GLOBAL PULSE

UNODC
United Nations Office on Drugs and Crime

MONITORING THE

IMPACT OF ECONOMIC CRISIS ON CRIME

Rapid Impact and Vulnerability Analysis Fund

UNITED NATIONS OFFICE ON DRUGS AND CRIME

Vienna

Acknowledgements

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The preparation of this report would not have been possible without the data and information provided by the following individuals:

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Executive Summary

Within the context of the United Nations Global Pulse initiative on monitoring the impact of crisis on vulnerable populations, this report presents the results of a unique cross-national analysis that aims to investigate the possible effects of economic stress on crime. Using police-recorded crime data for the crimes of intentional homicide, robbery and motor vehicle theft, from fifteen country or city contexts across the world, the analysis examines in particular the period of global financial crisis in 2008/2009. As economic crisis may occur over a relatively short timescale, this period, as well as – in many cases – up to 20 years previously, are examined using high frequency (monthly) crime and economic data.

The report finds that, whether in times of economic crisis or non-crisis, economic factors play an important role in the evolution of crime trends. Out of a total of fifteen countries examined, statistical modelling identifies an economic predictor for at least one crime type in twelve countries (80 percent), suggesting some overall association between economic changes and crime.

In eleven of the fifteen countries examined, economic indicators showed significant changes suggestive of a period of economic crisis in 2008/2009. Both visual inspection of data series and statistical modelling suggest that in eight of these eleven 'crisis' countries, changes in economic factors were associated with changes in crime, leading to identifiable crime 'peaks' during the time of crisis. Violent property crime types such as robbery appeared most affected during times of crisis, with up to two-fold increases in some contexts during a period of economic stress. However, in some contexts, increases in homicide and motor vehicle theft were also observed. These findings are consistent with criminal *motivation* theory, which suggests that economic stress may increase the incentive for individuals to engage in illicit behaviours. In *no* case where it was difficult to discern a peak in crime was any *decrease* in crime observed. As such, the available data do not support a criminal *opportunity* theory that decreased levels of production and consumption may *reduce* some crime types, such as property crime, through the generation of fewer potential crime targets.

Country	Geographic unit	Economic crisis (on visualization)	Crime type affected by economic crisis (on visualization)	Economic indicator identified as predictor of crime change (by statistical model)
Argentina	Buenos Aires	✓ (in 2002)	-	Share price index
Brazil	National	✓	n/a	Share price index, unemployment rate
	Rio de Janeiro		Robbery, motor vehicle theft	Treasury bill rate
	Sao Paulo		Homicide, robbery	Male unemployment rate, currency per SDR
Canada	National	✓	n/a	Treasury bill rate, unemployment rate, share price index, deposit rate
Costa Rica	National	✓	Robbery	-
El Salvador	National	✓	Homicide	-
Italy	National	✓	Robbery, motor vehicle theft	Real income
Jamaica	National	✓	Homicide, robbery	-
Latvia	National	✓	-	Youth unemployment rate
Mauritius	National	✓	-	Real income, currency per SDR
Mexico	National	✓	Robbery, motor vehicle theft	Male unemployment
Philippines	National	-	-	Deposit rate, share price
Poland	National	-	-	Treasury bill rate
Thailand	National	✓	Motor vehicle theft	Unemployment rate, real income
Trinidad and Tobago	National	✓	-	Real income, lending rate
Uruguay	Montevideo	-	-	GDP

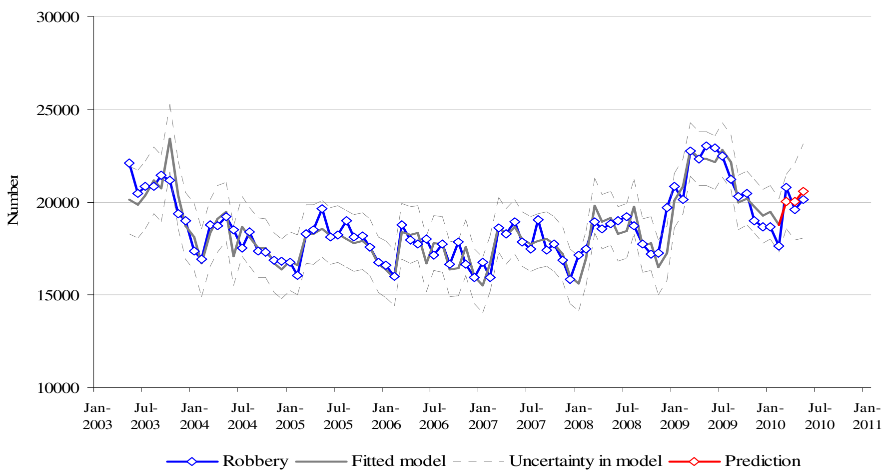
For each country/city a number of individual crimes and economic variables were analyzed. Across all combinations, a significant association between an economic factor and a crime type was identified in around

47 percent of individual combinations. For each country, different combinations of crime and economic predictors proved to be significant. Among the two methods used to analyze the links between economic and crime factors (visualization and statistical modelling), different combinations of factors were found to be significant and in five cases the two methods identified the same variables. Three out of these five cases represented city contexts rather than national contexts. This may indicate that associations between crime and economic factors are best examined at the level of the smallest possible geographic unit.

Where an association between one or more economic variables and crime outcomes were identified by statistical modelling, the model frequently indicated a lag time between changes in the economic variable and resultant impact on crime levels. The average lag time in the contexts examined was around four and half months. In this respect, it should be noted that the relationship between crime and economy is not necessarily uni-directional. Whilst there are theoretical arguments for why changes in economic conditions may affect crime, it could also be the case that crime itself impacts upon economic and developmental outcomes, such as when very high violent crime levels dissuade investment. During the statistical modelling process, crime was set as the 'outcome' variable and economic data as the 'independent' variable. As such, the model was *not* used to investigate the converse relationship – whether changes in crime could also help explain economic outcomes.

The statistical model proved successful at forecasting possible changes in crime for a number of crime type-country/city contexts. Forecasting for a period of three months using a statistical model with economic predictors proved possible with reasonable accuracy (both in terms of direction and magnitude) in a number of different contexts, including both in times of crisis and non-crisis. Many of the forecasts are sufficiently accurate to be of value in a practical scenario. Crime forecasts sometimes led, however, to underestimation of crime changes, suggesting that modelling of crime changes is not optimal when based on economic predictors alone. Indeed, economic changes are not the only factor that may impact levels of crime. The presence of youth gangs, weapons availability, the availability and level of protection of potential targets, drug and alcohol consumption and the effectiveness of law enforcement activity all play a significant role in enabling or restraining overall crime levels.

Crime forecasting using statistical modelling



Although the challenges remain significant, this report demonstrates that – with comparatively few resources – a lot may be learned from the application of analytical techniques to existing data. Continued methodological development, including the creation of an online data reporting 'portal', as well as the strengthening of exchange of information and experience, between countries, has the potential to lay the foundation of a strong 'early-warning' system. The analysis reported here does *not prove* the existence of relationships between economic factors and crime. It does provide strong indications that certain associations are present, and that much may be gained from further investigation. If the impact of economic stress on crime trends can be further understood, and even forecasted in the short-term, then there is the potential to gain much through policy development and crime prevention action.

Introduction

Initial work within the context of the United Nations Global Pulse initiative warns that world leaders "must watch for… indications of increased *social tensions*, *crime* and *violent outbreaks* in communities" as the financial crisis hits vulnerable populations worldwide.[1] This is based on the premise that crime victims and offenders represent vulnerable groups that are likely to increase in size in times of crisis.

If Member States and the international community are to meet this challenge, there is a need for *timely*, *accurate*, and *relevant* cross-national information on crime levels and trends.

With the support of the Rapid Impact and Vulnerability Analysis Fund (RIVAF), the United Nations Office on Drugs and Crime (UNODC) was tasked with providing the core data and accompanying analysis that could enable the early identification of potentially increasing crime trends.

The initiative does not begin in a knowledge vacuum. A significant body of work exists on the relationship between economic indicators and crime and violence. This work tends, however, to consist either of national 'in-house' research carried out by government ministries that examines the situation in just one country[2], or to exist in the academic literature.[3] Academic work, whilst it may have some cross-national focus, is frequently limited to analysis of publicly available or media-supplied information, and may not directly engage governments in the process of data collection and analysis.

UNODC has established substantive expertise in the area of crime prevention, including through work on the promotion and implementation of the United Nations Guidelines for the Prevention of Crime.[4] It also acts as the hub for crime and criminal justice statistics within the United Nations system. Through its 'United Nations Survey of Crime Trends and Operations of Criminal Justice Systems' (UN-CTS), UNODC has collected data from Member States since the 1970s. Data collected comprise police records by offence type, including both 'conventional crimes' such as intentional homicide, robbery, theft and burglary, and 'complex crimes', such as corruption and trafficking in persons.[5]

Whilst existing UNODC knowledge and capacity is well placed to meet the challenges of understanding the complex relationship between economic factors and crime, in order to meet the data and policy needs of Global Pulse, it became necessary to further expand and tailor existing UNODC data collection systems. In particular, in order to detect and respond to rapidly changing socio-economic situations, the *timeliness* and *periodicity* of data collection had to be increased, and the capacity for time series analysis in light of relevant economic data introduced.

This report describes findings from high frequency (monthly) crime and economic data available for fifteen countries – Argentina, Brazil, Canada, Costa Rica, El Salvador, Italy, Jamaica, Latvia, Mauritius, Mexico, Philippines, Poland, Thailand, Trinidad and Tobago, and Uruguay. The majority of data

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1 Voices of the vulnerable: The economic crisis from the ground up. Available at http://www.voicesofthevulnerable.net

2 See for example, United Kingdom Home Office, *Modelling and predicting property crime trends in England and Wales*. Available at: http://rds.homeoffice.gov.uk/rds/pdfs/hors198.pdf

3 For a recent review of the state of the literature, see Congressional Research Service, *Economic Downturns and Crime*, 28 July 2009.

4 Economic and Social Council resolution 2002/13, annex.

5 See http://www.unodc.org/unodc/en/data-and-analysis/Crime-Monitoring-Surveys.html?ref=menuside

considered are at national level although data for four cities – Buenos Aires, Montevideo, São Paulo, and Rio de Janeiro – are also examined. These countries and cities were chosen based on a number of factors including overall crime levels, experience of economic downturn during the 2008/2009 financial crisis, the ability to supply high frequency police-recorded crime data, and broad geographic distribution.

UNODC is extremely grateful for the constructive engagement of those countries that have provided data upon request, for the purposes of this analysis. Throughout the Global Pulse project on measuring the impact of the economic crisis on crime, a core group of countries consisting of those listed above, in addition to the CISALVA Institute in Colombia and the Netherlands, have been instrumental in the process of exchange of ideas, experience and knowledge. In particular, an informal expert meeting on the impact of economic crisis on crime held in Vienna from 1-2 November 2010 provided an opportunity for exchanging country experience on the perceived impact of economic crisis on crime, for reviewing preliminary data analysis carried out by UNODC, and for advising UNODC on the further development of the project.[6]

The **aims** of the project are twofold:

- To **identify** and **raise awareness** at global, regional and national level of the possible effects of economic stress on crime; and

- To work towards a **predictive capacity** for such effects at country level.

