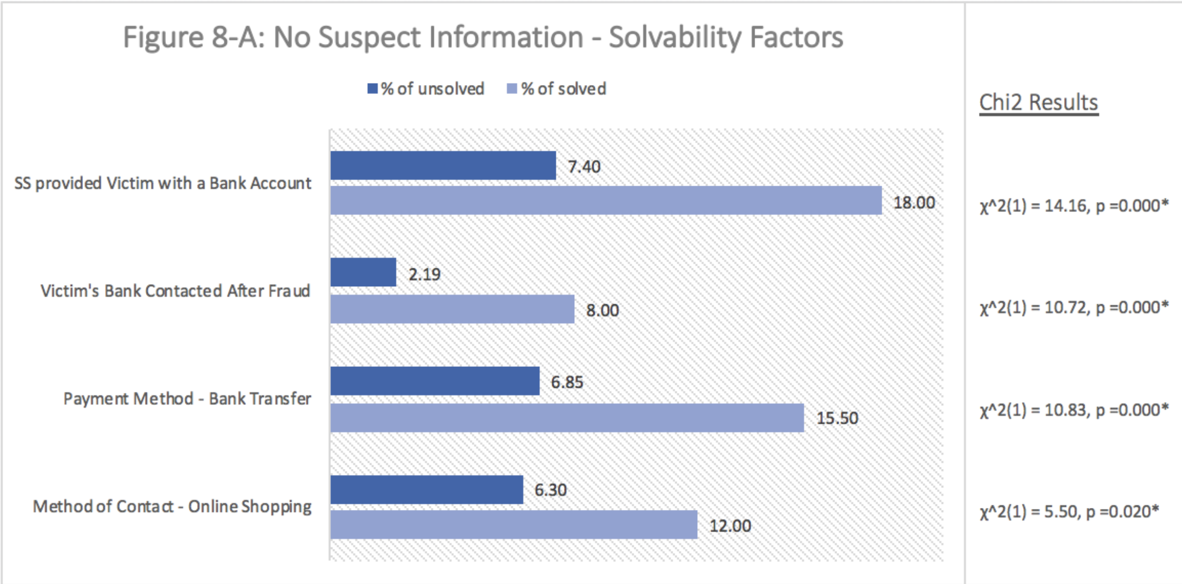


Figure 8-A: No Suspect Information - Solvability Factors
% of unsolved
% of solved
SS provided Victim with a Bank Account
7.40
18.00
Victim's Bank Contacted After Fraud
2.19
8.00
Payment Method - Bank Transfer
6.85
15.50
Method of Contact - Online Shopping
6.30
12.00
Chi2 Results
χ^2(1) = 14.16, p =0.000*
χ^2(1) = 10.72, p =0.000*
χ^2(1) = 10.83, p =0.000*
χ^2(1) = 5.50, p =0.020*

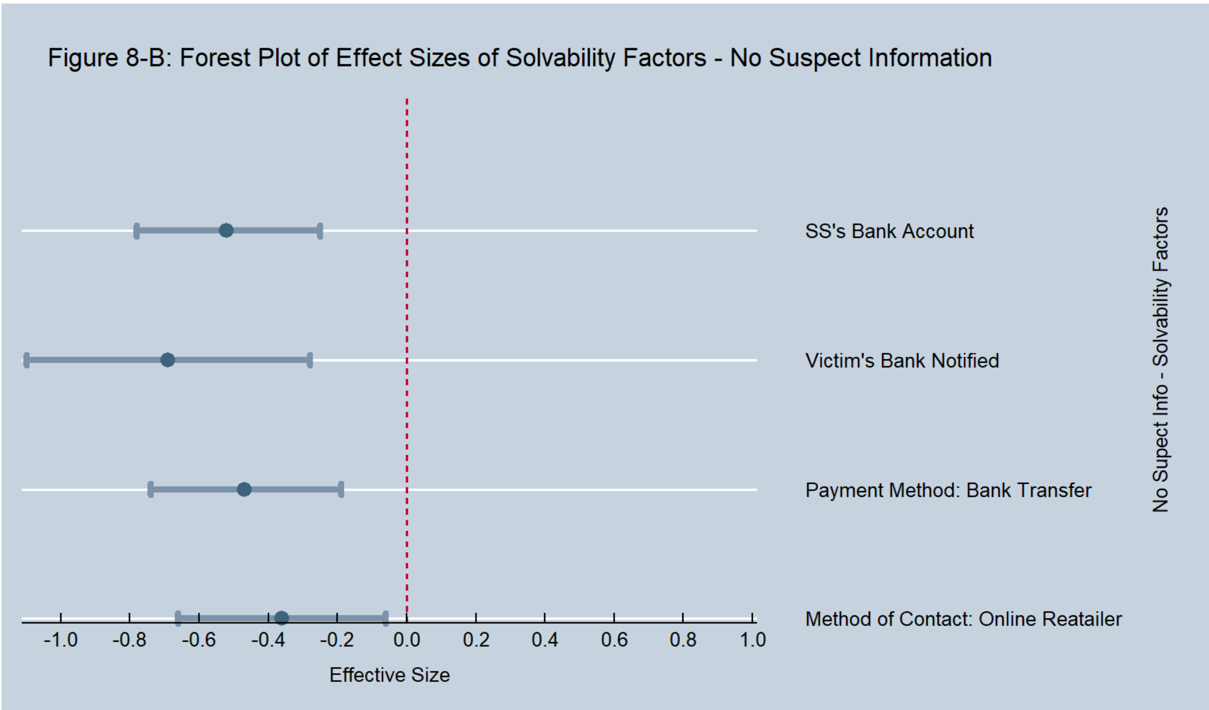


Figure 8-B: Forest Plot of Effect Sizes of Solvability Factors - No Suspect Information
SS's Bank Account
Victim's Bank Notified
Payment Method: Bank Transfer
Method of Contact: Online Reatailer
-1.0
-0.8
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
Effective Size
No Supect Info - Solvability Factors

3.4.3 Empirical Analysis

Up to this point, factors have *individually* been assessed to determine their relation to solvability. However, each case has a number of factors attached to it and the joint impact of presence/absence of factors on solvability needs to be accounted for by building a multivariate regression. This introduces the third research question which seeks to answer to what extent can solvability be predicted by determinants identified in this study.

A predictive logistic model is built up to estimate the effect of solvability and case-limiting factors on clearance. The dichotomous outcome variable, capturing whether cases are cleared or not, is used as our dependent variable. All factors identified to be related with solvability in *Sections 3.4.1.1* and *3.4.1.2* or which are believed to be of tactical importance are considered as possible explanatory variables[151]. To avoid model bias, correlation and multicollinearity tests are examined. Also, different iterations of the model are estimated before identifying our preferred model specification which most effectively forecasts clearance. The model is built using a randomly assigned half of the dataset, the *developmental* sample[152].

Table 3.7 presents the results. In column (1) a full list of potential predictors, the *unrestricted* model, is estimated whereas column (2) introduces the estimation results of the model which only includes factors that are, at least, significant at the 10 percent level; the *restricted* model.

To decide which model fits the data better, the likelihood ratio (LR) test is conducted. The LR test compares the goodness of fit between two statistical models by expressing how many times more likely the data are under each model. The null hypothesis states that the reduced model has a better goodness of fit. As shown at the end of Table 3.7, the LR test suggests that there is not statistically significant evidence in support of the *unrestricted*

[151] In addition to the three aforementioned tests (chi-squared, effective size and factor prevalence), each significant factor is included as a regressor in single predictor models to obtain Wald Z scores. Predictors with a significance level less than 0.25 are considered for further analysis. This allows us to determine predictors of a priori interest, before conducting the correlation and multicollinearity tests.

[152] The other half of the sample, the *validation* sample, is used to assess the predictive accuracy of the model; see Section 3.5.3.

model. Thus, the null is not rejected and we conclude that the *reduced* model fits the data better.

We also consider some mandatory case-limiting factors. These include cases where, the offender is believed to reside outside the PFA[153]; victim refuses to cooperate; victim does not want updates; victim reports the crime only for informational purposes and does not wish further investigation; victim's honesty is in question; suspect is dead and finally, the bank account provided by the suspect is international.

If any of these mandatory allocation rules apply then, the case is automatically filed. Thus, cases having any of these factors present are dropped from the dataset, and the two models are re-estimated. Afterwards, the LR test is conducted to compare the two 'mandatory' versions of the model; the *unrestricted* and *restricted*. The results are presented in columns (3) and (4) of Table 3.7, respectively. The test still pinpoints towards the *reduced* model.

In addition, although the excluded variables cannot *individually* predict clearance, we acknowledge that if they *coexist* with other factors then, they may be *jointly* significant – especially if the compilation of factors captures information not covered by other predictors. Thus, we examine joint significance by generating pairs of variables that have been shown to be unrelated to solvability from earlier individual tests (chi-squared, effective size and factor prevalence)[154]. This represents the *compilation* model and the results are presented in column (6). This model is compared against the *restrictive* model presented in column (2). For presentation purposes and for ease of comparison, the *restricted* model of column (2) is also presented in column (5). This time, the LR test signifies that the *compilation* model performs better.

Finally, column (7) re-estimates the model, using the same specification as in column (6), but also including the four factors that have been identified as significant in the absence of suspect information in *Section 3.4.2*. The LR test demonstrates that the *compilation* model,

[153] The case and all information collected up to that point are forwarded back to AF and then, to the corresponding PFA. Thus, in the systems of WWP and WMP, the case is marked as filed.
[154] As with previous estimations, single predictor models are also estimated to obtain Wald Z scores, in addition to the three tests, before conducting correlation and multicollinearity tests.

in column (6), performs better. Therefore, this becomes our preferred model specification and it is the one used in all remaining estimations moving forward.

Section 3.5.1 presents and discusses, in detail, the estimation results. Additional regression diagnostic tests showcasing the validity of the model are presented in *Appendix A.3.6*. The model's accuracy is tested on a validation sample in *Section 3.5.3*.

Table 3.7: Comparison of Regression Estimates

	(1) Unrestricted	(2) Restricted	(3) Unrestricted - No Mandatory	(4) Restricted - No Mandatory	(5) Restricted	(6) Compilation	(7) Compilation - cases without SS
Fraud Call for Service	1.02 ***	0.91 ***	1.03 ***	0.89 ***	0.91 ***	0.94 ***	0.84 ***
	(0.25)	(0.24)	(0.26)	(0.24)	(0.24)	(0.26)	(0.27)
Warning Indicators	0.58		0.91 **				
	(0.40)		(0.43)				
Part of a Series	2.01 ***	1.88 ***	1.91 ***	1.79 ***	1.88 ***	1.77 ***	1.73 ***
	(0.27)	(0.25)	(0.27)	(0.25)	(0.25)	(0.28)	(0.29)
Linked to Other Crimes	0.19		-0.02				
	(0.58)		(0.59)				
Advance Fee Payments Fraud	-0.18		-0.11				
	(0.50)		(0.51)				
Non-Investment Fraud	-0.42		-0.3				
	(0.42)		(0.43)				
Charity Fraud	-2.27 ***	-1.49 **	-2.24 ***	-1.51 **	-1.49 **	-0.75	-0.93
	(0.81)	(0.64)	(0.82)	(0.64)	(0.64)	(0.85)	(0.84)
Banking and Credit Industry Fraud	-1.73 ***	-1.75 ***	-1.69 ***	-1.74 ***	-1.75 ***	-1.12 ***	-1.18 ***
	(0.43)	(0.32)	(0.44)	(0.33)	(0.32)	(0.37)	(0.38)
Telecom Industry Fraud	-1.36		-1.42				
	(0.90)		(0.89)				
Corporate Employee Fraud	1.29	1.81 **	1.21	1.73 **	1.81 **	2.23 ***	2.1 **
	(0.95)	(0.88)	(0.94)	(0.88)	(0.88)	(0.85)	(0.85)
Computer Misuse Crime	-2.2 ***	-1.85 ***	-2.25 ***	-1.77 ***	-1.85 ***	-1.16 *	-1.2 *
	(0.74)	(0.63)	(0.77)	(0.66)	(0.63)	(0.65)	(0.66)
Cyber-Element in Fraud Committed	0.31		0.43				
	(0.31)		(0.32)				
Phone Scams	-2.32 ***	-2.51 ***	-2.04 ***	-2.31 ***	-2.51 ***	-1.79 ***	-1.7 ***
	(0.61)	(0.50)	(0.61)	(0.51)	(0.50)	(0.53)	(0.56)
Individual Fraud	-1.63 ***	-1.52 ***	-1.62 ***	-1.47 ***	-1.52 ***	-2.13 ***	-2.13 ***
	(0.43)	(0.31)	(0.44)	(0.32)	(0.31)	(0.37)	(0.38)
Identity Fraud	-0.71		-0.75				
	(0.49)		(0.50)				
Only 1 Victim	-0.07		-0.19				
	(0.30)		(0.32)				
Victim Complied with SS twice	0.23		0.19				
	(0.50)		(0.51)				
Victimised before Current Fraud	2.07 ***	2.08 ***	2.23 ***	2.12 ***	2.08 ***	2.24 ***	2.23 ***
	(0.50)	(0.47)	(0.54)	(0.50)	(0.47)	(0.51)	(0.52)
Vulnerable Victim	-0.35		-0.28				
	(0.38)		(0.39)				
Witness at the scene	-0.31		-0.43				
	(0.56)		(0.59)				
Fraud potentially witnessed	0.94		0.76				
	(0.91)		(0.91)				
Police visited the scene	0.72		0.62				
	(1.03)		(1.04)				
SS Information	4.51 ***	4.62 ***	4.48 ***	4.57 ***	4.62 ***	3.79 ***	3.97 ***
	(0.56)	(0.54)	(0.58)	(0.55)	(0.54)	(0.60)	(0.62)
Victim has Suspicions about SS	-1.59 ***	-1.54 ***	-1.65 ***	-1.55 ***	-1.54 ***	-1.35 ***	-1.34 ***
	(0.35)	(0.32)	(0.36)	(0.34)	(0.32)	(0.35)	(0.35)
Witness provides details about SS	0.45		0.42				
	(0.53)		(0.55)				
SS is known	0.3		0.36				
	(0.28)		(0.29)				
SS present own personal info to Victim	-2.44		-2.57				
	(2.36)		(2.38)				
SS provided victim with documents	0.23		0.13				
	(0.38)		(0.38)				
Evidence	-0.01		-0.01				
	(0.20)		(0.21)				
MG11 form	1.31 ***	1.31 ***	1.4 ***	1.37 ***	1.31 ***		
	(0.41)	(0.39)	(0.43)	(0.40)	(0.39)		

Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01
SS stands for suspect. Coefficients estimated using a logistic regression. After conducting correlation and multicollinearity tests, column (1) estimates all predictors identified by chi2, effective size and prevalence testing; column (2) presents only the significant coefficients of column (1), the *restricted model*. Columns (3) and (4) compare the unrestricted and restricted models, by excluding all cases that there is mandatory allocation; such when suspect is dead. Columns (5) and (6) contrast restricted and compilation model; the latter includes predictors that are jointly significant. Finally, column (7) assess another version of the compilation model by including variables that have been identified as significant when suspect information is not available.

Table 3.7 (*cont'd*): Comparison of Regression Estimates

	(1) Unrestricted	(2) Restricted	(3) Unrestricted - No Mandatory	(4) Restricted - No Mandatory	(5) Restricted	(6) Compilation	(7) Compilation - cases without SS
SS's Physical Description	2.21 ***	2.21 ***	2.2 ***	2.17 ***	2.21 ***	2.47 ***	2.47 ***
	(0.31)	(0.29)	(0.32)	(0.30)	(0.29)	(0.33)	(0.34)
SS described to have an accent	-1.4		-1.34				
	(0.92)		(0.96)				
SS calls from a withheld number	-0.01		-0.39				
	(1.06)		(1.08)				
Location of where Offence took place	2.11 ***	2.05 ***	2.08 ***	2.02 ***	2.05 ***	2.15 ***	2.07 ***
	(0.26)	(0.25)	(0.27)	(0.25)	(0.25)	(0.31)	(0.31)
SS's VRM known	1.22 **	1.33 **	1.49 **	1.56 **	1.33 **	1.27 *	1.28 *
	(0.60)	(0.57)	(0.64)	(0.61)	(0.57)	(0.66)	(0.66)
SS Personally Attended Place of Offence	-0.63	-0.63 *	-0.62	-0.65 *	-0.63 *	-0.94 **	-0.97 **
	(0.39)	(0.35)	(0.40)	(0.35)	(0.35)	(0.41)	(0.41)
CCTV footage	0.85 **	0.96 ***	1.05 ***	1.06 ***	0.96 ***	1.05 ***	1.08 ***
	(0.39)	(0.35)	(0.41)	(0.36)	(0.35)	(0.38)	(0.39)
SS caught at the scene	-0.56		-0.53				
	(1.09)		(1.10)				
SS Interviewed	1.06 *	0.93 *	1.05	0.92	0.93 *	0.67	0.65
	(0.62)	(0.54)	(0.65)	(0.56)	(0.54)	(0.59)	(0.59)
SS arrested	-0.46		-0.62				
	(0.65)		(0.66)				
Victim providing own personal info to SS	0.04		0.03				
	(0.50)		(0.52)				
Use of bank or credit card details	0.07		-0.07				
	(0.41)		(0.43)				
Online Payment	0.53	0.53 *	0.41	0.48	0.53 *	-0.43	-0.27
	(0.36)	(0.30)	(0.37)	(0.31)	(0.30)	(0.35)	(0.38)
Cheque Payment	0.05		-0.12				
	(0.58)		(0.59)				
Cash Payment	-1.79 ***	-1.66 ***	-1.91 ***	-1.68 ***	-1.66 ***	-2.24 ***	-2.32 ***
	(0.38)	(0.34)	(0.40)	(0.35)	(0.34)	(0.41)	(0.41)
SS personally contacting the victim	0.06		0.11				
	(0.32)		(0.32)				
Bank Transfer	0.58 *	0.55 *	0.53	0.52	0.55 *	-0.21	0
	(0.34)	(0.31)	(0.35)	(0.32)	(0.31)	(0.36)	(.)
Evidence & Warning Marker						0.93	1.06
						(0.74)	(0.75)
MG11 & Evidence						2.72 ***	2.72 ***
						(0.60)	(0.59)
SS's Phone Number & SS Info Confirmed by Third Party						0.5	0.69
						(0.41)	(0.43)
SS's Phone Number & SS Info can be Confirmed by Third Party						1.3 ***	1.2 ***
						(0.43)	(0.44)
Only 1 SS identified & Warning Marker						-0.3	-0.34
						(0.56)	(0.56)
Only 1 SS Identified & Linked Crime						0.23	0.23
						(0.68)	(0.69)
Bank Transfer & SS's Name Known						2.63 ***	2.78 ***
						(0.33)	(0.35)
Items Seized & Money Lost						1.32 **	1.3 **
						(0.53)	(0.52)
Card Payment & Only 1 SS identified						0.17	0.25
						(0.53)	(0.53)
Fraud Conducted using Social Media & Part of a Series						-1.02	-1.16
						(0.69)	(0.71)
Fraud Conducted using Social Media & Bank Transfer to SS's						-0.28	-0.07
						(0.66)	(0.71)
ssbankacc							-0.77 *
							(0.40)
vbankaft							-0.5
							(0.54)
mconretail							0.2
							(0.40)
Constant	-4.43 ***	-4.66 ***	-4.23 ***	-4.48 ***	-4.66 ***	-4.67 ***	-4.64 ***
	(0.71)	(0.57)	(0.71)	(0.58)	(0.57)	(0.62)	(0.63)
No of Observations	1514	1514	1384	1384	1514	1514	1514
Likelihood Ratio Test							
chi2 statistic	23.10		26.34		134.13		
p-value	0.63		*0.44*		*0.00*		

Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01
SS stands for suspect. Coefficients estimated using a logistic regression. After conducting correlation and multicollinearity tests, column (1) estimates all predictors identified by chi2, effective size and prevalence testing; column (2) presents only the significant coefficients of column (1), the *restricted model*. Columns (3) and (4) compare the unrestricted and restricted models, by excluding all cases that there is mandatory allocation; such when suspect is dead. Columns (5) and (6) contrast restricted and compilation model; the latter includes predictors that are jointly significant. Finally, column (7) assess another version of the compilation model by including variables that have been identified as significant when suspect information is not available.

3.5 Results

3.5.1 Regression Analysis

Table 3.8 presents the results of the multivariate regression analysis, using our preferred specification[155]. *Column (1)* presents the logistic regression coefficients whereas the odd-ratios are introduced in *column (2)*. The results are explained through odd-ratios[156] as, interpreting logistic coefficients does not provide any insightful information. Odd-ratios represent the probability of clearance against the probability of a case being undetected. Also, it should be noted that negative *coefficients (odds ratios* under unity*)* represent case-limiting factors whereas positive ones (*odds ratios* above unity) are considered as solvability predictors.

The results indicate that where the case is reported directly to the police and it is correctly recognised as a call-for-service, then the probability of case solvability is 2.56 times larger than the probability of a case being reported to AF and subsequently, been forwarded to the local force for investigation. As discussed, in *Section 3.6*, it is essential that local forces fully assess the information provided and acknowledge the needs of the victim before deciding whether the case should be reported to AF. If, during the time of the call, the call handler realises that the crime is currently being committed or has recently been committed then, the police should take steps to prevent or stop fraud.

Additionally, if fraud is part of a series, there is a higher probability of clearance. Usually, each individual case has limited information attached to it. Thus, if many crimes are linked enough evidence can be collected to start an investigation. Especially, for cases where there are no apparent investigative leads when case is assessed in isolation. The findings indicate that linked cases are 5.90 more likely to be solved.

Corporate employee fraud is the only type of fraud that has positive impact on solvability. This is unsurprising, since it is more likely that the offender will be known or police is able to

[155] As advanced earlier, our preferred specification is *column (6)* from Table 3.7.
[156] The transformation odds-ratio formula is $logit(p) = \ln(\frac{p}{1-p})$.

Table 3.8: Logistic Regression Estimates

	(1) Coefficients			(2) Odds Ratios		
Fraud Call for Service	0.94 (0.26)	***	[0.43,1.45]	2.56 (0.67)	***	[1.53,4.28]
Part of a Series	1.77 (0.28)	***	[1.23,2.32]	5.90 (1.65)	***	[3.41,10.20]
Charity Fraud	-0.75 (0.85)		[-2.42,0.91]	0.47 (0.40)		[0.09,2.49]
Banking and Credit Industry Fraud	-1.12 (0.37)	***	[-1.84,-0.39]	0.33 (0.12)	***	[0.16,0.68]
Corporate Employee Fraud	2.23 (0.85)	***	[0.56,3.90]	9.30 (7.94)	***	[1.75,49.56]
Computer Misuse Crime	-1.16 (0.65)	*	[-2.43,0.12]	0.31 (0.21)	*	[0.09,1.13]
Phone Scams	-1.79 (0.53)	***	[-2.82,-0.75]	0.17 (0.09)	***	[0.06,0.47]
Individual Fraud	-2.13 (0.37)	***	[-2.85,-1.40]	0.12 (0.04)	***	[0.06,0.25]
Victimised before Current Fraud	2.24 (0.51)	***	[1.24,3.23]	9.35 (4.75)	***	[3.45,25.31]
SS Information	3.79 (0.60)	***	[2.61,4.97]	44.3 (26.62)	***	[13.66,143.85]
Victim has Suspicions about SS	-1.35 (0.35)	***	[-2.03,-0.67]	0.26 (0.09)	***	[0.13,0.51]
SS's Physical Description	2.47 (0.33)	***	[1.81,3.12]	11.8 (3.94)	***	[6.14,22.69]
Location of where Offence took place	2.15 (0.31)	***	[1.55,2.76]	8.63 (2.65)	***	[4.72,15.76]
SS's VRM known	1.27 (0.66)	*	[-0.02,2.55]	3.55 (2.33)	*	[0.98,12.86]
SS Personally Attended Place of Offence	-0.94 (0.41)	**	[-1.74,-0.14]	0.39 (0.16)	**	[0.18,0.87]
CCTV footage	1.05 (0.38)	***	[0.30,1.80]	2.86 (1.09)	***	[1.35,6.04]
SS Interviewed	0.67 (0.59)		[-0.49,1.84]	1.96 (1.17)		[0.61,6.28]
Bank Transfer	-0.21 (0.36)		[-0.92,0.51]	0.81 (0.30)		[0.40,1.66]
Online Payment	-0.43 (0.35)		[-1.11,0.26]	0.65 (0.23)		[0.33,1.29]
Cash Payment	-2.24 (0.41)	***	[-3.04,-1.44]	0.11 (0.04)	***	[0.05,0.24]
Evidence & Warning Marker	0.93 (0.74)		[-0.52,2.38]	2.53 (1.88)		[0.59,10.82]
MG11 & Evidence	2.72 (0.60)	***	[1.55,3.89]	15.1 (9.02)	***	[4.70,48.69]
SS's Phone Number & SS Info Confirmed by Third Party	0.5 (0.41)		[-0.31,1.31]	1.65 (0.68)		[0.74,3.72]
SS's Phone Number & SS Info can be Confirmed by Third Party	1.30 (0.43)	***	[0.45,2.15]	3.67 (1.58)	***	[1.58,8.55]
Only 1 SS identified & Warning Marker	-0.3 (0.56)		[-1.40,0.79]	0.74 (0.41)		[0.25,2.21]
Only 1 SS Identified & Linked Crime	0.23 (0.68)		[-1.10,1.56]	1.26 (0.85)		[0.33,4.76]
Bank Transfer & SS's Name Known	2.63 (0.33)	***	[1.99,3.27]	13.8 (4.54)	***	[7.29,26.34]
Items Seized & Money Lost	1.32 (0.53)	**	[0.28,2.35]	3.73 (1.97)	**	[1.32,10.51]
Card Payment & Only 1 SS identified	0.17 (0.53)		[-0.86,1.20]	1.18 (0.62)		[0.42,3.32]
Fraud Conducted using Social Media & Part of a Series	-1.02 (0.69)		[-2.37,0.34]	0.36 (0.25)		[0.09,1.41]
Fraud Conducted using Social Media & Bank Transfer to SS's	-0.28 (0.66)		[-1.57,1.01]	0.76 (0.50)		[0.21,2.74]
Constant	-4.67 (0.62)	***	[-5.89,-3.44]			
No of Observations	1514			1514		
<u>Regression Diagnostic Tests</u>	statistic	p-value				
Pearson chi2	664.71	0.95				
Hosmer-Lemeshow chi2	10.36	0.24				
Linktest	2.02	0.04				

Notes: Standard errors in parentheses; 95% confidence intervals in brackets; * $p<0.10$, ** $p<0.05$, *** $p<0.01$
SS stands for suspect. Estimates calculated using Logistic Regression Analysis

follow-up on investigative leads. On the other hand, banking and credit industry as well as computer misuse fraud are less solvable. The estimates show that there is 67% and 69% decrease in the odds of clearing these cases, respectively. Although, one would expect banking fraud to have a high solvability rate, since the transactions can be traced, by delaying the investigative process, the offender is able to move fraudulently-obtained funds into other accounts, creating a complex money trail that it is difficult to follow-up. Also, the results indicate that where the offence is committed through a phone or where the fraud targets specifically an individual, case clearance is less likely.