The project attempts these aims through the development of an online tool for reporting of high frequency data and the statistical time series analysis of crime and economic data. In this report, retrospective analysis of time series for up to the last 20 years, often including the 2008/2009 period of financial crisis, is used to look for possible associations between crime and economic factors. Where *prima facie* evidence of such an association exists, a statistical model is used to explore whether knowledge of economic changes can be used to predict possible changes in crime events.

In addition to economic variables, changes in a large number of other factors, including the availability and degree of protection of potential crime targets, presence of youth gangs, drugs and weapons availability, drug and alcohol consumption, willingness to report crime, as well as methods and capacities for recording crime, may all significantly affect police-recorded crime trends. In principle, statistical modelling would ideally take account of such effects with a view to excluding or controlling for them. The analysis presented in this report does not do so as a result of limitations of time, data handling complexity, and data availability. As such, the statistical analysis should not be taken as a comprehensive model for the underlying factors that may influence crime levels and trends. Rather, the analysis is an exploratory attempt to consider whether changes in specific crime types over time may be associated in some sense with economic changes as at least *one component* of underlying factors.

[6] See UNODC, Report of the Informal Expert Meeting on the Impact of Economic Crisis on Crime, Vienna International Centre, 1-2 November 2010

Background: Crime and Economic Factors

The proposition contained in the 'Voices of the vulnerable' report – that the financial crisis could lead to 'increased crime' – certainly appears to be plausible. Criminal motivation theories, including strain theory, propose that illicit behaviours are caused, at least in part, by structurally induced frustrations at the gap between aspirations and expectations, and their achievement in practice.

Where the financial crisis is manifested through decreased or negative economic growth and widespread unemployment, large numbers of individuals may suffer severe, and perhaps sudden, reductions in income. This, in turn, has the potential to cause an increase in the proportion of the population with an (arguably) higher motivation to identify illicit solutions to their immediate problems. Whilst this may appear as a simple explanation for property crime, stress situations are also the cause of many violent crimes. Unemployed persons may become increasingly intolerant and aggressive, especially in their families. Violence among strangers may also increase in situations in which people do not have clear prospects for their future.

Whilst unemployment figures are often used as a key indicator for analysis of the effect of economic conditions on crime, official unemployment figures alone cannot provide a complete indicator of either the financial crisis itself or levels of population financial stress. They do not always take account, for example, of those employed in the informal sector, those supporting large or extended families through low-paid formal employment, or those who survive on remittances from workers abroad. Moreover, in addition to loss of employment, the financial crisis may also manifest itself through reduced government social expenditure, increased cost of basic consumer goods, and restrictions on local credit availability. Any or all of these may result in financial stress for individuals and communities, with no change in official unemployment figures.

Nonetheless, due largely to its availability and comparative simplicity, unemployment has been widely used in the literature as a proxy for 'economic activity' in the investigation of the relationship between economic downturns and criminal events.[7] A number of these studies do find small statistically significant correlations between unemployment and property crime rates. This relationship tends to hold true more often for property crime than for violent crime types.[8] However, literature reviews show large disparities in the magnitude of the correlation between unemployment and crime, with some studies identifying weak relationships, others a significant relationship, and still others no relationship between unemployment and crime rates. The reasons for this are manifold. First of all, not many people, even facing severe financial problems, may not think of turning to crime and may even seek more desperate solutions. Increased suicide rates, for example, are observed at times of crisis.[9] Secondly, criminal-opportunity theory suggests that at the same time as income stress could provide incentives to commit crime, decreased levels of economic production and consumption associated with economic slowdown, in addition to increased concentrations of (unemployed) persons around potential property crime targets (houses, cars) may reduce opportunities to commit crime. Proponents of this theory argue that this is the case for both property and violent crime.[10]

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7 See for example, Levitt, S.D., Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not, *The Journal of Economic Perspectives*, vol. 18, no. 1 (2004), pp. 163-190

8 Raphael, S., Winter-Ebmer, R., *Journal of Law and Economics*, vol. 44, no. 1 (2001), pp. 259-283

9 See for example, Rushing, W.A. Income, unemployment and suicide: an occupational study, *The Sociological Quarterly,* vol. 9, no.4 (1968), pp. 493-503

10 Cantor, D., Land, K.C., Unemployment and crime rates in the post-World War II United States: A theoretical and empirical analysis, *American Sociological Review*, vol. 50, no.3 (1985), pp.317-332

Further criminological factors that may impact on the relationship include the introduction and adoption of better security systems and devices, possible shifts away from 'traditional' property crimes such as theft to new types of acquisitive crime such as computer fraud, and the impact of government policy aimed at reducing crime.[11] In addition, crime series data demonstrate that crime levels are often subject to *long-running* trends that may be related to a complex interplay of gradually changing socio-economic factors. Such factors have been proposed to determine an 'equilibrium' or underlying level of crime, with short-term changes tending to be 'corrected back' in subsequent years. In addition to long-running trends, crime levels may also be affected on a medium-term *seasonal* basis.[12] Seasonal crime level increases may typically be observed during summer for instance. As such, any time series analysis of the act of (comparatively) short term economic crisis must be placed within the context of such long-run and medium term trends.[13]

Moreover, it must be remembered that *police-recorded crime* itself is generally a poor proxy for underlying crime levels. Crime figures recorded by the police are a construct both of the factors leading a person to report an act as a 'criminal offence' to the police, and the factors that lead a police officer to determine that an offence has indeed occurred, to classify that offence, to make an administrative record, and for that individual record to be included in aggregate statistics. In addition to any impact on underlying crime levels, it is possible that economic factors may impact on the police recording process itself; perhaps through a direct affect on levels of police resources or through indirect effects, such as the level of motivation and diligence of police officers.

From a statistical perspective, the apparent strength of the relationship between unemployment (as a proxy for economic activity) and crime can also be affected by the geographic unit chosen for analysis (city, province/state or country), the time period over which the analysis is completed, the method chosen to account for long-run trends, and the extent to which other variables that may affect crime levels (most notably demographics) are controlled for. The analytical model chosen to identify the nature of the relationship between economic and crime variables can also have a significant impact on the results obtained. Two variables could appear correlated under an ordinary test of significance. This could, however, be because they are independently affected by the same common third factor and have no true relationship between themselves. In addition, some variables may simply move together by chance.

Finally, it should be noted that the relationship between crime and economy is not necessarily uni-directional. Whilst there are theoretical arguments for why changes in economic conditions may affect crime, it could also be the case that crime itself impacts upon economic and developmental outcomes, such as when very high violent crime levels dissuade investment. Although statistical tests are able to show some relationship, or association, between variables, they cannot necessarily determine the *direction* or *causality* within that relationship. As such, statistical models cannot give a full picture of either the full nature of crime-economy relationships or *of what causes crime*. They are not designed to explain crime. Rather, they may allow a broad understanding of pressures on crime trends, and to predict how such pressures might influence trends in the future.[14] With respect to crime forecasting using statistical models, it is important to understand that such models *do not predict the future level of crime*. Instead, they *estimate* what changes in (specific types of) crime are likely to occur as a result of economic changes *assuming no other factors*, such as government polices to reduce crime, are at work.

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[11] See note 2, at p. 9

[12] See, for example, Cohen, J., Gorr, W., Durso, C. Estimation of crime seasonality: A cross-sectional extension to time series classical decomposition. Available at: www.heinz.cmu.edu/research/132full.pdf

[13] See note 2, at p.4.

[14] See note 2, at p. 2.

Data Collection and Analysis

The terms 'crime' and 'economic crisis' have become commonplace in everyday language, media, and even diplomatic and academic discourse. Yet these comparatively simple words denote complex concepts. Whilst specific statistical indicators may be available for each, such measurements often represent broad proxies at best and do not capture the complexity of the impact of crime victimization or economic stress as experienced by individuals, families, communities, cities, or countries. Measurement of each concept individually is challenging, even before any attempt to examine association between the two.

Measuring crime

'Crime' is a concept that is not subject to one single statistical measure. Rather, approaches to the measurement of crime have focused on individual defined crime events, such as theft, rape, or burglary. Such data may be derived from either or both of official police-recorded crime statistics or population-based crime victimization surveys. Each of these approaches has its own advantages and disadvantages.[15]

From a theoretical perspective, as discussed above, economic factors may have the potential to impact upon not only forms of property crime, but also on violent crime. With a view to including both of these crime categories in the analysis, the crime types of:

- (i) intentional homicide;
- (ii) robbery; and
- (iii) motor vehicle theft

were chosen for time series analysis. These crime types have the advantage of being comparatively well defined, often reported to law enforcement officials following victimization (due to their comparative seriousness, as well as insurance claim incentives in the case of motor vehicle theft), and being commonly available in crime statistics at national level.

Possible associations between economic factors and the three crime types selected may occur over multiple timescales and over different geographical units. Where unemployment rates rise in the long-term (such as a period of ten years) for example, this may also be associated with long-term increases in robbery rates over the same period. This association may be visible at national level, or only in certain sub-national geographic units.

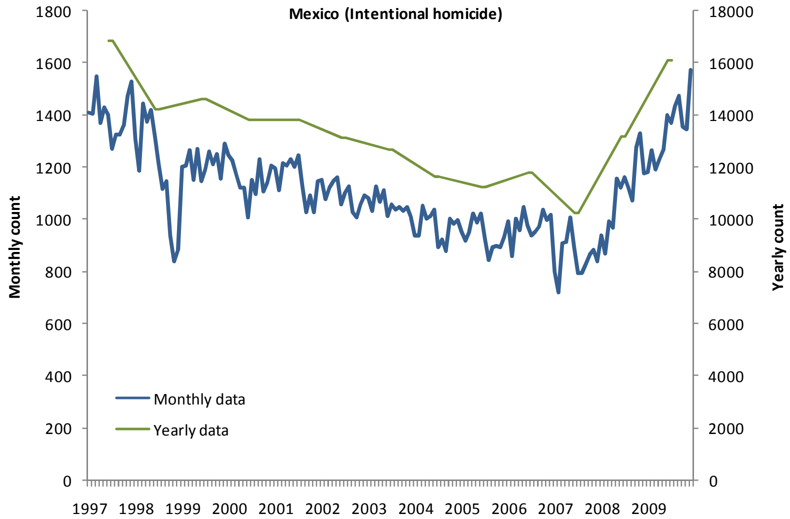
On the other hand, the monitoring of impact of economic *crisis* on forms of crime can be expected to be concerned with rapid, *short-term* changes in both variables. Both of crime rates and economic situations have the potential to change significantly within the course of one year, requiring high frequency data if such changes are to be explored. In particular, as demonstrated in some countries during the recent 2008/2009 financial crisis, sharp economic changes may arise and abate within timescales of one to two years or less.[16] As discussed below, the timescale of changes itself impacts upon the analytical statistical technique used to investigation possible associations.