In addition, prior victimisation suggests higher likelihood of detection. In fact, cases where victims have repetitively been targeted by offenders are 9 times more likely to be solved. There are a few reasons as to why this is the case. Repeat victimisation is usually associated with higher losses. Our dataset suggests that, on average, victims who suffer repeated criminal victimisation lose £10,000 more than victims with no prior victimisation. It is also possible that due to repeat victimisation, there is more evidence that the local force can look at and investigate. Further, 55% of the cases have a known offender, presumably, making investigation easier.

Knowing the suspect is one of the most significant solvability factors identified in this analysis and this is consistent with the literature. Cases, where victim or witness provide any indication as to who the offender is, are 44.3 times more likely to be solved than cases where no information is provided about the suspect. This is unsurprising, and it has been consistent through all previous tests and estimations. Fraud investigation is inherently unique and complicated. Therefore, having no investigative leads makes it even more difficult to clear the case.

On the other hand, the analysis identifies the variable capturing whether victim has suspicions about who might have committed the offence as a case-limiting factor. Although, this might seem strange, this variable only captures whether the victim can recollect the circumstances under which the offence has been committed. For instance, consider a case where the offender persuaded the victim that he/she was calling from victim's bank and the victim provided own bank information which subsequently have been used by the offender to commit a fraud. The victim will have a suspicion as to why funds are missing from their bank account, how and when victimisation took place and whether the offender sounded as a male or female. The only other information that can be of any investigative importance is by contacting the victim's call provider and requesting the phone number and personal details of the offender to be released. However, if the call was made using a withheld or international number, contacting the call provider will be of no assistance to the investigation.

Other factors used during investigatory process which help in the identification of the offender include physical description of the suspect, suspect's VRM details, CCTV footage, whether the location of offence is known, and whether the suspect personally attended the place of offence. All are statistically positively significant to solvability, except the latter. If suspect's physical description is available, then the probability of clearance is about 12 times higher than cases without any. The odds of cases where VRM details and CCTV footage is available are about 255% and 186% higher than the odds of cases where these details are unavailable.

Further, the findings indicate that using cash as a payment method, decreases case solvability by 89%. Cash payments make it almost impossible to identify who the offender is, especially if the offender is unknown. However, even if there is an indication as to who the suspect is, it is difficult to prove that the fraud has been committed by the identified individual. This finding is different from the conclusions drawn when we *individually* assess the significance of factors on solvability in *Section 3.4.1*. Therefore, this provides further evidence as to why logistic multivariate models are more useful when examining predictors on solvability rather than individually examining the effect of each factor on solvability[157].

Moreover, all statistically significant compilation variables included in the model have a positive sign suggesting case solvability. Indicatively, cases where an MG11 report is completed by the victim *and* evidence has been collected experience 15.1 times higher odds of solvability whereas when suspect's phone number is known *and* the call provider had been conducted to obtain the personal information of the offender, clearance is 3.67 times more likely. Also, in cases where the victim has lost money *and* the police was able to seize

[157] Additionally, Appendix A.3.6 presents the findings from various regression diagnostic tests, providing further confidence about the model specification.

items that either were provided by the suspect – e.g. a business card – or are proof of fraud – e.g. copy of a cheque – are 3.73 times more likely to be solved. Finally, case solvability is 13.8 larger when the payment was made through a bank transfer *and* the suspect's name is known. This allows the police to contact suspect's bank and request more information such as, the address registered when the account was opened. Also, the police can check its own databases such as, Genie, to test for any records of the suspect or linkages to other crimes.

Effectively, the logistic model answers the solvability problem by summing the above case-limiting and solvability factors that might be present in each case. The sum can then be compared against a cut-off value to determine whether the case should be allocated for further investigation or be filed. *Section 3.5.2* discusses how we decide upon the most appropriate cut-off point.

3.5.2 Cut-Off Point

The logistic regression produces coefficients for each solvability and case-limiting factors included the model. This allows for predictive *case solvability scores* to be estimated which are then compared against a cut-off value. These scores are estimated by weighting each factor by its predictive capability. As solvability factors have a positive sign whereas case-limiting variables are negative; the higher the score, the more solvable the case is. Cases are allocated to an officer for further investigation if the case solvability score is equal to or higher than the cut-off value. Alternatively, the case is filed.

Nevertheless, there is a trade-off that needs to be addressed before identifying the optimal cut-off value since two types of error can occur. First, incorrectly allocating a case when it should have been filed; *type I error;* and second, incorrectly filing a case when it should have been allocated; *type II error*. By reducing the probability of one type, the error of the other type heightens. That is, to ensure no case is incorrectly filed, many cases will be incorrectly allocated as a result. On the other hand, ensuring no incorrect allocation, produces incorrect filing of cases that should have been allocated and, potentially, been cleared. Thus, a compromise needs to be made.

The cut-off point can be optimised either by accounting for limited police resources or by identifying a level of balance between case solvability of detectable crimes and wasting resources on unsolvable frauds[158]. Therefore, the objective is to maximise the case-filing capabilities of the model while limiting incorrect filing when fraud is solvable. Effectively, this approach ensures that the number of victims been let down by police investigation is at its bare minimum.

To identify the optimal cut-off point, different evaluation methods are examined. Table 3.9 compares different cut-off points, ranging from 0.5 to 0.68, and the errors rates produced at each one. *Appendix A.3.6* presents the full-range (0.1 to 0.99) of cut-off values considered. The number of cases correctly allocated and filed as well as incorrect allocation and filing are estimated. This allows to calculate various ratios that help us identify which cut-off point best satisfies the set-out objectives. Some of which are: the *true-positive-rate (TPR)* which estimates the percentage of correctly allocated cases; the *true-negative-rate (TNR)* indicating the percentage of cases being correctly filed; the *false-positive-rate (FPR)* which calculates the percentage of incorrectly allocated cases and the *false-negative-rate (FNR)* estimating the percentage of cases being incorrectly filed. The latter two ratios represent the type I and type II errors, respectively.

Further, Table 3.9 evaluates the predictive accuracy of the model at each cut-off point by cross-validating case solvability against the predicted values. Further, the Youden Index is considered. It determines the point where the TPR and TNR is maximal. Another method used to assess the optimal cut-off value is by estimating the ROC[159] curve. The predictive capabilities of the model to distinguish between positive and negative outcomes is captured by the Area under the ROC curve (AUC). The AUC[160] is a value that ranges between 0.5 and 1.0. A value of 0.5 – the reference line – implies that the predictive power of the model is no better than chance whereas a value of 1.0 suggests perfect discriminating capabilities. In

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[158] It is vital that any solvability model is also politically acceptable (Fixsen et al., 2005), irrespective of the proposed enhanced investigatory efficiencies. Caution not to damage police reputation should be a priority. Public's perception about and trust to police should not change. Public should not feel discouraged to report a fraud due to believing their case will not receive the attention it requires. Equally important, police should entrust evidence-based research and not fear being exposed to excessive reputational risk.

[159] ROC stands for Receiver-Operating Characteristic and represents a visual display of the overall performance of the model.

[160] Also known as c-statistic or concordance index.

other words, AUC estimates the overall percentage of correct categorisation. Typically, values over 0.8 indicate a strong model. ROC curve is illustrated in Figure 3.10. Graphically, the optimal cut-off point on the ROC curve represents the minimum distance[161] to the upper left corner, where both TPR and TNR are equal to 1.

As demonstrated in Table 3.9, all three methods indicate that a cut-off value equal to 0.64 is optimal[162]. At this point, the overall predictive accuracy (ACC) of the model is maximised by correctly classifying 91.35% of the cases. Specifically, the model correctly allocates 87.45% of the reports whereas 95.41% of cases are correctly filed. This further suggests that the error rates are minimised; since the number of incorrectly filed cases is minimised while ensuring the waste of resources on incorrectly allocated cases is kept at minimum. In turn, this ensures that the number of victims been let down is also reduced. The Youden Index and AUC support this finding. At the cut-off point of 0.64, the Youden Index is at maximal rate whereas the AUC is equal to 97%. This indicates that the model has exceptionally good predictive capabilities.

Although, no direct comparison can be made with other solvability studies, the findings indicate that our designed model performs better, in terms of predictive capabilities and accuracy, compared to the literature. For instance, the estimated accuracy of Eck's (1983) burglary solvability model is 85%; whereas the model developed by Olphin (2015) correctly classifies 67% of non-domestic violent offences.

[161] The minimum distance is equal to: $\sqrt{(1 - TPR)^2 + (1 - TNR)^2}$

[162] Since the provided dataset does not distinguish between cases by severity of harm, we assume that each case *weights* the same in terms of severity.

Table 3.9: Comparison of Cut-Off Points, *Developmental Sample*

		Cut-Off Points									
		0.5	**0.52**	**0.54**	**0.56**	**0.58**	**0.6**	**0.62**	**0.64**	**0.66**	**0.68**
Number of Cases											
Correctly Allocated		694	693	690	687	684	683	678	676	665	663
Correctly Filed		672	679	682	683	690	690	695	707	710	710
Incorrectly Allocated	*Type I error*	69	62	59	58	51	51	46	34	31	31
Incorrectly Filed	*Type II error*	79	80	83	86	89	90	95	97	108	110
Ratios											
Total Positive Ratio	TPR	89.78	89.65	89.26	88.87	88.49	88.36	87.71	87.45	86.03	85.77
Total Negative Ratio	TNR	90.69	91.63	92.04	92.17	93.12	93.12	93.79	95.41	95.82	95.82
False Positive Rate	FPR	9.31	8.37	7.96	7.83	6.88	6.88	6.21	4.59	4.18	4.18
False Negative Rate	FNR	10.22	10.35	10.74	11.13	11.51	11.64	12.29	12.55	13.97	14.23
Accuracy/Overall Correct Classification	**ACC**	**90.22**	**90.62**	**90.62**	**90.49**	**90.75**	**90.69**	**90.69**	**91.35**	**90.82**	**90.69**
Positive Predictive Value	PPV	90.96	91.79	92.12	92.21	93.06	93.05	93.65	95.21	95.55	95.53
Negative Predictive Value	NPV	89.48	89.46	89.15	88.82	88.58	88.46	87.97	87.94	86.8	86.59
False Discovery Rate	FDR	9.04	8.21	7.88	7.79	6.94	6.95	6.35	4.79	4.45	4.47
False Omission Rate	FOR	10.52	10.54	10.85	11.18	11.42	11.54	12.03	12.06	13.2	13.41
Positive Likelihood Ratio	LR+	9.64	10.71	11.21	11.35	12.61	12.83	13.85	19.06	20.59	20.50
Negative Likelihood Ratio	LR-	0.11	0.11	0.12	0.12	0.12	0.13	0.13	0.13	0.14	0.15
Diagnostic Odds ratio	DOR = LR+ / LR-	85.55	94.90	96.07	94.07	101.85	102.70	106.69	144.93	142.52	138.06
Youden Index		80.47	81.28	81.30	81.04	81.47	81.48	81.50	82.86	81.98	81.59
min Distance		13.82	13.31	13.36	13.61	13.48	13.52	13.71	13.36	14.46	14.83