[15] For a discussion on cross-national crime data collection see Alvazzi del Frate, A. International Crime Data Collection: Priorities for the United Nations. *Forum on Crime and Society*, Vol.5(1), 2006. pp. 3- 20

[16] See for example, Ivashina, V., Scharfstein, D. Bank Lending during the financial crisis of 2008. *Journal of Financial Economics*, 97 (2010). pp 319-338

Figure 1 shows the additional information available in monthly crime data as compared to yearly data in the example of intentional homicide in Mexico. Annual figures are plotted in green and monthly figures in blue.

Figure 1 – Comparison of monthly and yearly crime data



In order to ensure that analysis was as sensitive as possible to short term changes in economic and crime factors, monthly data on the three crime types of international homicide, robbery and motor vehicle theft were collected from the fifteen countries listed in Table 1. In the case of three countries – Argentina, Brazil and Uruguay – it proved possible to collect city level data. For all remaining countries, national level data were collected.

Table 1 – Countries and coverage of data collection

Country	Geographic representation	Institution providing data	Coverage
Argentina	Southern America	Ministry of Justice	Buenos Aires
Brazil	Southern America	Ministry of Justice	São Paulo Rio de Janeiro National
Canada	Northern America	Ministry of Justice	National
Costa Rica	Central America	Ministry of Justice	National
El Salvador	Central America	Ministry of Justice and Public Security	National
Italy	Southern Europe	Ministry of Justice	National
Jamaica	Caribbean	Ministry of National Security	National
Latvia	Northern Europe	National Police	National
Mauritius	Eastern Africa	Central Statistics Office	National
Mexico	Central America	National Institute of Statistics and Geography	National
Philippines	South-Eastern Asia	National Police Commission	National

Poland	Eastern Europe	Ministry of Justice	National
Thailand	South-Eastern Asia	Royal Thai Police	National
Trinidad and Tobago	Caribbean	National Police	National
Uruguay	Southern America	Ministry of Interior	Montevideo

Data on the three crime types were sourced from statistics derived from police-recorded offence records. As set out in Table 1, these were provided to UNODC either directly by national police forces, or through ministries of justice or interior, or through national statistical offices. Police-recorded data can be considered to be largely comparable across time (provided that police recording practices do not change during the time series) for any individual country or city. They do, however, have the disadvantage of frequent limitations in cross-national comparability and of concealing a certain 'dark figure' of crime that is not reported to the police.

In principle, information about non-reported crime could be obtained through population-based crime victimization surveys. Such surveys aim to collect direct information on victimization by particular crime types from a sample of the general (or target) population. This data can then be used to calculate an estimated prevalence rate for each crime type. It is very rare, however, for population-based crime victimization survey data to be available on the monthly basis required for the type of analysis envisaged by this project. As a result, all data presented in this report are derived from police-recorded data.

As noted above, police-recorded statistics face a number of challenges when it comes to cross-national comparability. These derive from: (a) differences between the definitions and classifications of crime events; (b) differences in recording practices and counting and coding rules; and (c) differences in reporting behaviours of crime victims and witnesses.

Crime statistics from different countries and sources are typically generated using different definitions. As a result, simple comparison of the number of crimes in different countries that appear, on the face of it, to be recorded under similar headings, may in fact be highly misleading. The act of 'unauthorized entry to a house with intent to steal' for example, may be recorded as 'burglary' under the law of one country, but 'aggravated theft' in another. The crime named 'assault' in two different countries may require physical contact in one country, but not in the other. In addition, it must be remembered that police systems are more usually optimized for operational purposes (including the need to record evidence for use in identifying and charging a suspect) rather than for the generation of aggregate statistics *per se*. Reported crime events may be recorded at the point of initial reporting, at some point during investigation, or only after an investigation has been completed. Only the most serious criminal act in a linked series of events (such as a robbery followed by homicide) may be recorded, or each act may be recorded separately. Finally, where victim or witness reporting rates to the police differ significantly by country, then straight comparison of resulting police statistics is likely to be misleading.

With a view to improving the comparability of the three police-recorded crime types collected for this project, standard crime definitions – based on the international United Nations Survey of Crime Trends and Operations of Criminal Justice Systems (UN-CTS)[17] – were supplied to countries in a dedicated data collection instrument developed for the project.

[17] See http://www.unodc.org/unodc/en/data-and-analysis/United-Nations-Surveys-on-Crime-Trends-and-the-Operations-of-Criminal-Justice-Systems.html

Table 2 – Crime definitions

Completed intentional homicide	Death deliberately inflicted on a person by another person, including infanticide and excluding attempts
Robbery	The theft of property from a person, overcoming resistance by force or threat of force. Where possible, the category "Robbery" should include muggings (bag-snatching) and theft with violence, but should exclude pick pocketing and extortion.
Motor vehicle theft	The removal of a motor vehicle without the consent of the owner of the vehicle. "Motor Vehicles" includes all land vehicles with an engine that run on the road, including cars, motorcycles, buses, lorries, construction and agricultural vehicles.

Definitions were accompanied by a standard data collection format that included extensive metadata questions on the content of national offences, in addition to questions on the geographical coverage of police-recorded crime data, counting units, the time lag between offence identification and recording, and the presence of significant breaks in the crime data series. Results from the seven countries that were able to supply the metadata are included in Annex 1 to this report.

In the context of this project, initial exploratory analysis of national crime and economic data *aggregated* at the *global* and *regional* level was first undertaken. Preliminary results demonstrated however that aggregation (at least with data from countries listed in Table 1) provided no meaningful correlation or relationship over time, at least prior to any attempt to account for data content and methodology differences.[18] As a result, the focus of analysis was changed to the individual national (or city) level. All results presented in this report therefore relate to the *individual data-providing entity*, whether a country or city.

Where data are *not* aggregated or otherwise compared directly (as in this report), the role of metadata and data harmonisation becomes more limited. Provided that data content and methodology remain the same throughout any individual time series examined, analysis may be taken as valid for that particular series in and of itself. As such, whilst metadata have informed the results presented in this report (such as in the identification and exclusion of time periods where data recording rules changed), an extensive process of metadata analysis and data harmonisation has not been conducted.

Understanding differences in the content and methodology of crime data is the first step towards overcoming such challenges. Once such differences are understood, however, it is necessary to commence a process of data *harmonisation*. This requires both direct work with countries to obtain data that is matched as closely as possible to standard definitions and recording approaches, as well as examination of ways in which remaining data differences may be accounted for in the analysis process.

For the present analysis, the three crime types (intentional homicide, robbery, and motor vehicle theft) can be considered to capture broadly similar phenomena in each country. However, the metadata show that these are not identical across all countries examined. As such, whilst each country or city analysis may reveal (or not) a particular relationship between crime and economic factors, it must be borne mind that the demonstration of a relationship in one country but not

[18] See UNODC (2010), Report of the Informal Expert Meeting on the Impact of Economic Crisis on Crime, 1-2 November 2010.

another could be due to cross-national differences in the crime phenomenon examined or the way in which it is recorded and reported.

Measuring economies

In the same way as for the measurement of crime, no single measure easily captures the complexity of economic pressures on individuals. Even with respect to the concept of economic 'crisis', for example, no general consensus exists as to how this is defined. One common view is that disruptions in financial markets rise to the level of crisis when the flow of credit to households and businesses is constrained and the real economy of goods and services is adversely affected. In this respect, the linked concept of 'recession' is often defined as a fall in GDP for three consecutive quarters. The adverse effect on the economy may also be reflected in unemployment figures, as well as changes in consumer prices.[19]

For the purposes of this analysis, economic indicators including gross domestic product, consumer price index (CPI), real income, unemployment rate (disaggregated by age groups and sex where possible), share price index, lending rate, treasury bill rate, and currency units per special drawing rights (SDR) were obtained for time series analysis against police-recorded crime data. Economic data were sourced from the International Monetary Fund international financial statistics database[20] and supplemented with economic data from national statistical offices where necessary. Economic data were obtained on a monthly basis where possible. Where monthly series were not available for particular indicators, quarterly data were obtained and interpolated as appropriate. Where city-level crime data was collected, efforts were also made to collect relevant city-level economic data. In particular, it proved possible to obtain unemployment data for Buenos Aires, Rio de Janeiro and São Paulo.

In the collection of economic data and its subsequent analysis, no single economic indicator was given particular priority. Whereas GDP, unemployment rate, and CPI (and its derivative, real income) may be considered as key indicators, in practice all economic variables were viewed as somehow indicative of the broad underlying (socio)-economic situation. Indeed, preliminary principal component analysis of the economic variables showed that many economic variables are closely interrelated and can in principle be reduced to a limited number of components that account for much of the variance in the original separate variables.[21] Unemployment, for example, is related to GDP insofar as higher unemployment reduces private consumption, wages paid, production and exports.

[19] See for example, *Averting Financial Crisis,* CRS Report for Congress, 21 March 2008. Available at: http://fpc.state.gov/documents/organization/103688.pdf

[20] http://www.imfstatistics.org/imf/

[21] For an example of application of a principle components approach to economic indicators see: Mehrotra, A., Pääkkönen, J. (2011) *Comparing China's GDP statistics with coincident indicators*, Bank of Finland Discussion Paper.

Visualizing economic crisis and its relationship with crime

One starting point for analysis of the relationship between economic crisis and crime is the simple *visualization* of periods of economic crisis by plotting available economic and crime indicators. Whilst, as noted above, economic indicators can be closely related, it is also useful to plot indicators separately in order to gain a clear picture of changes in specific measures. Such an approach can help identify, and to some extent, quantify, times of economic hardship or 'crisis' and any possible impact on crime levels.

Results from data visualization

Visualization of crime and economic series shows that it is possible in many cases to draw initial conclusions about the presence or absence of periods of economic crisis, as well as possible impacts on police-recorded crime, from simple examination of data plots.

Of the **fifteen** countries included in this analysis and listed in Table 1, visualization of data suggests that **eleven** showed significant changes in economic indictors (primarily CPI, GDP and unemployment) during the period 2008/2009 that may tentatively be termed economic 'crisis'. Only the Philippines, Poland, and Uruguay (Montevideo), were identified as likely having *not* entered a period of significant economic downturn in 2008/2009.[22] Out of these **eleven** countries that experienced economic downturn in 2008/2009, **seven** showed identifiable *increases* in at least one of the crime types examined. Only in Latvia, Mauritius and Trinidad and Tobago was it difficult to discern any particular increase in crime during the 2008/2009 period of economic downturn.[23] In none of these cases, however, was any *decrease* in crime observed.

Notably, whilst increases in the crime type of robbery were most often apparent, it was also possible to identify peaks in homicide and motor vehicle theft in some country or city contexts. This is consistent with criminological theories that propose theoretical mechanistic links between both increases in property crime *and* potentially violent crime during periods of economic stress. It is important to note, however, that the mere observation of apparently linked changes in two time series is not conclusive as to the nature or direction of any possible relationship between the two variables.