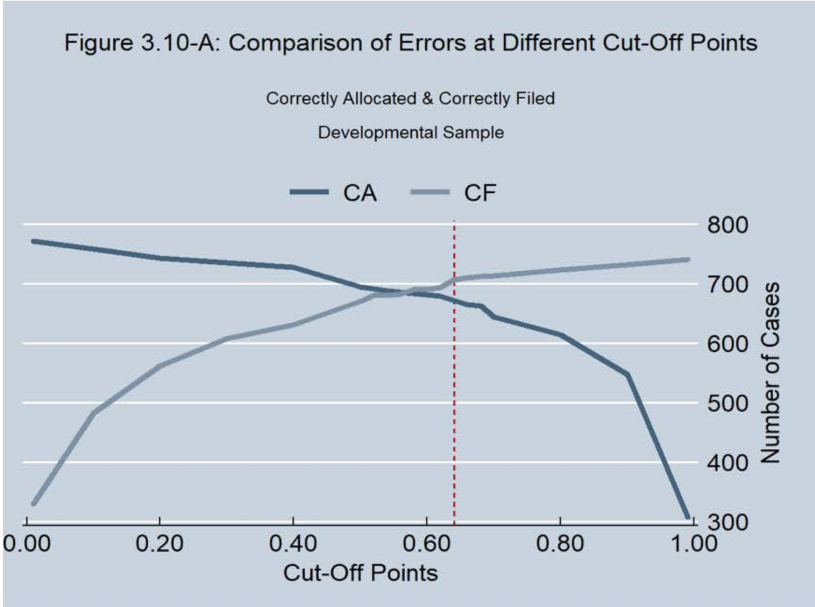


Figure 3.10-A: Comparison of Errors at Different Cut-Off Points

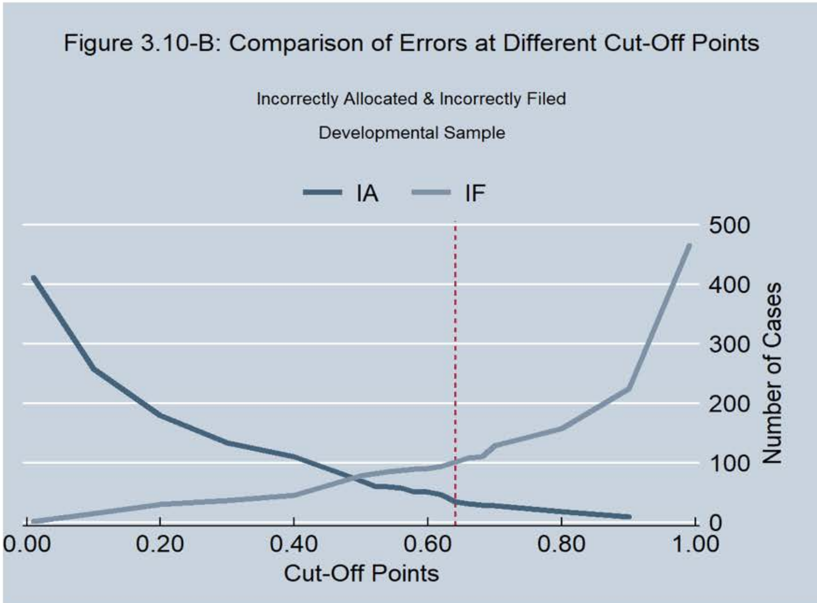


Figure 3.10-B: Comparison of Errors at Different Cut-Off Points

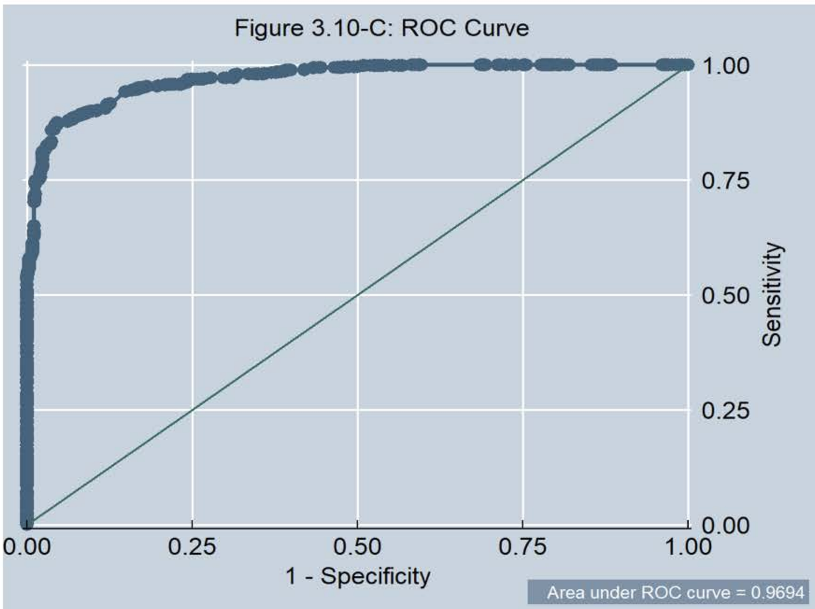


Figure 3.10-C: ROC Curve

3.5.3 External Validity of the Model: Testing on a Validation Sample

For our third research question, asking whether factors identified in this study can forecast case solvability, to have real validity, it is important to evaluate the predictive capabilities of the model on a different dataset than the one used to build it. This introduces our fourth research question which asks whether how accurate are the predictive capabilities of the developed model, i.e. whether the model is externally valid.

To answer this, the predictive model developed above is tested on a randomly allocated sample, of equal size. This approach not only ensures unbiased estimates, as the model is not tested on the same dataset that it was built but it also provides external validation since it is the closest to a real-life randomised controlled trial.

As shown in Table 3.10, the overall accuracy of the model is still very high. At the identified optimal cut-off point, the accurate prediction of fraud outcomes, as estimated by the ACC ratio, is equal to 89%; with 85% of the cases being correctly allocated and 93% correctly filed. As before, the Youden Index and the AUC (min distance) are estimated. Figure 3.11 provides a graphical representation of the ROC curve. The forecasted estimates are extremely encouraging and very close to the findings produced using the *developmental sample*.

Table 3.10: Comparison of Cut-Off Points, *Validation Sample*

		Cut-Off Points									
		0.5	**0.52**	**0.54**	**0.56**	**0.58**	**0.6**	**0.62**	**0.64**	**0.66**	**0.68**
Number of Cases											
Correctly Allocated		682	681	680	678	670	668	667	653	651	649
Correctly Filed		656	660	660	665	669	669	671	689	689	689
Incorrectly Allocated	*Type I error*	86	82	82	77	73	73	71	53	53	53
Incorrectly Filed	*Type II error*	91	92	93	95	103	105	106	120	122	124
Ratios											
Total Positive Ratio	TPR	88.23	88.10	87.97	87.71	86.68	86.42	86.29	84.48	84.22	83.96
Total Negative Ratio	TNR	88.41	88.95	88.95	89.62	90.16	90.16	90.43	92.86	92.86	92.86
False Positive Rate	FPR	11.59	11.05	11.05	10.38	9.84	9.84	9.57	7.14	7.14	7.14
False Negative Rate	FNR	11.77	11.90	12.03	12.29	13.32	13.58	13.71	15.52	15.78	16.04
Accuracy/Overall Correct Classification	**ACC**	**88.32**	**88.51**	**88.45**	**88.65**	**88.38**	**88.25**	**88.32**	**88.58**	**88.45**	**88.32**
Positive Predictive Value	PPV	88.80	89.25	89.24	89.80	90.17	90.15	90.38	92.49	92.47	92.45
Negative Predictive Value	NPV	87.82	87.77	87.65	87.50	86.66	86.43	86.36	85.17	84.96	84.75
False Discovery Rate	FDR	11.20	10.75	10.76	10.20	9.83	9.85	9.62	7.51	7.53	7.55
False Omission Rate	FOR	12.18	12.23	12.35	12.50	13.34	13.57	13.64	14.83	15.04	15.25
Positive Likelihood Ratio	LR+	7.61	7.97	7.96	8.45	8.81	8.78	9.02	11.83	11.79	11.75
Negative Likelihood Ratio	LR-	0.13	0.13	0.14	0.14	0.15	0.15	0.15	0.17	0.17	0.17
Diagnostic Odds ratio	DOR = LR+ / LR-	57.17	59.58	58.85	61.64	59.61	58.30	59.47	70.74	69.37	68.04
Youden Index		*76.64*	*77.05*	*76.92*	*77.33*	*76.84*	*76.58*	*76.72*	*77.33*	*77.07*	*76.82*
min Distance		*16.52*	*16.24*	*16.34*	*16.09*	*16.56*	*16.77*	*16.72*	*17.09*	*17.32*	*17.56*

Figure 3.11-A: Comparison of Errors at Different Cut-Off Points

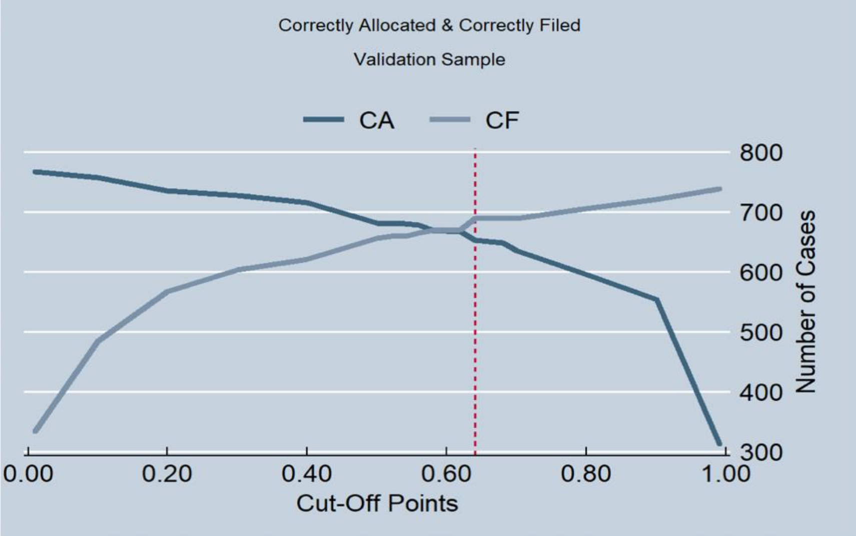
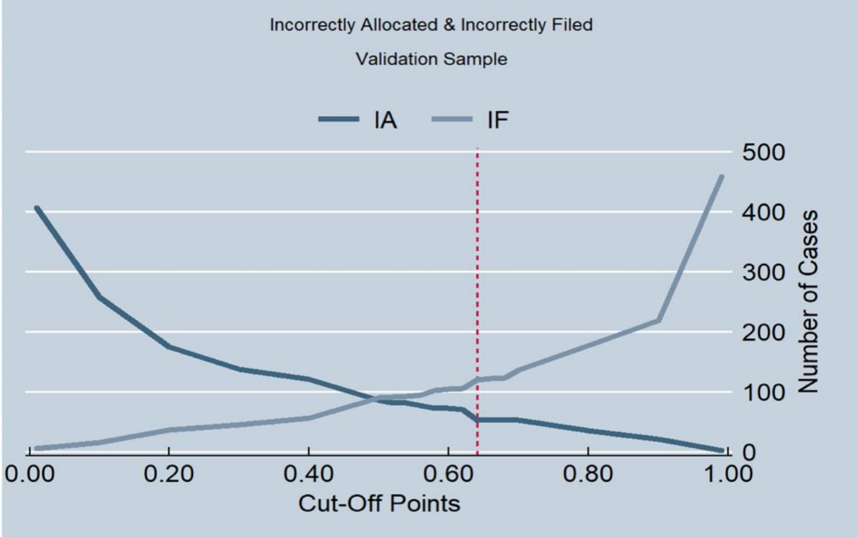


Figure 3.11-B: Comparison of Errors at Different Cut-Off Points



3.6 Data Limitations and Further Remarks

Police's data download tools are designed for investigative purposes rather than for research. Thus, data collection was acutely time-consuming. Data had to be requested and downloaded from various police systems. Incident reports are not stored in a way that supports empirical analysis without a lot of data cleansing and coding. It is, therefore, essential that any determinants of solvability are stored electronically, allowing for quicker and more effective utilisation of the available information.

Also, it is unfortunate that we do not know how the NFIB's *Know Fraud* database determines which fraud cases should be further considered or not. This information is not currently available publicly or for research purposes. It should be noted that AF's system identifies links and potential patterns, it is not a solvability model nor does it predict case clearance. Nevertheless, it would have been useful to compare the accuracy of the two in terms of predictive clearance capabilities and contrast solvability or case-limiting factors considered, if any.

Further, the predictive model developed in this study signifies substantial increases in accuracy which in turn, facilitate significant reductions in incorrectly allocated cases. Effectively, lower allocation levels can either lead to higher standards of service for correctly allocated frauds – and potentially induce higher detection rates – or provide dramatic financial and resource savings, as less investigators are involved in cases where not enough evidence exist for the fraud to cleared.

Unfortunately, the available dataset does not allow for a cost-benefit analysis to be conducted[163]. It would have been interesting and insightful to know exactly how many officers are assigned for fraud investigation and how many hours are devoted on each case. If these were known, the wastage of resources, before and after any increases in efficiency, could have been compared. Such analysis enables more informed decisions and suggestions to be made.

[163] Roman's *et al*. (2008) study remains to-date the only cost-benefit analysis of solvability. He studies the effectiveness of DNA as an investigatory tool.

Additionally, although the accuracy of the model is examined above using various econometric techniques such as, performing regression diagnostic tests and testing the model on a validation sample, we acknowledge that a randomised implementation trial allows for a more comprehensive assessment and testing of the model's effectiveness in real time.

Despite these difficulties and limitations, this study develops a detailed dataset and conducts a comprehensive statistical analysis that helps police understand the optimal use of limited investigative resources by identifying solvability and case-limiting factors.

As part of our future agenda, it is important to recognise that frauds directly dealt by the police are more likely to be solved. This might be simply due to taking immediate action. As demonstrated in the analysis, in cases where money is lost, it is usually the victim who transfers funds to the offender's bank account. These bank accounts are often opened and managed by the fraudsters in the United Kingdom. Hence, there are viable investigative leads that the local force can use to identify the offender. However, within 24 hours, the fraudulently-obtained funds are typically transferred to various other bank accounts either within the United Kingdom but often to a different jurisdiction or internationally.