Table 3 specifies those contexts in which a period of economic crisis and a possible impact on crime could be identified by visualization. The table shows that increases in robbery were most often identified (six country or city cases), followed by motor vehicle theft (four cases), followed by homicide (three cases). Interestingly, homicide appeared associated with economic changes in countries with generally high violence levels – Brazil, El Salvador and Jamaica. This may be linked to differences in homicide *typology* between countries. Many countries in Latin America, for example, show high violence levels driven by homicides linked with gangs and other criminal activity. It is possible that such typologies show higher sensitivity to economic changes than homicides linked to intimate or family, which make up a significant proportion of total homicides in countries in Europe and Asia.[24]

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[22] Whilst Argentina (Buenos Aires) experienced economic crisis in 2002, insufficient data were available to identify whether similar events occurred in 2008/2009

[23] Insufficient data were available to identify whether the economic crisis in 2008/2009 led to changes in any of the crime types in Canada.

[24] See Geneva Declaration, Second Global Burden of Armed Violence Report. 2011, Chapter 3, *forthcoming*

Table 3 – Results from data visualization

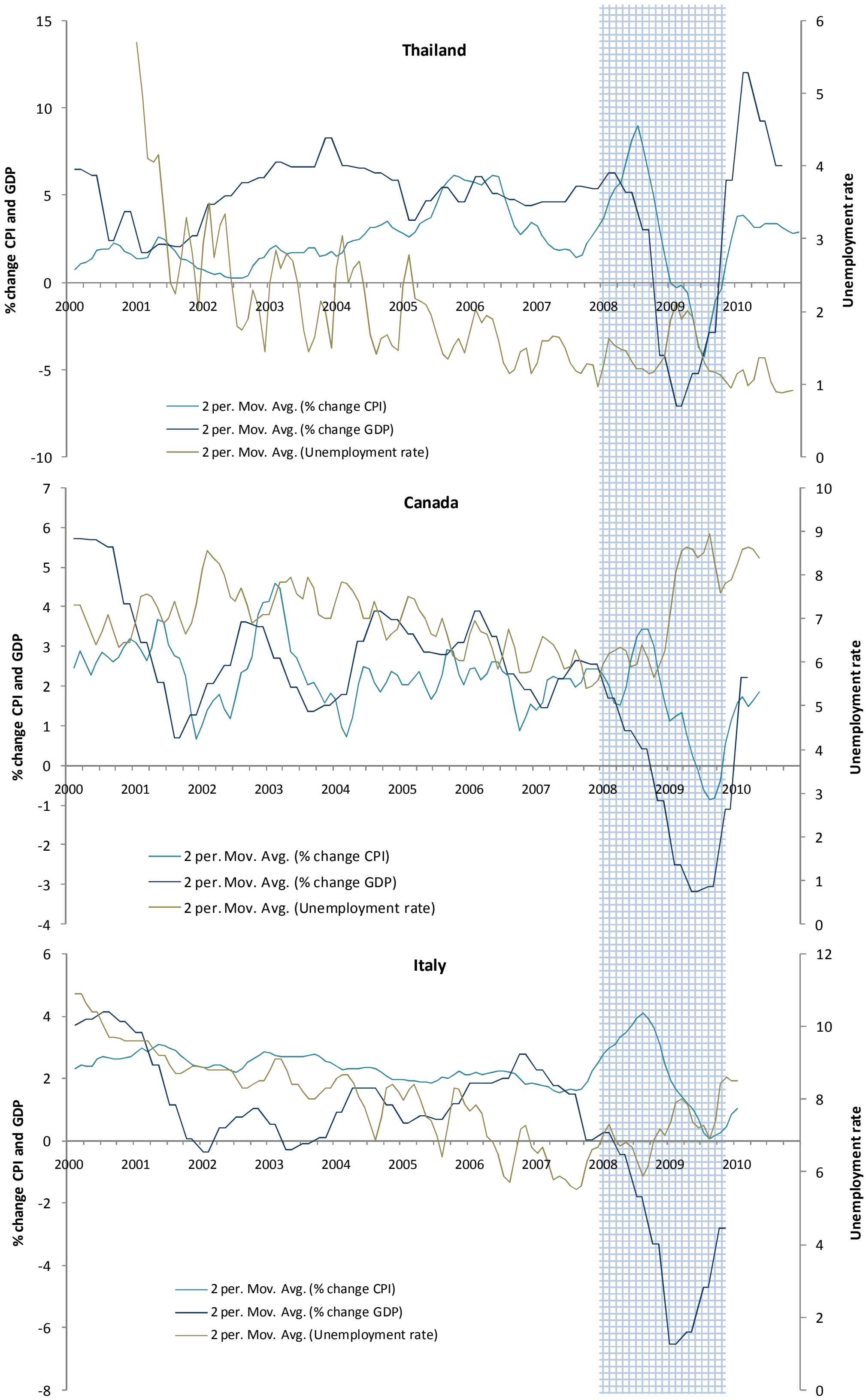
Country	Geographic unit	Crisis (on visualization)	Response (on visualization)		
			Homicide	Robbery	Motor vehicle theft
Argentina	Buenos Aires	✓ (in 2002)	-	-	-
Brazil	National	✓	Insufficient data		
	Rio de Janeiro		-	✓	✓
	Sao Paulo		✓	✓	-
Canada	National	✓	Insufficient data		
Costa Rica	National	✓	-	✓	-
El Salvador	National	✓	✓	-	-
Italy	National	✓	-	✓	✓
Jamaica	National	✓	✓	✓	-
Latvia	National	✓	-	-	-
Mauritius	National	✓	-	-	-
Mexico	National	✓	-	✓	✓
Philippines	National	-	-	-	-
Poland	National	-	-	-	-
Thailand	National	✓	-	-	✓
Trinidad and Tobago	National	✓	-	-	-
Uruguay	Montevideo	-	-	-	-

Examples of the data plots used to construct Table 3, showing periods of crisis and non-crisis, and crime response and non-response, are included in this chapter. It must, however, be remembered that the process of 'identification' of a period of 'crisis', or of an 'impact' on crime by visualization is highly subjective, particularly where monthly data show significant fluctuation in levels from month to month. As such, the findings in Table 3 merely represent a starting point for discussion and later statistical analysis. Indeed, an important finding of this chapter is that in many contexts (including where long running crime trends are pre-existing) visualization is insufficient to identify whether a relationship exists between economic factors and changes in crime. In addition, the suggestion of the existence of a period of economic downturn and an impact on crime by visualization is unable to identify whether economic changes are *causal* of crime changes or to take account of changes in other factors that may also impact upon crime levels.

Visualizing economic crisis

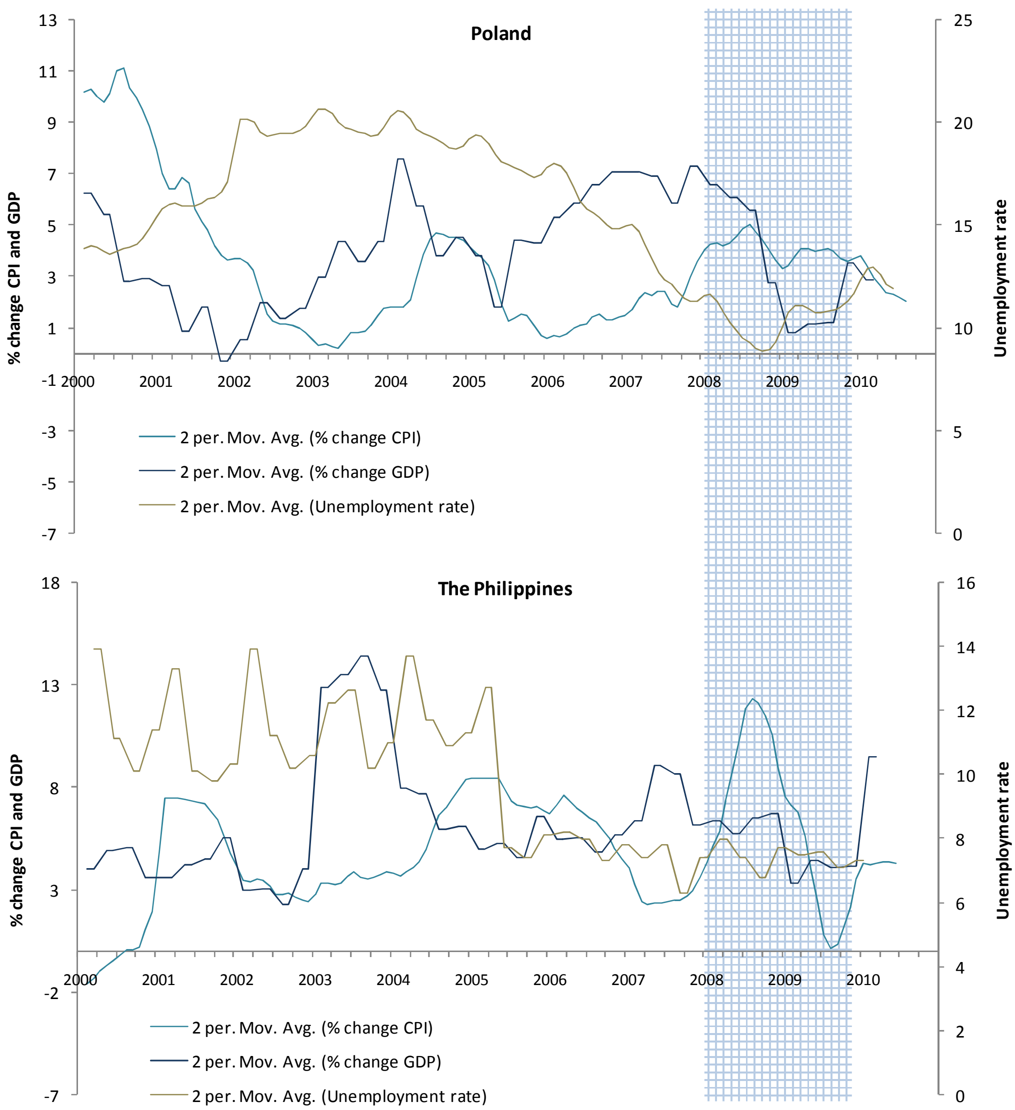
Figure 2 shows three examples – Thailand, Canada and Italy – from the fifteen countries included in the analysis where economic indicators show significant changes during the recent 2008/2009 global financial crisis. For each country, percentage change in CPI (monthly) and GDP (quarterly) are plotted together with unemployment rate (monthly) for the period 2000 – 2010. A two-period moving average is used for the purposes of clearer visualization. In each case, the period is characterized by slowing, and eventually negative GDP growth, rises in consumer prices and, to varying extents, short to medium term increases in unemployment. It should be noted that each of these variables shows considerable variation over the time period. Unemployment rates, for example, are significantly higher in both Thailand and Italy in the early part of the time period than during 2008/2009. Nonetheless, the three time series do demonstrate concerted changes, particularly in GDP, that occurred in all three (non-geographically linked) countries around the time of the global financial crisis.

Figure 2 – Visualizing economic crisis in 2008/2009



In contrast, Figure 3 shows two examples – Poland and the Philippines – where CPI, GDP and unemployment do not show significant changes in 2008/2009. Whilst GDP growth does slow in Poland a little, the decrease is no greater than in 2002. Similarly, whereas consumer prices do rise in the Philippines in late 2008, this is not accompanied by a significant decrease in GDP or rise in unemployment. Overall, whilst trends at the global level may have impacted certain economic indicators in these countries in 2008/2009, it is likely that the underlying national economic situation did not reach 'crisis' level during this time.

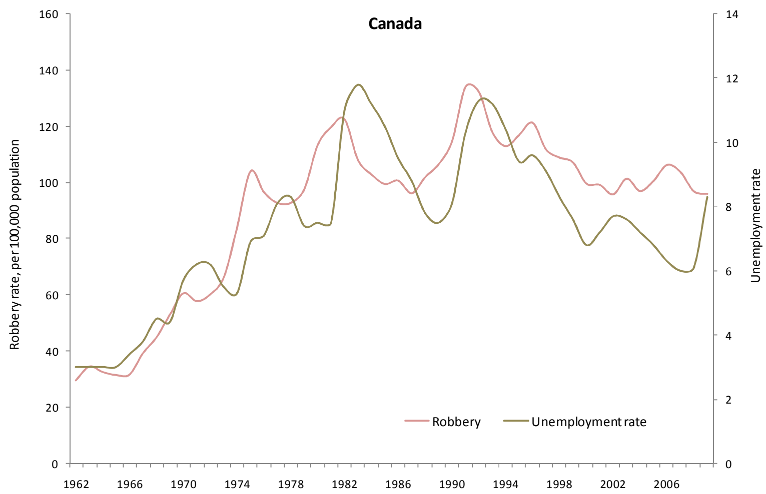
Figure 3 – Escaping economic crisis



Inclusion of a range of country situations in the analysis group is important when it comes to investigating the impact of crisis on crime. Analysis of both yearly and monthly data in a number of contexts demonstrates that relationships may already exist between economic factors and crime levels over the long term and during periods of usual economic activity.

Figure 4 shows, for instance, a long term relationship between robbery and unemployment rates in Canada from yearly data between 1962 and 2009. The yearly data demonstrate that increases in unemployment over the longer term are associated with increases in robbery. The existence of such a long term relationship suggests that robbery may also be impacted in this particular context by short term 'crisis' changes in economic conditions. Nonetheless, when it comes to (comparatively) short-term periods of crisis, unusual economic conditions may lead to the creation of new or different relationships between economic factors and crime that depart from established long-term relationships. During crisis, economic factors may become more significant than in periods of non-crisis, or established relationships between economic factors may change. As such, a cross-national investigation of the impact of economic crisis on crime should take into account both countries which have experienced periods of crisis, as well as those that have not.

Figure 4 – Long term relationship between crime and unemployment



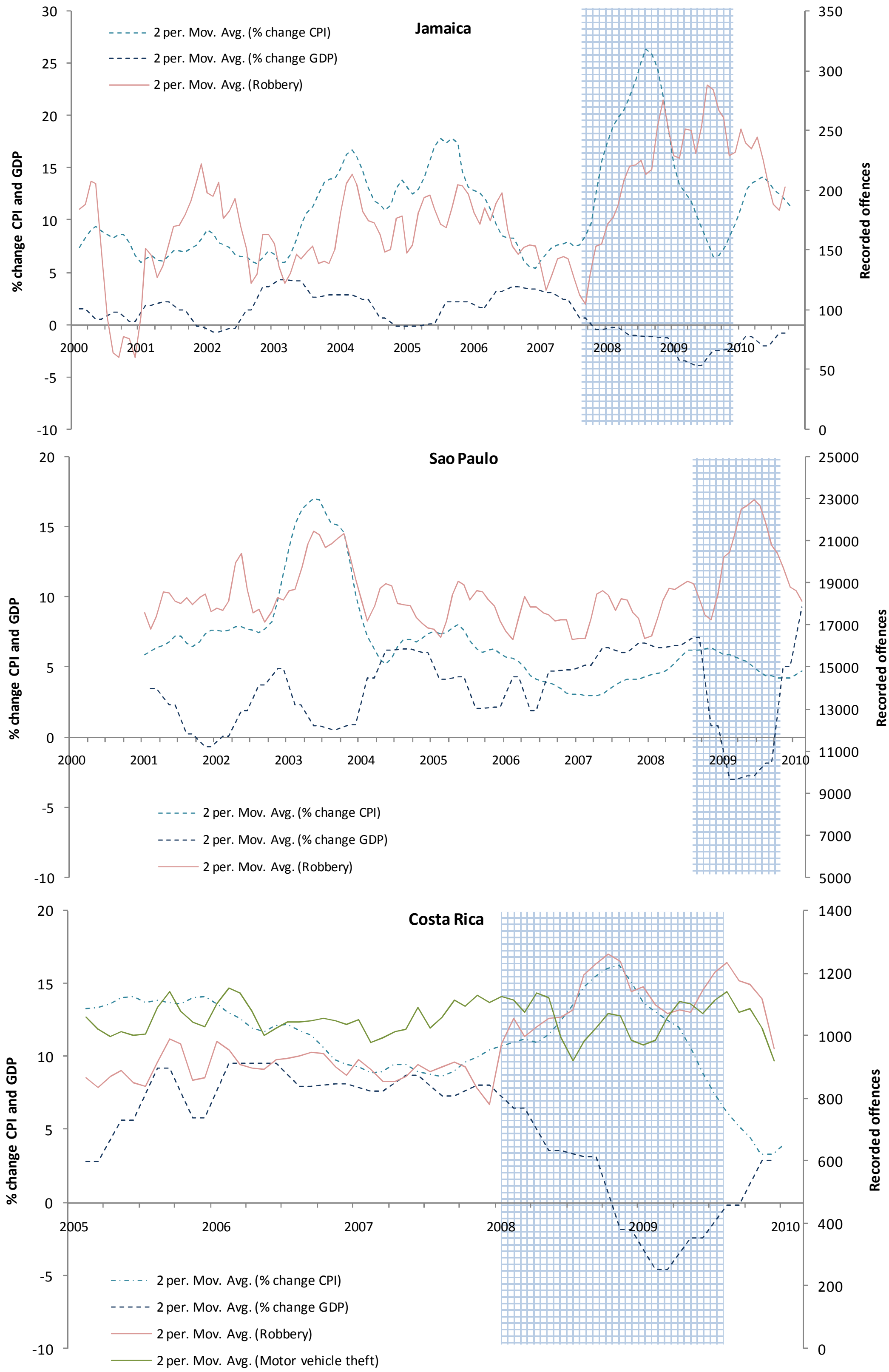
Visualizing the impact on crime

In order to visualize the relationship between economic factors and crime over short time scales, including the 2008/2009 period of crisis, Figure 5 below shows monthly police-recorded robbery data plotted alongside economic variables for three examples – Jamaica, São Paulo, and Costa Rica. Trends in GDP and CPI suggest that all of these countries experienced economic 'crisis' in 2008/2009, evidenced by negative GDP growth and rising consumer prices.

Simple visual inspection suggests that in each of these contexts (two countries and one city), there was an increase in the level of police recorded robbery during the period of economic hardship. In Jamaica, the month with the greatest number of robberies (July 2009) recorded a number over twice as great as in July 2007. The average number of recorded robberies in 2008/2009 was one and half times greater than in the previous seven years. In São Paulo, a peak in police-recorded robbery in March 2009 was some twenty percent greater than March 2007, and in Costa Rica a peak in October 2008 was around thirty percent higher than robbery levels in October 2007. In each case, levels of police-recorded robbery appear to begin some return to pre-crisis levels during 2010. Visual inspection also suggests that some relationship between levels of police-recorded robbery and economic factors also existed prior to 2008/2009. Police-recorded robbery appears to be higher during times of increasing consumer prices in Jamaica between 2000 and 2007, and a peak in consumer prices in São Paulo in 2003 coincides with an increase in police-recorded robbery.

The visualization also shows that not all crime types may be affected in the same way during periods of financial crisis. Police-recorded motor vehicle theft in Costa Rica, for example does not appear to show any particular increase in 2008 or 2009.

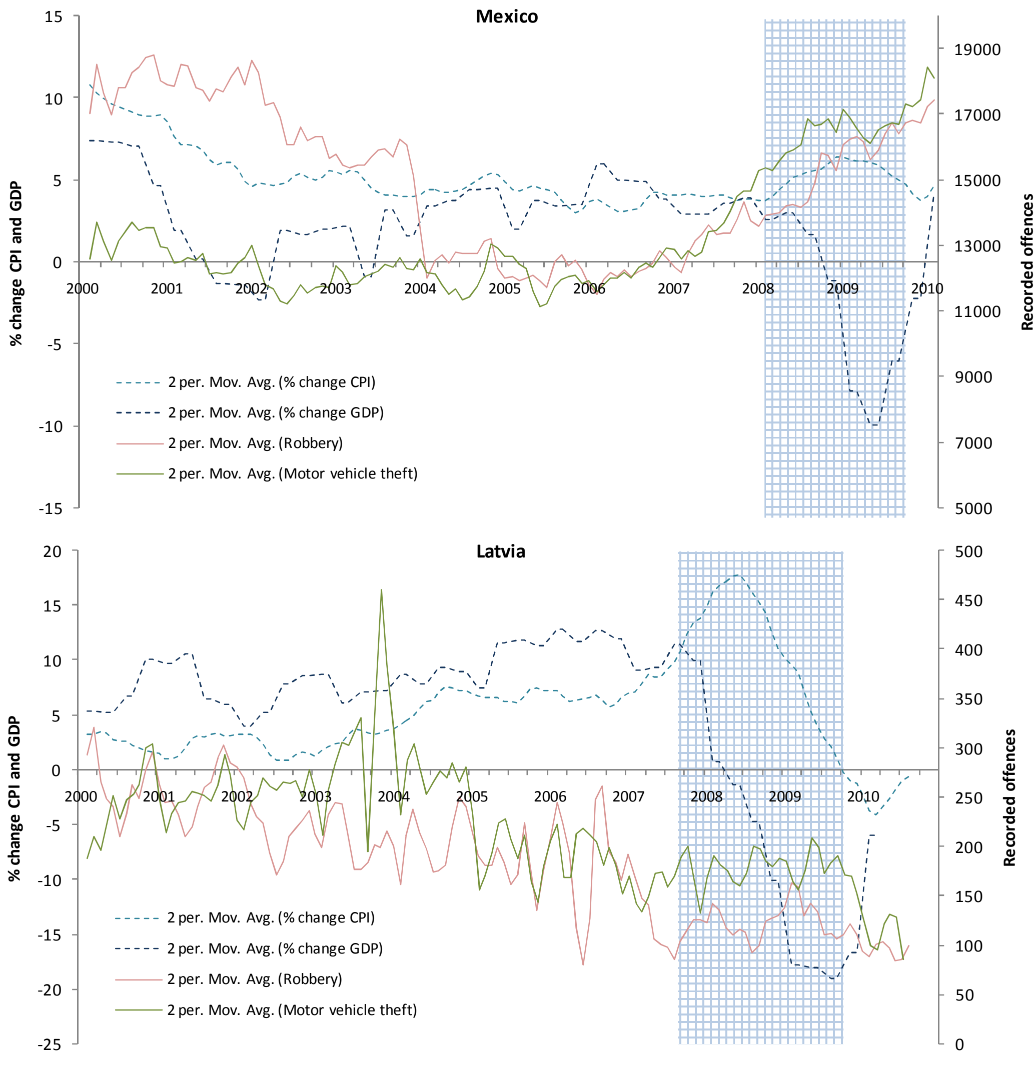
Figure 5 – Visualizing impact on crime during economic crisis



The countries in Figure 5 exemplify contexts where, although month to month fluctuation exists, the overall trend is basically flat. In such situations, any relationship between economic factors and crime is often visually clearer, as short-term increases in crime levels may show as clear ‘peaks’. In contrast, where a pre-existing trend exists (either increasing or decreasing crime levels) the short-term impact of changes in underlying factors may be harder to identify. In the case of Mexico plotted in Figure 6, for example, both robbery and motor-vehicle theft show a clear increasing trend from 2006 to the end of 2010. Mexico experienced negative GDP growth in 2009, combined with an increase in consumer prices. Visual inspection suggests that the increase in robbery and motor vehicle theft may have been greater around 2008/2009 than in other years between 2006 and 2010. It is difficult to tell by eye, however, and the example well shows the limits of drawing conclusions from visual inspection of data alone.