This creates a complex money trail that is both difficult and time-consuming to investigate while bearing a significantly lower probability of clearance. Therefore, the police have a limited window to act. If the victim is directed to AF, it will take at least 30 days for the crime report to be allocated to an officer and more days before administering crime investigation (HMIC, 2015). Thus, not taking immediate action gives the offender an invaluable opportunity to keep the funds while avoiding detection. Thus, to optimise the opportunities of response, it is necessary that the police correctly recognises and handles calls-for-service cases before redirecting victims to AF.

3.7 Conclusion

Fraud and cybercrime victimisation are higher than violent and property crime victimisation (ONS, 2017; Action Fraud, 2018); with victims, and the UK economy, experiencing a huge financial loss. Therefore, effective clearance of fraud offences is vital. Higher solvability rates can not only reinforce public's trust on whether police are able to maintain order but hopefully, it can deter potential offenders from engaging in fraud altogether (Von Hirsch *et al.*, 1999).

However, to understand solvability, it is essential that the optimal use of scarce investigative resources is also understood. Ultimately, local forces aim to effectively use their limited resources to maximise the optimal outcome, which is higher clearance rates. This is an implicit resource constraint condition that needs to be accounted for when identifying the optimal outcome since itself is subject to the available police resources.

A predictive solvability model allows us to understand how the presence or the absence of certain variables affects case clearance. Despite analytical models being more rigorous and objective than human decision-makers (Kahneman and Egan, 2011); only rarely do police forces use statistical models to optimally choose investigative resource allocation (Sherman, 2013).

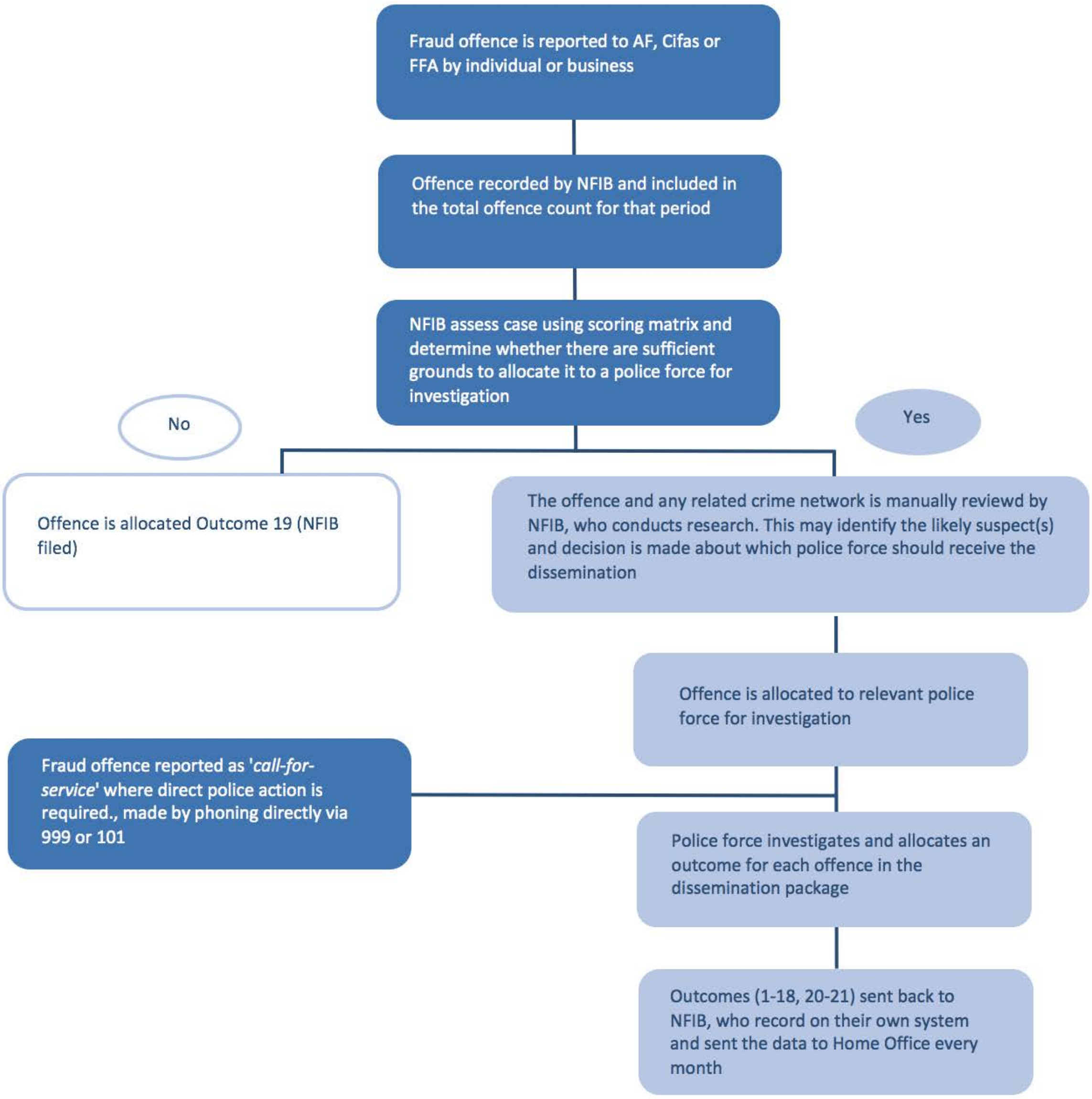
The data used in this research allow for an empirically-based analysis of fraud solvability by utilising both automated police identifiers and non-electronically recorded predictors using officer reports and investigation plans. This facilitates high model accuracy and in-depth precision since the dataset used is more detailed than only automatically recorded variables were used for the analysis. The accuracy of the model is also externally validated using a separate random sample.

Although, no statistical model is perfectly accurate, our model performs well. Using the *developmental* sample, the predictive model correctly allocates 91.35% of the cases. More specifically, the model correctly predicts allocation 8.8 times out of 10. Even more importantly, 9.5 out of 10 cases are correctly filed; ensuring very little wastage of scarce resources. Thus, we recommend use of predictive models to aid human decision-making.

Appendix A.3

A.3.1 Fraud Reporting

Figure A.3.1 Fraud Reporting



Source : Home Office (2017), "Crime Outcomes in England and Wales: year ending March 2017"

A.3.1.1 Types of Fraud

As most frauds are self-reported, even though the type of fraud is available in the dataset, for some cases, there is no guarantee that type of fraud chosen by the victim is the type of fraud that the victim has experienced. Since it is not updated by AF or the PFAs. Thus, a substantial amount of time was spent on assigning the correct type of fraud to each case, as per NFIB's fraud counting rules.

Identifying the type of fraud for each case is of twofold importance. First, different types of fraud require different investigation methods to ensure solvability and second, inherently, different types of fraud are more difficult to investigate and subsequently, more difficult to solve. Each one of these statements is explained in turn.

Including the type of fraud as a solvability factor in the logistic model makes sense since each type of offence allows for different investigative possibilities to be explored. Consider, for example, a fraud involving a stolen credit card. Police can investigate whether the credit card has been used and if it has, examine how it has been used. If it was used to withdraw money from an ATM then, CCTV footage may be available. If it was used to get a refund for goods and/or services that the offender did not get, or to buy goods and/or services directly from other suppliers then, a CCTV enquiry can be made. If, however, the payment was made online, the police can contact the online supplier (e.g. eBay, amazon etc) and request the delivery address of the offender and the name used to complete the transaction. If, however, the card has been used in another crime, that adds another amount of information.

On the other hand, in case of phone frauds, police can ask the victim to disclose their phone provider which will then be contacted to request a list of phone calls been made at the victim's landline. Given the time-interval in which fraud took place, police can identify the phone call(s) that are likely made by the offender. Then, the police can request, from the victim's phone provider, more details such as, the exact phone number used, who it belongs to, the bank account attached to it. If the offender's name and/or personal details cannot be identified at this stage, the police can go directly to the bank and request that information.

These are just two simple examples demonstrating the lines of enquiry that are available to local forces, depending on the type of fraud committed, and which can then be pursued further to identify the offender and ensure, case clearance.

However, the type of fraud may be correlated with some of the other solvability factors considered in the model. For that reason, correlation and multicollinearity tests are conducted. *Section 3.4.1* discusses in detail the steps taken to avoid model specification bias due to multicollinearity among regressors.

Further, as explained above, AF "*records NFIB fraud and cyber-enabled and cyber-dependent crime*[164]*, such as Computer Misuse Act offences like hacking […] through its contact centre and online reporting tool*" (Home Office, 2018). For that reason, we specifically requested from AF the NFIB fraud categorisations. These were provided for each case available in the sample.

Obtaining this information was of importance as we wanted to examine whether assigning the wrong type of fraud to a case has a negative effect on solvability. Unless the victim is deemed as old and/or vulnerable, in which case the officer is the one completing and submitting the online form on victim's behalf, the victim self-reports the fraud and provides the details on the incident via AF's online portal. However, usually, the victim is unaware of the differences between the various NFIB fraud counting rules, resulting in the wrong NFIB code been assigned to the case or in empty entries.

Thus, to account for the possibility of incorrect fraud classification and estimate its effect on solvability, if any, we create a dummy variable for each one of the 63 NFIB fraud types and we classify each case to one of these categories. Table 3.1 provides a complete list of the NFIB Fraud counting rules.

In effect, this enables us not only to include different types of fraud in the solvability model and examine whether certain types of fraud are more likely to be solved than others, but it also allows us to create a variable capturing whether the victim correctly specified the type

[164] Action Fraud is only liable to record NFIB fraud and cybercrimes. If other notifiable offences are apparent in a case, the victim is referred to its local force. Similarly, for non-NFIB recorded frauds – such as Other Fraud and Forgery – and cyber-enabled offences – such as blackmailing through social media – police is still the one responsible to record them (Home Office, 2018).

of fraud committed against him/her. Thus, we are able to examine whether false fraud categorisation minimises the probability of clearance.

Fraud categorisation becomes even more complicated when more than one types of fraud can be attached to each case. In these instances, the most serious offence is used to classify the case. Home Office's NFIB counting rules define each type of crime in detail as well as explain the procedure to be followed when multiple fraud offences have been committed.

A.3.2 Outcome Variable

In the literature, various outcome measures are used. US solvability studies employ arrest as an outcome variable just as often as UK studies use detections (Paine, 2012). That is due to both countries requiring a prosecutor to approve arrest. However, arrest is not a fitting outcome variable for the UK, since for a suspect to be arrested, the police needs to only make reasonable justifications as to who the offender might be. This results in many arrests but not necessarily to formal sanctions. Another alternative is conviction (Williams and Sumrall, 1982). Despite conviction being the outcome of a criminal trial, proving whether suspect is guilty of the crime being accused of, there are various reasons preventing offender's conviction, other than lack of evidence. Thus, conviction may be a misleading measure of solvability.

Effectively, most studies in the UK literature, use sanction detections as an outcome measure (Burrows *et al.*, 2005; Donnellan, 2011; Paine, 2012). A sanction detection is attached to any police-recorded crime where an identified suspect is declared as the person responsible for the committed crime. As a result, an official sanction is issued, and the offender is made aware of the full implications of his/her actions. Over the years, critics have argued that non-sanction detections are susceptible to manipulation (Bloch and Bell, 1976) or bias (Greenwood, 1970). Their argument is that some cases with the same amount of evidence attached to them, are not sanctioned. However, this is only true for a small number of cases.

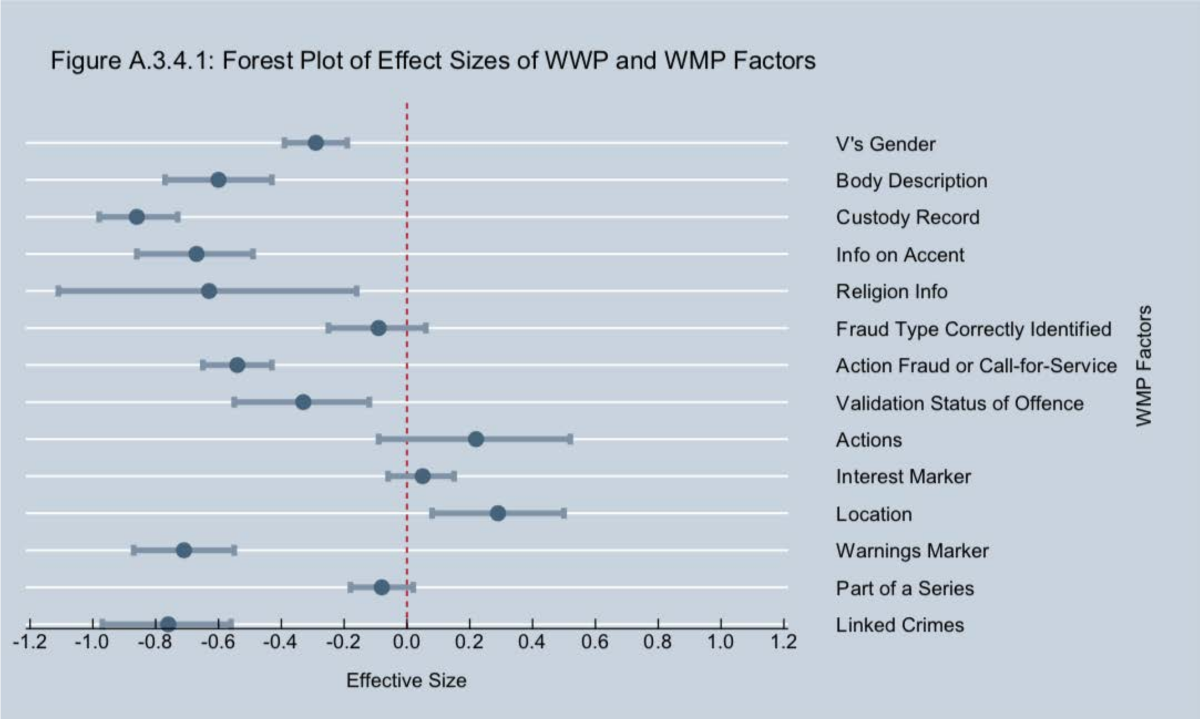
A Home Office (2011) report shows that non-sanction detections only include cases where, although sufficient evidence exist, either the offender is deceased or, it was not deemed appropriate to prosecute the offender even though the police was able to do so. The evidential requirements for each one of these 'labels' are the same in every case being examined; so at least there is a sense of uniformity. In addition, as explained above, as of April 2013/14, Home Office implemented a positive outcome approach to determine crime detection. This method avoids any of the aforementioned concerns and provides the most rigorous and thorough outcome measure available. Thus, this empirical analysis employs positive outcomes as an indication of case clearance.

A.3.3 Continuous Variables

Table A.3.3.1: Time Elapsed between Offences being Committed and Fraud Investigation

	Obs	Mean	Std.Dev.	Min	Max	5th Perc	95th Perc
Days between							
Record created and Case been Cleared Up	1512	170.83	210.71	0	1062	0	635
Record created and Fraud First been Committed	4012	167.46	469.32	0	6670	0	943
Record created and Fraud Last been Committed	2787	64.16	211.83	0	4431	0	294
First and Last time Fraud been Committed	2787	147.92	435.13	0	6600	0	1047

A.3.4 Effective Size



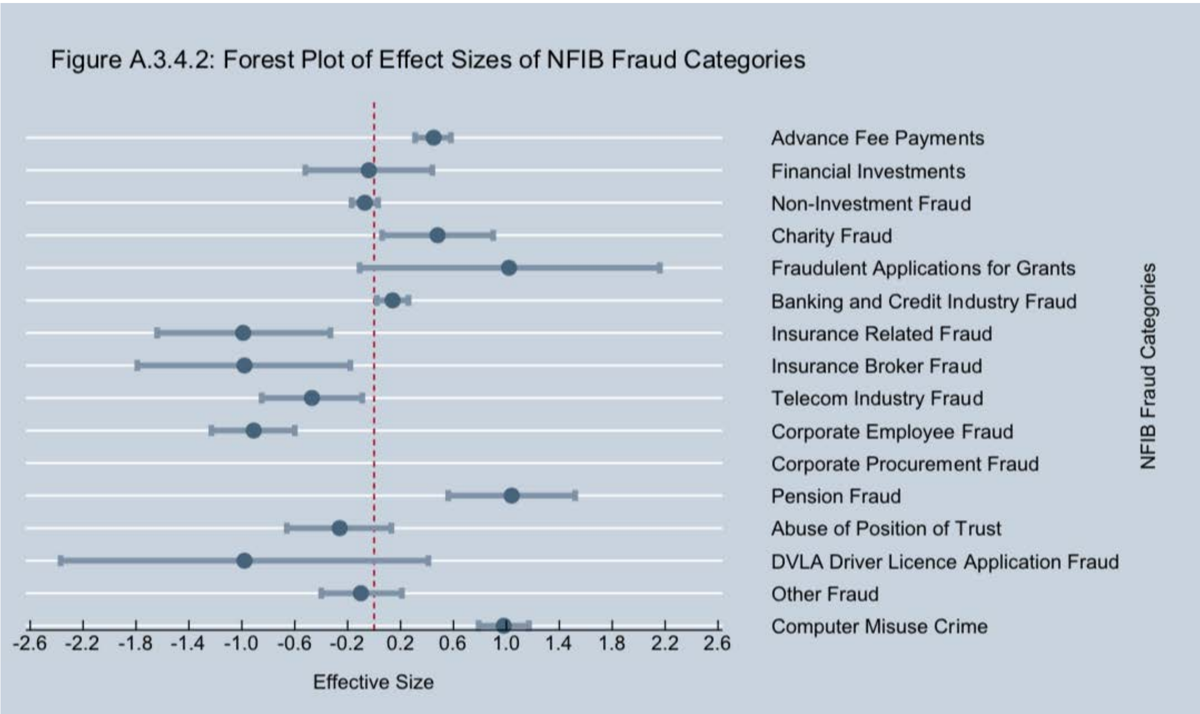


Figure A.3.4.3: Forest Plot of Effect Sizes of Victim Information

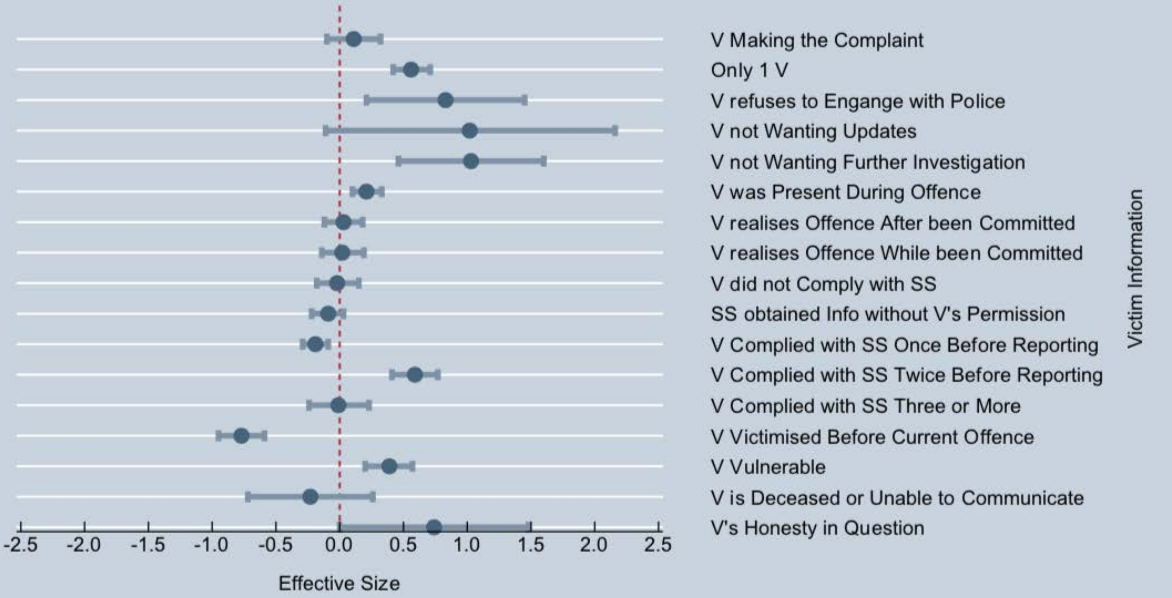


Figure A.3.4.4: Forest Plot of Effect Sizes of Case Characteristics

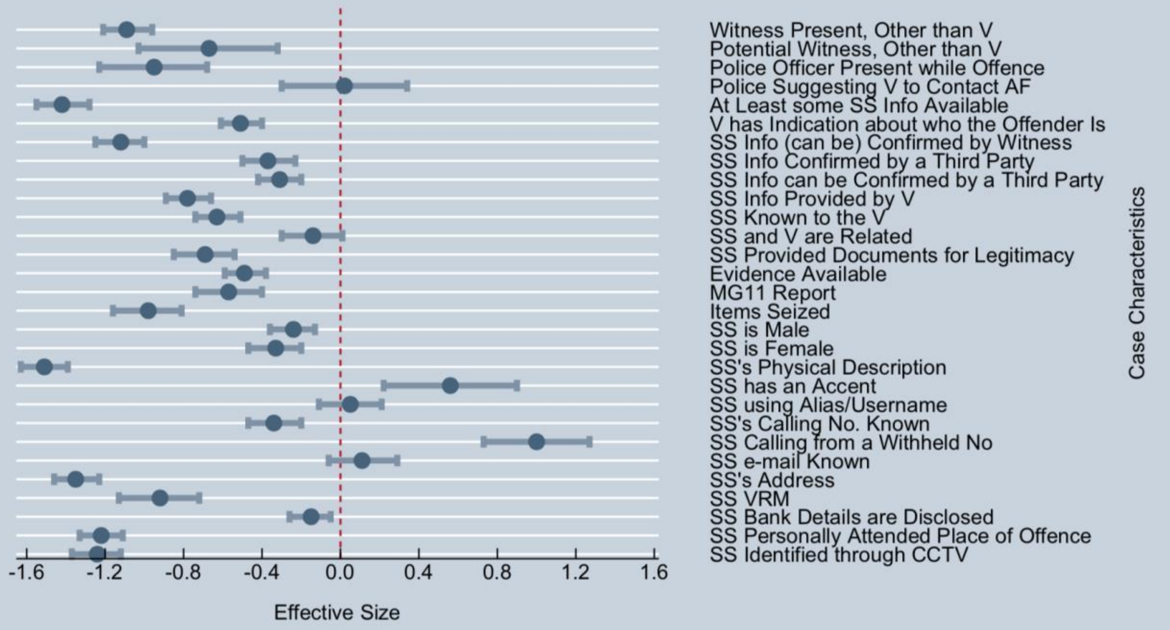


Figure A.3.4.5: Forest Plot of Effect Sizes of Reasons for Fraud

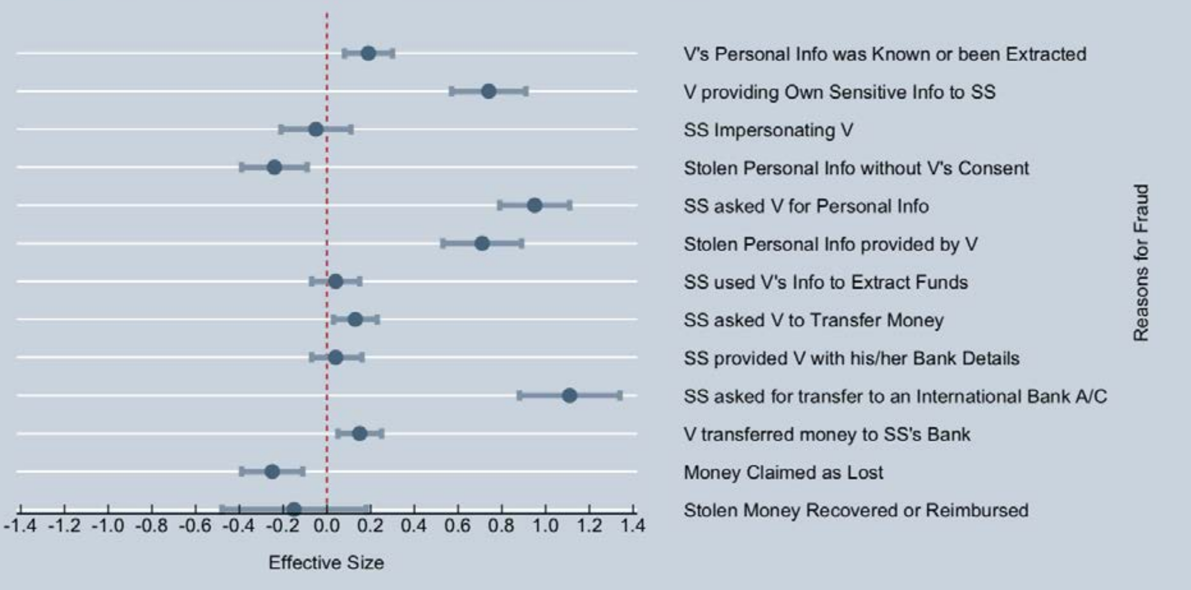
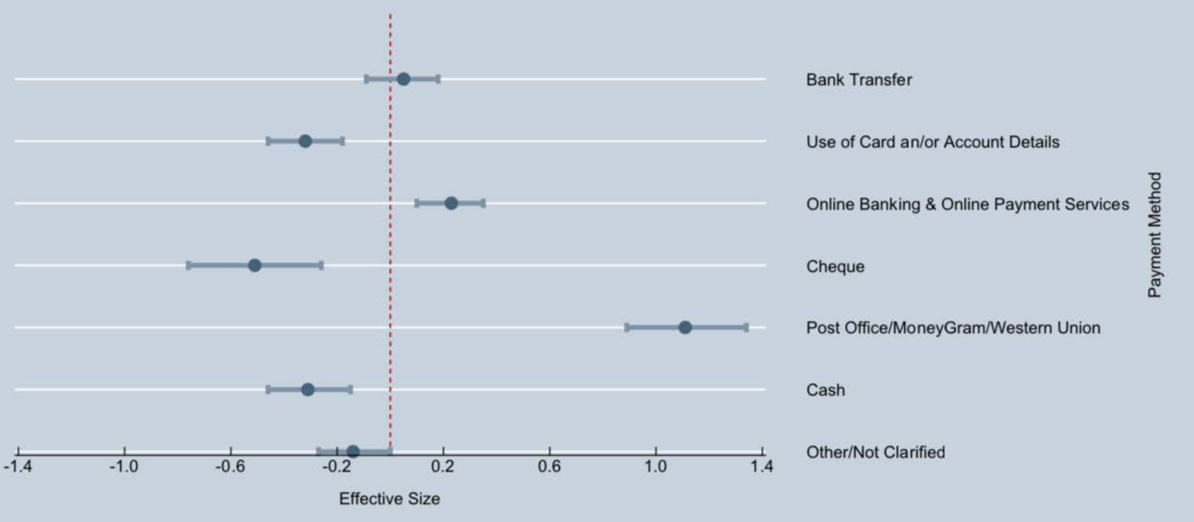