Other countries, such as Latvia also plotted in Figure 6 below, show clear changes in economic variables during 2008/2009 but no particular discernable effect at all on police-recorded crime. Whilst small peaks did occur in police-recorded robbery and motor vehicle theft during the period of economic crisis in 2009/2009 in Latvia, it is by no means clear that these are any greater, and in many cases are significantly smaller, than usual monthly fluctuation seen prior to the period of crisis.

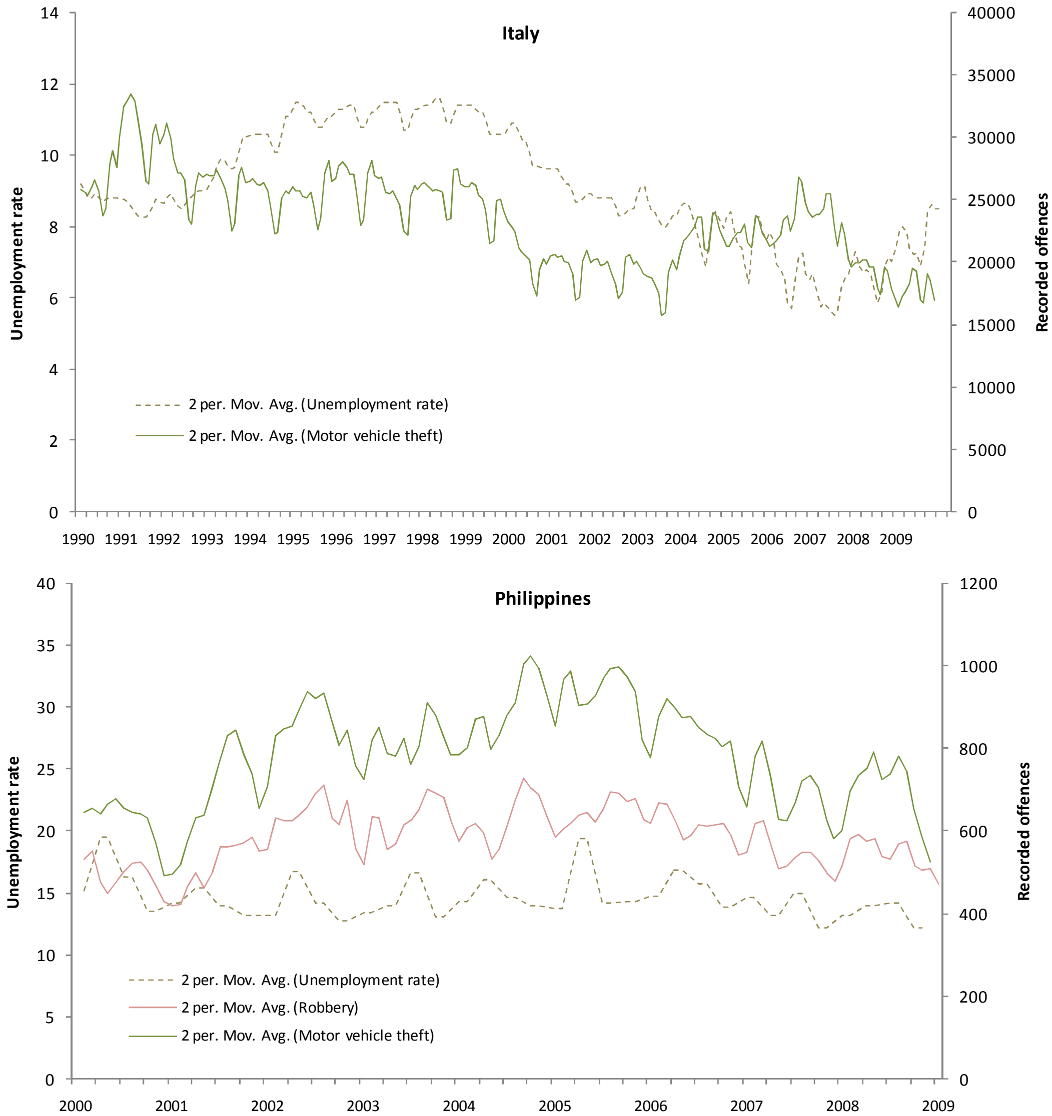
Figure 6 – Visualizing impact in difficult cases



Finally, visualization can reveal the challenge of *seasonality* in crime and economic data. It has been recognized for a number of years that some types of crime event follow seasonal patterns. Seasonal patterns have been found to vary depending upon crime type, with many crime types typically higher in summer than winter months, but some such as robbery peaking in holiday seasons, such as December.[25] Seasonality is also present in economic time series, such as unemployment, due to varying levels of activity of seasonal industries such as crop production, agriculture, fishing, heavy and civil engineering construction, and museums, historical sites, zoos and parks.[26]

In some cases, seasonal variations in economic factors may move consistently together with seasonal variations in crime. In Figure 7 below, for example, both unemployment and motor vehicle theft in Italy show a consistent short-term drop in August of each year. Similarly, in the Philippines, seasonal peaks in unemployment line up well with periodic peaks in robbery and motor vehicle theft.

Figure 7 – Visualizing crime and economic seasonality



25 See for example: United States Department of Justice, Bureau of Justice Statistics, *The Seasonality* of *Crime Victimization*. May 1988. NCJ-111033.

26 See for example: Statistics Canada, *Seasonality in employment*, 1999.

It is possible, in the example of Italy, that the seasonal decrease in unemployment is a contributing factor to the concomitant short-term decrease in motor vehicle theft. It could, however, also be the case that a third non-related seasonal factor that happens to align at the same time of year (such as an increase in the number of persons using their car for vacation) is instead largely responsible for the observed periodic decrease in motor vehicle theft. Questions of causation are notoriously difficult and it is not the aim of this analysis to develop proofs of the true causal effect of economic variables. Nonetheless, the visualizations above demonstrate the important point that if *associations* between variables are shown, then at least a *plausible hypothesis* is needed that could explain any potential causative effects.

Conclusions from data visualization

The data plots presented in this chapter indicate that a reasonable amount of analysis can be carried out by visualization of data alone. The analysis suggests that – amongst the countries examined – economic downturn was widespread in 2008/2009, with over 70 percent of countries showing visible changes in core economic indicators such as GDP and unemployment. Amongst those countries that experienced such downturn, over 60 percent also appeared to experience short term increases in at least one crime type. Crime types affected included both violent and property crime. In some cases, increases were significant, representing up to a two-fold increase. In no country were crime decreases observed.

Such an approach is imprecise, however, and the data plots presented in this chapter show that whilst some associations may be clear on visual inspection alone, relationships between underlying economic and dependent crime variables become significantly more complex where long-running trends or seasonal patterns (in either crime or economic variables) exist. Fluctuations in a long-running economic trend (such as long-term increasing unemployment) may have the potential to impact crime, even though short-term changes in a long-term gradient may not be easily visualized. As such, the challenge is to develop a statistical analytical approach that is capable of detecting and modelling such associations.

Statistical analysis of crime and economy time series

This section moves beyond visualization of crime and economic variables with a view to developing a statistical approach that can:

- identify whether a relationship exists between economic factors and changes in crime series; and
- *predict* likely *future* changes in crime variables based on known changes in economic factors and past trends.

In order to meet these aims, a statistical model was developed and applied to the economic and time series previously examined by visualization. The model described in this chapter uses a 'best-fit' approach to determine whether the description of the crime series can be improved by the inclusion of an economic predictor variable. All available economic data series from the IMF International Financial Statistics database as well as national statistical offices, where available, were used as input for the model. Where an economic predictor is included, the model offers the possibility to *forecast* likely changes in crime trends based on existing information from the historical crime trend together with information from the economic predictor.

Results from statistical analysis

Table 4 presents the results from statistical modelling of data from the fifteen countries. Out of the **fifteen** countries examined in total, the 'best-fit' statistical model included an economic predictor in the model for at least one crime type in **twelve** countries. The inclusion of an economic indicator by the model for a particular crime in a particular country or city context means that the economic factor can help describe the evolution of the crime series, suggesting some possible *relationship* between crime and an economic factor in that context. Whilst, as described below, the results from the model do not always match with results from visualization, the selection of economic predictors in **80 percent of all countries examined**, nonetheless confirms the general finding that economic factors frequently play some role in crime trend changes.

Due to the limited number of countries examined, it is difficult to say whether economic factors are more often associated with changes in crime outcomes during periods of crisis than non-crisis. The results do, however, indicate, that economic changes can be important during *both* economic crisis and *non*-crisis.

Out of **eleven** countries which showed evidence of economic crisis in 2008/2009 on visualization, the model included an economic predictor for at least one crime type in **eight** of these cases. These were not, however, always the same countries as where an impact of crisis on crime had initially been identified by visualization. Out of the seven countries where an impact of crisis on crime had been initially identified by visualization, the best-fit model included an economic predictor in four of the same cases (Brazil, Italy, Mexico, and Thailand), although not always for the same crime type as on visualization. In Costa Rica, El Salvador, and Jamaica, a possible crime-economy relationship was identified visually but not detected by the model. In all three countries where there was *no* evidence of crisis (The Philippines, Poland and Uruguay), the model identified an economic predictor, suggesting that economic factors are also important during times of non-crisis. As with visualization, the model also confirmed that changes in economic factors may be associated with changes in *all three* crime types of intentional homicide, robbery and motor vehicle theft.