Figure A.3.4.6: Forest Plot of Effect Sizes of Payment Method



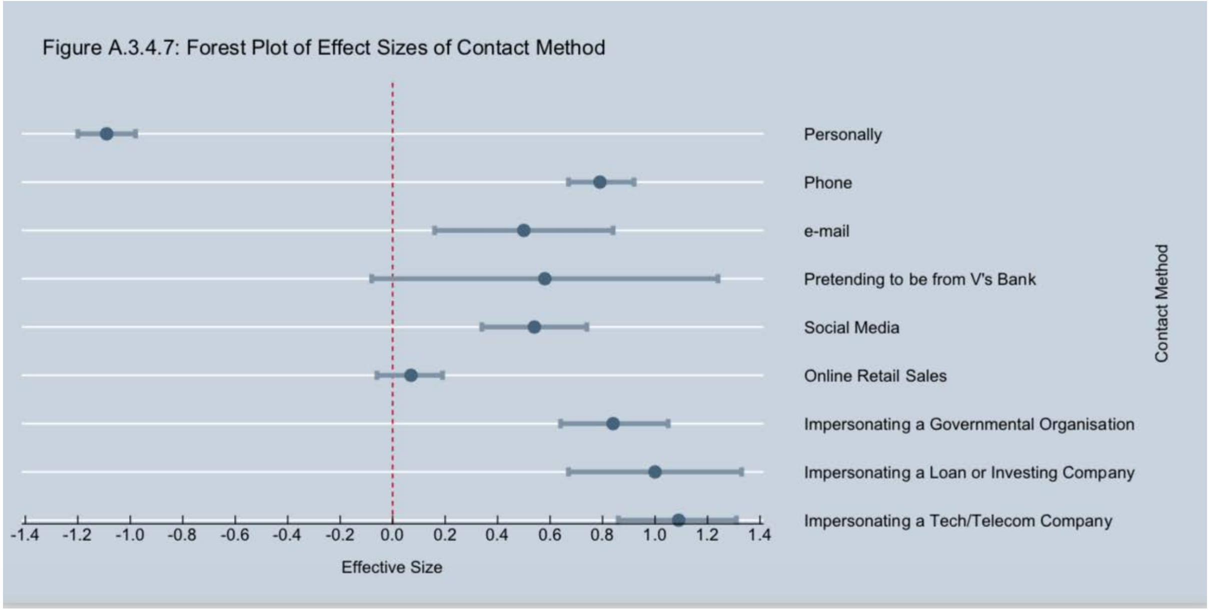


Figure A.3.4.7: Forest Plot of Effect Sizes of Contact Method
Personally
Phone
e-mail
Pretending to be from V's Bank
Social Media
Online Retail Sales
Impersonating a Governmental Organisation
Impersonating a Loan or Investing Company
Impersonating a Tech/Telecom Company
Contact Method
-1.4 -1.2 -1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4
Effective Size

A.3.5 Factor Prevalence

Appendix A.3.5.1: Factor Prevalence

	% in sample with Factor
WWP & WMP Factors	
Victim's Gender	51.25
Offender's Body Description	10.30
Custody Record	23.91
Ethnicity	2.91
Nationality	61.96
Accent Info	8.52
Info on Religion	1.12
Correct Type of Fraud Reported	11.36
Action Fraud or Call-for-Service Reporting	68.69
Offence Validation Status	5.94
Action Marker	2.77
Interest Marker	32.03
Location	93.66
Warning Marker	11.29
Part of a Series	45.77
Other Linked Crime	6.27
Types of Fraud	
Advance Fee Payments	16.78
Financial Investmetns	1.12
Non Investment Fraud	49.54
Charity Fraud	1.45
Fraudulent Appl. for Grants	0.20
Banking and Credit Industry Fraud	22.46
Insurance Related Fraud	0.59
Insurance Broker Fraud	0.40
Telecom Industry Fraud	1.78
Corporate Employee Fraud	2.64
Pension Fraud	1.12
Fraud by Failing to Disclose Information	0.59
Abuse of Position of Trust	1.65
DVLA Driver Licence Application Fraud	0.13
Other Fraud	2.84
Computer Misuse Crime	7.99
Cybercrime	39.10
Phone Scams	16.05
Victim Information	
V Making the Complaint	93.66
Only 1 V	84.94
V Refused to Make an Official Complaint	0.66
V does not Want Updates	0.20
V does not Want Further Investigation	0.79
V was Present when Offence Happened	75.17
Fraud Realised only after being committed	86.92
Fraud Realised while been committed	10.83
V did NOT comply with the SS(s)	10.30
V Complied with SS(s) without Permission	20.01
V Complied with SS(s) once Before Reporting	49.67
V Complied with SS(s) twice Before Reporting	9.11
V Complied with SS(s) three+ Times Before Reporting	4.76
V Victimised Before Current Offence	8.65
V Vulnerable or Old	8.12
V Deceased or Unable to Communicate	1.06
V's Honesty in Question	0.46
Case Characteristics	
Witness, Other than V	22.19
Potential Witnesses, Other than V	2.05
Police Officer Present while Offence Taking Place	3.63
Police Officer Attended Scene After Offence	2.51
Case Characteristic (*cont'd*)	
At least some SS(s) Info Available	79.66
V has Indication about who the Offender is	63.47
SS(s) Info can be Confirmed by Witness	22.99
SS(s) Info Confirmed by a Third Party (e.g. bank)	17.70
SS(s) Info can be confirmed by a Third Party (e.g. bank)	29.46
SS(s) Info Provided by the V(s)	71.14
SS(s) Known to the V	31.97
SS(s) & V are related	11.49
SS(s) Provided V with Documents to Pursuade Legitimacy	12.62
Evidence Available	38.38
MG11 Report	9.58
Items seized	9.58
SS(s) is Male	74.57
SS(s) is Female	17.57
SS(s)'s Physical Description Provided	36.86
SS(s) has Accent	2.25
SS(s) using Alias/Username	11.10
SS(s)'s Phone Number Known	16.45
SS(s) Calling from a Withheld Number	3.70
SS(s)'s e-mail Known	8.78
SS(s)'s Address (or where Offence Took Place) Known by V	50.26
SS(s)'s Vehicle Registration Mark (VRM)	6.67
SS(s)'s Bank Details are disclosed	37.85
# of bank accounts (at least 1)	40.03
SS(s) Personally Attended Place of Offence	42.54
SS(s) Identified through CCTV/Mobile ID Device	22.52
Reason of Fraud	
V's personal info was known or been extracted	30.91
V providing own sensitive info to suspect?	9.71
SS impersonating V, i.e. using v's personal details	11.43
Stolen personal info without V's knowledge	12.75
SS asked for Personal Info	11.89
Stolen Personal Info, Bank Details provided by V	8.65
SS used V's personal details to extract money from V or a third party	27.01
SS asked V to transfer funds	55.68
SS provided V with his/her bank details	24.57
SS asked V to transfer funds to an international bank account	5.35
Transferred funds to SS bank account or handed money out	52.31
Money claimed as lost?	84.08
Stolen money recovered or reimbursed?	2.38
Payment Methods	
Bank Transfer	15.65
Use of Card and/or Account Details	16.18
Online Banking & Online Payment Services	20.41
Cheque	4.29
Post Office/MoneyGram/Western Union	5.42
Cash	12.62
Other/Not Clarified	17.37
Method of Contact	
Personally	41.41
Phone	21.73
e-mail	2.25
Pretending to be from V's Bank	0.59
Social Media	6.87
Online Retail Sales	20.48
Impersonating a Gvernmental Organisation	6.41
Impersonating a Loan or Investing Company or PPI	2.38
Impersonating Tech/Telecom Companies	5.48

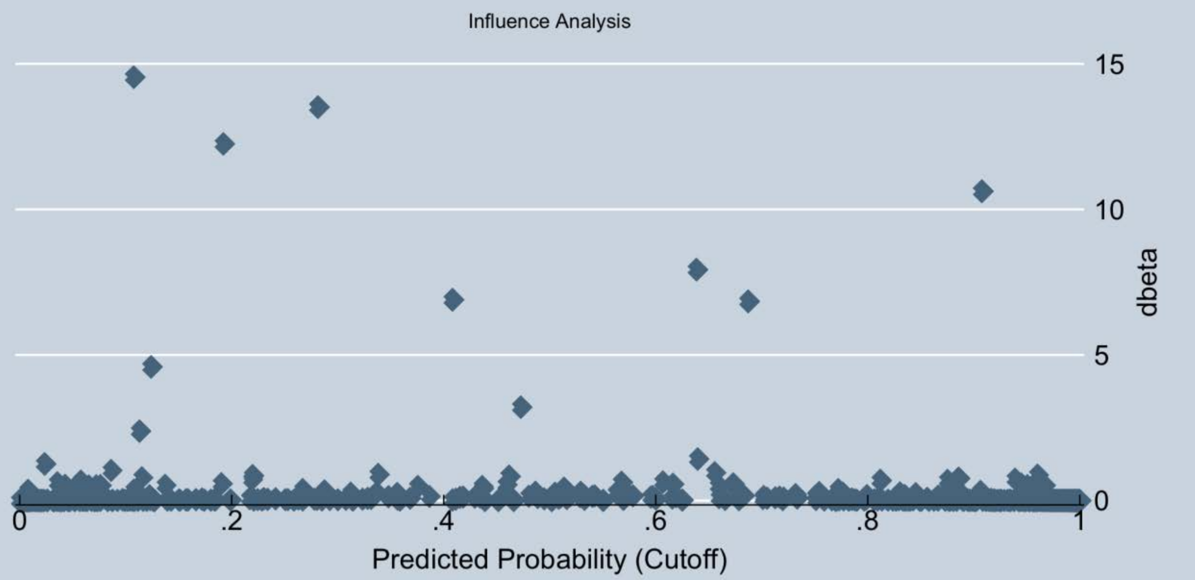
Notes: V stands for Victim and SS(s) for Suspect(s)

A.3.6 Regression Diagnostic Tests

To ensure the model specification is valid, further regression diagnostic tests are estimated; see Table 3.8. First, two goodness-of-fit tests are employed: the Pearson and the Hosmer-Lemeshow. Both compare observed and expected observations of outcome events; with the latter creating subgroups of the data – within each group, cases have a similar predicted probability of the outcome event. Failing to reject the null hypothesis indicates that the model is a good fit to the data. Second, the model specification is tested using the Link Test. It evaluates whether the current model is an adequate fit of the data – the null hypothesis –, or a different specification is required – alternative hypothesis. As shown in Table 3.8, below regression results, all three tests provide support to the current model and specification.

Further, the Pregibon Delta-Beta, *dbeta*, is an influential statistic which is estimated to assess whether inclusion or exclusion of a specific case, or a covariate pattern, affects the estimated coefficients. Small dbeta values, typically less than unity, indicate no influential patterns in the dataset whereas large values of dbeta, usually greater than unity, suggest that individual or covariate pattern is influential. Figure A.3.6.1 illustrates the estimated influential statistic. As demonstrated, dbeta values are less than 0.15. This indicates that the absence of influential points; which is reassuring.

Figure A.3.6.1: Pregibon Delta Beta Statistic



Note: This test provides a measure of the extent to which inclusion or non-inclusion of a case changes the estimated coefficients

It is also important to test if the model, built using the *developmental sample*, is a good fit on the *validation sample*. The goodness-of-fit tests are re-estimated using the second randomly allocated sample to assess the model's calibration. The ROC curve, estimating the model's discrimination capabilities (between positive and negative outcomes) in the validation sample, is also produced. Both tests provide satisfactory evidence on the validity of the model.

In addition, although the above regression diagnostic tests suggest a good fit overall, they do not ensure correct classification of individual predictions. Thus, a threshold probability, i.e. a cut-off point, estimated based on the individual profile of each case's covariate is more useful, since it informs police as to which cases should be allocated or filed. *Section 3.5.2* explains how the most effective classification is selected.