Where an economic predictor is identified by the statistical model, the model also identified the *lag time* between changes in the predictor and the resultant outcome. During the statistical modelling process, crime was set as the 'outcome' variable and economic data as the 'independent' variable. As such, the model was *not* used to investigate the converse relationship – whether changes in crime could also help explain economic outcomes. All lag times are therefore zero or positive, with the model looking for changes in crime that can (in part) be described by earlier or contemporaneous changes in economic predictors. The different predictors listed in Table 4 showed a range of lag times, from zero months to 15 months, with an average of around four and half months. At least some lag was included in around three quarters of cases, with just one quarter of cases showing zero lag time. Interestingly, predictors that may be expected to represent a closer proxy to direct economic stress on populations – such as unemployment rate – showed generally shorter lag times than predictors that concern the general economic situation more generally, such as share price. This did not, however, hold true in all contexts, with unemployment also showing longer lag times in a number of countries.

With respect to the economic indicators selected by the model, it is interesting to note that these were varied, and included share price index, unemployment rate, treasury bill rate, real income, lending rate, and GDP. As noted earlier in this report, emphasis need not be placed on the *particular* economic indicator selected. Possible mechanistic links between certain predictors (such as unemployment) and crime outcomes are of course easier to propose than for other predictors (such as share price index). However, all predictors are to some extent indicative of the underlying socio-economic situation and may act as effective proxy measures for levels of economic stress experienced by potential crime perpetrator populations.

Table 4 – Results from statistical modelling

Country	Geographic unit	Economic crisis (on visualization)	Crime type affected by economic crisis (on visualization)	Economic predictor and crime type combinations identified by statistical model
Argentina	Buenos Aires	✓ (in 2002)	-	Share price index – motor vehicle theft
Brazil	National	✓	n/a	Share price index and unemployment rate – motor vehicle theft
	Rio de Janeiro		Robbery, motor vehicle theft	Treasury bill rate – motor vehicle theft
	Sao Paulo		Homicide, robbery	Male unemployment rate – homicide, currency per SDR – robbery and motor vehicle theft
Canada	National	✓	n/a	Treasury bill rate and unemployment rate – homicide, share price index and unemployment rate – robbery, share price index and deposit rate – motor vehicle theft
Costa Rica	National	✓	Robbery	-
El Salvador	National	✓	Homicide	-
Italy	National	✓	Robbery, motor vehicle theft	Real income – homicide
Jamaica	National	✓	Homicide, robbery	-
Latvia	National	✓	-	Youth unemployment rate – homicide
Mauritius	National	✓	-	Real income – homicide, currency per SDR – robbery
Mexico	National	✓	Robbery, motor vehicle theft	Male unemployment – homicide and robbery
Philippines	National	-	-	Deposit rate and share price – robbery, share price – motor vehicle theft
Poland	National	-	-	Treasury bill rate – homicide and robbery
Thailand	National	✓	Motor vehicle theft	Unemployment rate – robbery, real income – motor vehicle theft
Trinidad and Tobago	National	✓	-	Real income and lending rate – homicide
Uruguay	Montevideo	-	-	GDP – robbery and motor vehicle theft

Overall, as discussed in this chapter, the statistical model appeared to match conclusions from visualization of data most effectively for *smaller* geographic units, such as cities. Rio de Janeiro and São Paulo, for example, feature among the contexts where the best-fit model included economic predictors, *and* an economic downturn and crime response could be inferred from visualization. It is likely that throughout a country, associations between economic factors and crime have *elasticities* (that is, response characteristics) that vary from place to place according to local conditions. Aggregation of these contexts into a single *national* figure may not therefore result in coherent analysis. These lessons suggest that statistical analysis may be best carried out at the local level and with the longest possible high-frequency data time series.

Selection of the analytical method

In light of both the need to identify whether a relationship may exist between economic factors and changes in crime series, as well as the need to predict likely future changes in crime variables, a statistical methodology based on autoregressive integrated moving average (ARIMA) modelling was chosen.

The ARIMA methodology generates a model that describes the evolution of the crime outcome variable. This model enables prediction of the current value in the crime time series based on the past observations of the crime series itself as well as past random errors. The model may also be extended to allow for current and past observations in economic time series to be included in the model as predictors. The process is essentially akin to 'curve fitting' through a generate-and-test approach and has become a popular time series method of forecasting that is widely used in many fields. One leading text on econometric analysis notes, for example, that "*… as a methodology for building forecasting models, this set of tools and its empirical counterpart have proved as good as and even superior to much more elaborate specifications*."[27]

ARIMA analysis can be carried out in SPSS statistical package using a built-in routine that is able to automatically select the optimal

Identifying time series relationships

In order to understand the rationale behind the statistical approach adopted, it is necessary to briefly examine approaches to statistical analysis.

Taking *non*-time series data as a starting point, the first standard approach to analysis of a relationship between two sets of data can be regression analysis. A regression model (whether linear, exponential or otherwise), together with a measure of goodness of fit could be used to demonstrate whether a relationship existed between the two variables. Where one was found, this would not necessarily be interpreted as causal in any sense.

When data are looked at over time, *time series* analysis can be undertaken to assess more complex relationships between the two variables which account for intrinsic properties of the variables (such as seasonality) and can evaluate if the two variables 'move together' over time in a *cointegration relationship*.[i] A cointegration relationship means that although two variables may wander extensively in time, they never drift too far apart. If series are found *not* to be cointegrated then the conclusion is that there is no long-term equilibrium equation that joins the variables together. In practice, finding a cointegration relationship between selected time series variables is not always possible. Indeed, such a relationship is not a common finding. Whilst a cointegration relationship cannot be taken as proof of causation, it is nonetheless an important indicator that variables are likely to be genuinely linked through some mechanism in reality. Previous analysis of car-jacking and unemployment in São Paolo for example is able to show a cointegration relationship between car-jacks, male unemployment, and the vehicle price index (as a proxy for the demand in illicit cars and parts).[ii]

Following initial examination of the time series data available from the fifteen countries in this project, it was decided that cointegration analysis would not be suitable in light of the number of countries and quality of data available. Based on the São Paulo experience, even with a plausible mechanistic hypothesis, limited geographic area, and specific and local economic data, *still* a third variable (a proxy for demand for illicit goods) was needed before a cointegration relationship could be demonstrated.

ARIMA models, introduced by Box and Jenkins (1970) in the context of economic forecasting, on the other hand, do not formally show the existence of such long-term equilibrium. They do, however, enable the combination of historical data to a flexible specification for the dynamics of the time series to produce a satisfactory model, combined with predictive capacity.[iii]

i Two or more series are cointegrated if they are individually integrated (of the same order) and there exists a linear combination of them which has a lower order of integration than the original series

ii Rizzi, R. (Department of Economics, Universidade de São Paulo) *Understanding how economic factors impact motor vehicle robbery: a time-series approach*. November 2010. Presentation at UNODC informal expert group meeting on monitoring the impact of economic crisis on crime

iii Box, George and Jenkins, Gwilym (1970) *Time series analysis: Forecasting and control*. San Francisco: Holden-Day

27 Greene, W.H. (2003) *Econometic Analysis* – 5th Edition, Prentice Hall, at p. 619.

ARIMA model. When the software is 'fed' with a police-recorded crime series such as robbery for a particular country, together with a number of economic series for that country (such as GDP, CPI, or unemployment), the routine is able to identify whether one or more economic indicators are able to improve the model in describing the crime time series.

Where this is the case, the ARIMA output will include the economic variable(s) as a *predictor* in the model equation.[28] Such inclusion means that the economic variable makes a statistically significant contribution to describing the monthly variation, or *fluctuation*, in the crime time series. It is in this sense that the term '*relationship*' is used in the aims of statistical analysis set out on page 24.

Comparing results from visualization and statistical modelling

Table 4 highlights the wide range of contexts in which a relationship may exist between economic factors and crime outcomes, both during times of crisis and non-crisis.

Table 4 also shows, however, results by individual crime – country/city combination. Sufficient crime and economic data were available for ARIMA modelling in 51 crime – country/city combinations. Out of these 51 combinations, the best-fit ARIMA model included an economic predictor in 24 cases, suggesting *some relationship* between crime and economic factors in around 47 percent of combinations investigated.

ARIMA, stationarity, and cointegration

A *stationary* time series is one in which the statistical properties of the series (such as the mean and variance) do not change over time. If time series are found to be stationary, ARIMA is appropriate for forecasting purposes. Where series are not stationary and a cointegration relationship exists, the application of ARIMA methodology is still possible, but differencing of variables may waste valuable information concerning long running equilibriums in the data. In such circumstances, the construction of an 'error correction model' (ECM) may be technically superior to the ARIMA methodology.

For the purposes of the analysis presented in this report, preliminary tests were carried out to examine the stationarity of data series. It was not possible to show that all series subjected to ARIMA analysis were in fact stationary (including after differencing for seasonality and possible transformation), and tests proved inconclusive for a number of countries. In these cases, the ARIMA methodology may be less than optimal if a cointegrating equation exists. Further analysis outside of the scope of this project would be required in order to determine whether the construction of an ECM would provide superior results. The table at Annex 3 to this report shows the outcome of unit root tests, the identification of economic predictors by the ARIMA model, as well as lag times, for each crime – country/city combination individually.

These 24 combinations occurred equally across the three crime types. An economic predictor was found in 8 cases for each of intentional homicide, robbery, and motor vehicle theft. There appeared to be no particular pattern in the distribution of economy-crime associations across country/city contexts. In some contexts, such as Canada, for example, the model identified an economic predictor for each of homicide, robbery and motor vehicle theft. In other contexts, such as Thailand or the Philippines, the model identified economic predictors in only one or two crime types.

The model was not, however, always effective at identifying economic predictors for combinations where a peak in a particular crime type had already been noted by visualization. Out of the 14 individual crime – country/city combinations where visualization suggested some impact on a

[28] The inclusion/non-inclusion of an economic predictor by the ARIMA routine in practice is subject to some methodological disadvantages. In particular, where crime seasonality is high, the ARIMA routine is frequently able to describe the series based on seasonal effects alone (without the need for inclusion of economic predictors), *even if* the seasonal effects are associated in practice with underlying economic factors. In addition, due to differencing by the model, it does not reflect situations where a long-running trend is associated with underlying economic factors. This means that the model can be considered generally cautious on the inclusion of economic predictors. The non-inclusion of an economic predictor does not, as such, rule out that the economic variable is in some way associated with the crime series.

particular crime type during the 2008/2009 financial crisis, ARIMA modelling identified an economic predictor for that particular combination in just five cases. These are highlighted in the table in Annex 3:

(i) robbery in Mexico (male unemployment, lag = 0 months);

(ii) motor vehicle theft in Rio de Janeiro (treasury bill rate, lag = 8 months);

(iii) motor vehicle theft in Thailand (real income, lag = 0 months);

(iv) homicide (male unemployment rate, lag = 1 month) in São Paulo; and

(v) robbery (currency per SDR and treasury bill rate, lag = 3 months) in São Paulo.