A.3.7 Cut-Off Point

Table A.3.7.1: Comparison of Cut-Off Points, *Developmental Sample*

Cut-Off Value p	logit(p)	CA	CF	IA	IF	TPR	TNR	FPR	FNR	PPV	NPV	FDR	FOR	ACC	LR+	LR-	DOR	Youden Index	min Distance
0.01	-4.60	772	330	411	1	99.87	44.53	55.47	0.13	65.26	99.70	34.74	0.30	**72.79**	1.80	0.00	619.85	*44.41*	*55.47*
0.10	-2.20	758	483	258	15	98.06	65.18	34.82	1.94	74.61	96.99	25.39	3.01	**81.97**	2.82	0.03	94.60	*63.24*	*34.87*
0.20	-1.39	743	562	179	30	96.12	75.84	24.16	3.88	80.59	94.93	19.41	5.07	**86.20**	3.98	0.05	77.76	*71.96*	*24.47*
0.30	-0.85	736	608	133	37	95.21	82.05	17.95	4.79	84.70	94.26	15.30	5.74	**88.77**	5.30	0.06	90.93	*77.26*	*18.58*
0.40	-0.41	728	631	110	45	94.18	85.16	14.84	5.82	86.87	93.34	13.13	6.66	**89.76**	6.34	0.07	92.80	*79.33*	*15.95*
0.50	0.00	695	671	70	78	89.91	90.55	9.45	10.09	90.85	89.59	9.15	10.41	**90.22**	9.52	0.11	85.41	*80.46*	*13.82*
0.52	0.08	691	680	61	82	89.39	91.77	8.23	10.61	91.89	89.24	8.11	10.76	**90.55**	10.86	0.12	93.94	*81.16*	*13.43*
0.54	0.16	688	681	60	85	89.00	91.90	8.10	11.00	91.98	88.90	8.02	11.10	**90.42**	10.99	0.12	91.87	*80.91*	*13.66*
0.56	0.24	686	683	58	87	88.75	92.17	7.83	11.25	92.20	88.70	7.80	11.30	**90.42**	11.34	0.12	92.85	*80.92*	*13.71*
0.58	0.32	684	690	51	89	88.49	93.12	6.88	11.51	93.06	88.58	6.94	11.42	**90.75**	12.86	0.12	103.98	*81.60*	*13.41*
0.60	0.41	682	690	51	91	88.23	93.12	6.88	11.77	93.04	88.35	6.96	11.65	**90.62**	12.82	0.13	101.40	*81.35*	*13.64*
0.62	0.49	679	694	47	94	87.84	93.66	6.34	12.16	93.53	88.07	6.47	11.93	**90.69**	13.85	0.13	106.66	*81.50*	*13.72*
0.64	0.58	672	707	34	101	86.93	95.41	4.59	13.07	95.18	87.50	4.82	12.50	**91.08**	18.95	0.14	138.35	*82.35*	*13.85*
0.66	0.66	665	710	31	108	86.03	95.82	4.18	13.97	95.55	86.80	4.45	13.20	**90.82**	20.56	0.15	141.02	*81.84*	*14.58*
0.68	0.75	663	712	29	110	85.77	96.09	3.91	14.23	95.81	86.62	4.19	13.38	**90.82**	21.92	0.15	147.98	*81.86*	*14.76*
0.70	0.85	644	713	28	129	83.31	96.22	3.78	16.69	95.83	84.68	4.17	15.32	**89.63**	22.05	0.17	127.12	*79.53*	*17.11*
0.80	1.39	615	723	18	158	79.56	97.57	2.43	20.44	97.16	82.07	2.84	17.93	**88.38**	32.75	0.21	156.34	*77.13*	*20.58*
0.90	2.20	548	732	9	225	70.89	98.79	1.21	29.11	98.38	76.49	1.62	23.51	**84.54**	58.37	0.29	198.09	*69.68*	*29.13*
0.99	4.60	308	741		465	39.84	100.00	0.00	60.16	100.00	61.44	0.00	38.56	**69.29**		0.60	0.00	*39.84*	*60.16*

Notes: logit(p) = ln(p/1-p) . All estimates are in percentages (%) and calculated using a randomly allocated *developmental sample*. The definitions of the above abbreviations are, CA: Correctly Allocated; CF: Correctly Filed; IA: Incorrectly Allocated; IF: Incorrectly Filed; TPR: Total Positive Ratio (sensitivity); TNR: Total Negative Ratio (specificity); FPR: False Positive Rate (type I error); FNR: False Negative Rate (type II error); PPV: Positive Predictive Value (precision); NPV: Negative Predictive Value; FDR: False Discovery Rate; False Omission Rate; ACC: Accuracy/Overall Correct Classification; LR+: Positive Likelihood Ratio; LR-: Negative Likelihood Ratio; DOR: Diagnostic Odds Ratio. The Youden Index is estimated by summing sensitivity and specificity whereas the minimum distance ratios estimate the minimum distance of each cut-off value to the point where both sensitivity and specificity are equal to 1. Ideally, the optimal cut-off has the highest accuracy ratio, maximises DOR, minimises LR- and Distance, and maximises Youden Index.

Table A.3.7.2: Comparison of Cut-Off Points, *Validation Sample*

Cut-Off Value p	logit(p)	CA	CF	IA	IF	TPR	TNR	FPR	FNR	PPV	NPV	FDR	FOR	ACC	LR+	LR-	DOR	Youden Index	min Distance
0.01	-4.5951	767	335	407	6	99.22	45.15	54.85	0.78	65.33	98.24	34.67	1.76	**72.74**	1.81	0.02	105.22	*44.37*	*54.86*
0.10	-2.1972	757	485	257	16	97.93	65.36	34.64	2.07	74.65	96.81	25.35	3.19	**81.98**	2.83	0.03	89.29	*63.29*	*34.70*
0.20	-1.3863	736	567	175	37	95.21	76.42	23.58	4.79	80.79	93.87	19.21	6.13	**86.01**	4.04	0.06	64.45	*71.63*	*24.07*
0.30	-0.8473	728	604	138	45	94.18	81.40	18.60	5.82	84.06	93.07	15.94	6.93	**87.92**	5.06	0.07	70.81	*75.58*	*19.49*
0.40	-0.4055	716	621	121	57	92.63	83.69	16.31	7.37	85.54	91.59	14.46	8.41	**88.25**	5.68	0.09	64.47	*76.32*	*17.90*
0.50	0.0000	682	656	86	91	88.23	88.41	11.59	11.77	88.80	87.82	11.20	12.18	**88.32**	7.61	0.13	57.17	*76.64*	*16.52*
0.52	0.0800	681	660	82	92	88.10	88.95	11.05	11.90	89.25	87.77	10.75	12.23	**88.51**	7.97	0.13	59.58	*77.05*	*16.24*
0.54	0.1603	680	660	82	93	87.97	88.95	11.05	12.03	89.24	87.65	10.76	12.35	**88.45**	7.96	0.14	58.85	*76.92*	*16.34*
0.56	0.2412	678	665	77	95	87.71	89.62	10.38	12.29	89.80	87.50	10.20	12.50	**88.65**	8.45	0.14	61.64	*77.33*	*16.09*
0.58	0.3228	670	669	73	103	86.68	90.16	9.84	13.32	90.17	86.66	9.83	13.34	**88.38**	8.81	0.15	59.61	*76.84*	*16.56*
0.60	0.4055	668	669	73	105	86.42	90.16	9.84	13.58	90.15	86.43	9.85	13.57	**88.25**	8.78	0.15	58.30	*76.58*	*16.77*
0.62	0.4895	667	671	71	106	86.29	90.43	9.57	13.71	90.38	86.36	9.62	13.64	**88.32**	9.02	0.15	59.47	*76.72*	*16.72*
0.64	0.5754	653	689	53	120	84.48	92.86	7.14	15.52	92.49	85.17	7.51	14.83	**88.58**	11.83	0.17	70.74	*77.33*	*17.09*
0.66	0.6633	651	689	53	122	84.22	92.86	7.14	15.78	92.47	84.96	7.53	15.04	**88.45**	11.79	0.17	69.37	*77.07*	*17.32*
0.68	0.7538	649	689	53	124	83.96	92.86	7.14	16.04	92.45	84.75	7.55	15.25	**88.32**	11.75	0.17	68.04	*76.82*	*17.56*
0.70	0.8473	636	689	53	137	82.28	92.86	7.14	17.72	92.31	83.41	7.69	16.59	**87.46**	11.52	0.19	60.35	*75.13*	*19.11*
0.80	1.3863	596	706	36	177	77.10	95.15	4.85	22.90	94.30	79.95	5.70	20.05	**85.94**	15.89	0.24	66.04	*72.25*	*23.41*
0.90	2.1972	554	721	21	219	71.67	97.17	2.83	28.33	96.35	76.70	3.65	23.30	**84.16**	25.32	0.29	86.85	*68.84*	*28.47*
0.99	4.5951	314	739	3	459	40.62	99.60	0.40	59.38	99.05	61.69	0.95	38.31	**69.50**	100.47	0.60	168.52	*40.22*	*59.38*

Notes: logit(p) = ln(p/1-p) . All estimates are in percentages (%) and calculated using a randomly allocated *validation sample*. The definitions of the above abbreviations are, CA: Correctly Allocated; CF: Correctly Filed; IA: Incorrectly Allocated; IF: Incorrectly Filed; TPR: Total Positive Ratio (sensitivity); TNR: Total Negative Ratio (specificity); FPR: False Positive Rate (type I error); FNR: False Negative Rate (type II error); PPV: Positive Predictive Value (precision); NPV: Negative Predictive Value; FDR: False Discovery Rate; False Omission Rate; ACC: Accuracy/Overall Correct Classification; LR+: Positive Likelihood Ratio; LR-: Negative Likelihood Ratio; DOR: Diagnostic Odds Ratio. The Youden Index is estimated by summing sensitivity and specificity whereas the minimum distance ratios estimate the minimum distance of each cut-off value to the point where both sensitivity and specificity are equal to 1. Ideally, the optimal cut-off has the highest accuracy ratio, maximises DOR, minimises LR- and Distance, and maximises Youden Index.

Conclusion

Deteriorating labour market opportunities can shift an individual's incentives to engage in legitimate or illegitimate acts. In the first two chapters we assess the link between *monetary* economic indicators, using a panel-data model, for the U.S. and England and Wales, respectively. We believe that benefit measures capture incentives for individuals' crime incentives as advanced by theoretical models, it is the expected illegal and legal *returns* that motivate an individual's decision making.

In the *first* chapter, a dynamic model is estimated to assess to what extent business cycles affect the rate of burglary. To approximate business cycles we use two economic indicators: unemployment and income benefits. The model also controls for criminal justice factors. Both internal lagged values and external instruments are used to address potential endogeneity issues. Also, by exploiting a mitigating mechanism implemented by the U.S. government during the latest recession, we are able to examine how unemployment benefit extensions affect burglary rates.

The empirical results indicate that *at-the-margin* individuals positively respond to increases in income benefits as they increase the opportunity cost of offending and thus, they are less likely to engage in criminal activities. By re-estimating the model during the latest recession, undoubtedly the most severe economic downturn among the three business cycles examined, we find that the size of the effect is larger. Our interpretation is that the greater the economic depression, the more effective are the increases in income benefits.

On the other hand, unemployed individuals also respond to lengthening the time when they can claim unemployment by committing crimes. This is evident by re-estimating our model during the latest business cycle where eligible unemployed recipients were provided benefits for an extended duration, leading to prolonged periods of unemployment. This, we argue occurs as lengthening the period of benefits lowers the incentive to look for work which may also reduce the opportunity cost of crime.

The *second* chapter empirically assess the relationship of economic indicators and different types of crime, in England and Wales. Our contribution is threefold. First, the crime-inequality link is re-examined by developing a novel Gini coefficient using individual-level data. Second, specific economic indicators capturing the incentives of the unemployed and the economically disadvantaged are used. Third, we explicitly account both for the dynamic nature of crime and potential endogeneity of economic and law enforcement factors in the crime equation.

In line with the literature, we find that violent crimes are not affected by economic incentives. Rather, violent criminals are more responsive, both in short- and long-run, to changes in the probabilities of apprehension and sentence lengths than property offenders. Property crime is more likely to be induced by financial motives, our findings are consistent with that indicating significant effects of economic indicators on crime, with the effect being more prevalent during the long-run. We find that lower unemployment and income benefit payments and higher levels of income inequality increase financially motivated crimes.

Key policy implications are derived from these essays on the effect of economic incentives on crime. Both studies demonstrate that increases in legal earnings of disadvantaged groups, as measured by assistance payments, can reduce financially motivated crimes. This is due to facing higher opportunity cost by participating in illegitimate activities.

Finally, the *third* chapter undertakes an empirical analysis of fraud solvability. The rapid expansion of digital technology has allowed fraudsters to commit traditional crimes in a larger scale while also developing new types of crime altogether. Unsurprisingly, fraud and cybercrime victimisation are higher than violent and property crime victimisation. Although fraud is hugely unreported, there are still numerous cases being investigated by local police forces with minimal probabilities of clearance which in turn stretches the already limited investigative resources available. Thus, effective allocation of limited resources is vital to maximise clearance rates.

The chapter builds a predictive model which identifies solvability and case-limiting factors of fraud and computer misuse crimes by utilising preliminary investigative information from cases referred to Warwickshire and West Mercia Police. This is the first study to develop a solvability model for fraud to increase investigatory efficiency by addressing the implicit resource constraint.

Further, we evaluate optimal cut-off values, between case filing and allocation, by minimising the trade-off between incorrect filling and false case allocation. The model is externally validated by testing its predictive capabilities on a separate dataset. The findings indicate that local forces can effectively utilise investigative resources when adopting statistical allocation models that capitalise on information collected during preliminary investigation.

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