This means, for these five particular combinations:

- a period of economic downturn in 2008/2009 can be visualized from economic indicators;
- the particular crime type shows a peak during the period of economic downturn on visualization; and
- one or more economic variables (listed above) are included as a predictor by the ARIMA for that crime series, including the period of 2008/2009 crisis

Each of these combinations makes some theoretical sense. Robbery in Mexico, for example, was some 20 percent higher in the third quarter of 2009 than in 2007, whilst male unemployment was some 80 percent higher. Motor vehicle in Thailand was around 30 percent higher at the start of 2009 than at the start of 2007, with real income having dropped by about 7 percent over the same time period. Police-recorded robbery was around 20 percent higher in average throughout 2009 in São Paulo than in 2007. Negative GDP growth was experienced by Brazil in 2009 with rising interest rates and currency per SDR up until the end of 2008. Lag times selected by the model were generally shorter for predictors such as unemployment and real income and longer for more general 'economic health' predictors such as lending rates. The inclusion by the ARIMA model of economic predictors in these circumstances confirms that such economic changes may be associated with changes in crime outcomes. Whilst the model cannot explain the underlying mechanism, the results indicate that it is possible to identify economy-crime relationships in time series data that includes specific situations of economic crisis.

In the other 9 crime – country/city combinations where visualization suggested that a period of economic crisis may have led to changes in crime, the ARIMA process unfortunately did not select a best-fit model that included any economic predictors. Reasons for this could include the possibility that economic factors did not play a significant role in crime outcomes during the 'non-crisis' period of the crime series analysed by the model. Alternatively, it may be possible that a 'peak' seen on visualization during the time of economic crisis was not in fact significantly greater than the usual month to month crime fluctuation. As described in Annex 3, the model is sensitive to the time period of analysis and it may be that different results would be achieved either where a longer time series is available, or indeed, by focusing more specifically on the time of economic crisis.

Finally, it is notable that three out of five of the particular combinations in which the results from statistical modelling and visualization match well are *city* contexts. This suggests that the relationship between economic factors and crime may be strongest when viewed at the level of smaller, urban, geographic units. This may be due to the fact that economic hardship could be more closely related to motivations to commit crime in urban than in rural areas. Alternatively, or in addition, focusing on the smaller city level rather than the country level could provide a more homogenous population of potential offenders who may tend to act more similarly than the whole population of potential offenders at national level. As such, aggregation of different *elasticities* of the economy-crime relationship at national level may result in loss of important relationship information visible only at a more local level.

Conclusions from ARIMA modelling

The ARIMA results indicate clearly that, across a range of contexts, at both country and city level, and whether economic crisis occurs or not, economic factors likely play a role in describing the evolution of specific crime series. In contexts where time series data included a period of economic crisis in 2008/2009, the model identified economic predictors for crime outcomes in eight out of eleven countries, suggesting that crime levels are an important phenomenon to be monitored during period of crisis.

This knowledge could be used to advocate for the development of policies to lessen the impact on crime during times of economic crisis. When it comes to specific crime policy making, however, the important questions (having identified contexts where economic factors may play a role in crime evolution) are: *how much* do economic changes affect crime, and can knowledge of economic factors be used to predict crime changes? The next section of this report considers the possibilities for crime forecasting in this context.

Forecasting crime trends

The ARIMA methodology is especially suitable for *forecasting* of possible future developments in a crime series, based on the best-fit model. In particular, where the best-fit model includes an economic predictor for a crime – country/city combination, *known* changes in economic variables can be used to forecast possible evolutions in the particular police-recorded crime series. In such cases, the forecast is based both on the past trend in the crime series itself, as well as on the effect of economic variable.

In order to test the forecasting capability of the ARIMA models, the final *three months* of the crime series were removed for each of the 24 crime – country/city combinations where an economic predictor was identified. The ARIMA model was then used together with the economic predictor(s), to forecast ahead for three months. The resulting forecast was compared with the known actual series. This section presents four examples of forecast results.

Results of crime forecasting

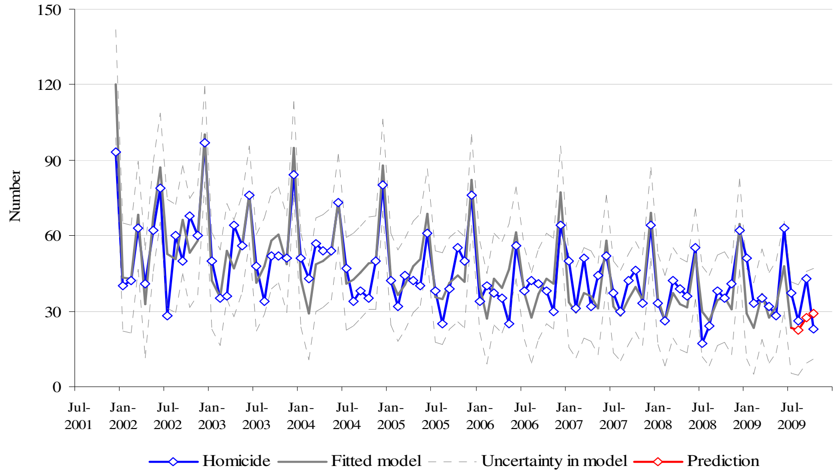
Comparison of crime forecasts with actual observed crime values suggests that:

- Forecasting for a period of three months using the ARIMA model with economic predictors proved possible with reasonable accuracy (both in terms of direction and magnitude) in a number of different contexts, including both in times of crisis and non-crisis. Many of the forecasts are sufficiently accurate to be of value in a practical scenario. Forecasts much longer than a few months, however, generated confidence limits too large to be of practical use;
- Frequent underestimation of the magnitude of crime changes on a monthly basis by the ARIMA model suggests, however, that there are other factors affecting crime outcomes. As such, crime forecasts also sometimes led to underestimation in predicting crime changes based on economic predictors alone;
- As with the generation of ARIMA models overall, forecasting may work best in limited geographic areas when a plausible hypothesis can rationally explain a potential economy-crime association;
- Where a high degree of seasonality exists in a crime series this can aid at least in the directionality (if not the magnitude) of forecasts due to knowledge of the past seasonal evolution of the crime trend;
- Where the statistical model has not had the chance 'to learn' from a period of economic crisis, forecasts may not necessarily be accurate during subsequent periods of crisis that are outside of the range of experience of the model. Certain economic predictors may become more or less important during extreme economic conditions;
- As with statistical models in general, forecasts do not identify causality in outcomes. It is possible that feedback mechanisms (such as high crime levels leading to closure of businesses and increased unemployment) exist in practice that can lead to inaccurate forecasts.

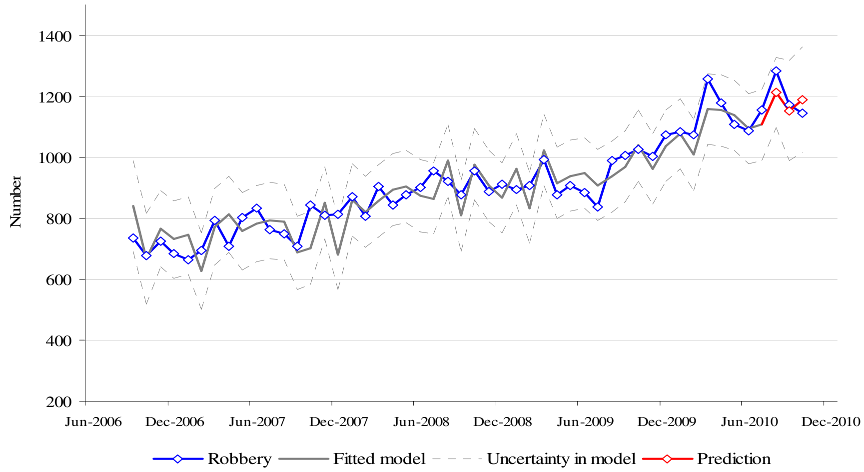
Figure 8 shows predictions for a number of example contexts, including where no period of economic crisis was identified, where a period of economic crisis occurred during long-running existing trends, and using city, rather than national data, following a period of economic crisis. The individual forecast plots correspond to intentional homicide in Poland, robbery in Uruguay, motor vehicle theft in Buenos Aires, intentional homicide in Mexico, and robbery in São Paulo. In each case, the actual crime series data is shown in blue, the ARIMA best-fit model in grey, and 95% confidence intervals for the model as dotted lines. A three month forecast, produced by removing the last three months of crime data but allowing the model to use economic data for these months, is shown in red.

Figure 8 – Crime forecasting

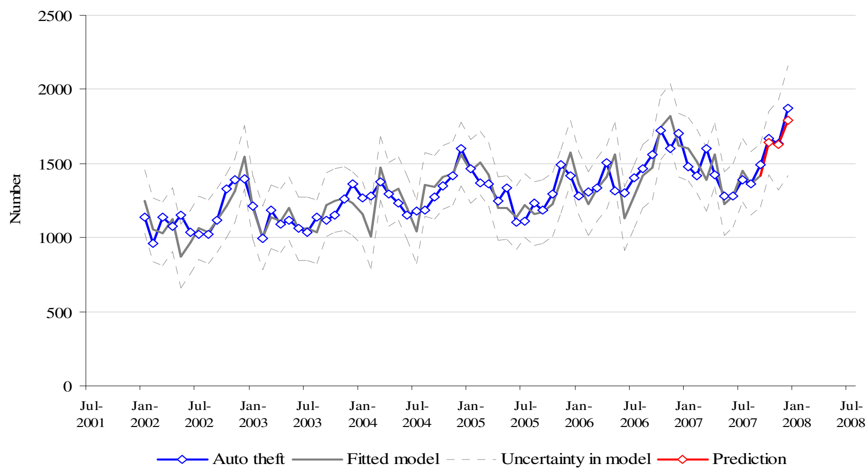
Poland, intentional homicide



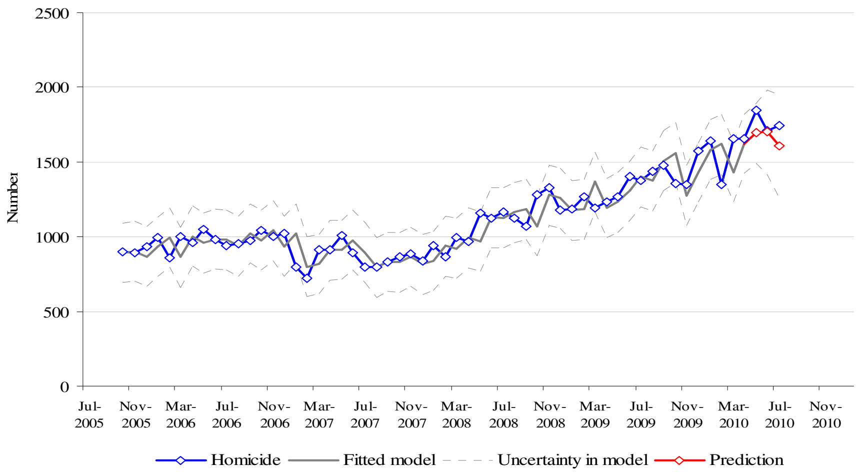
Uruguay, robbery



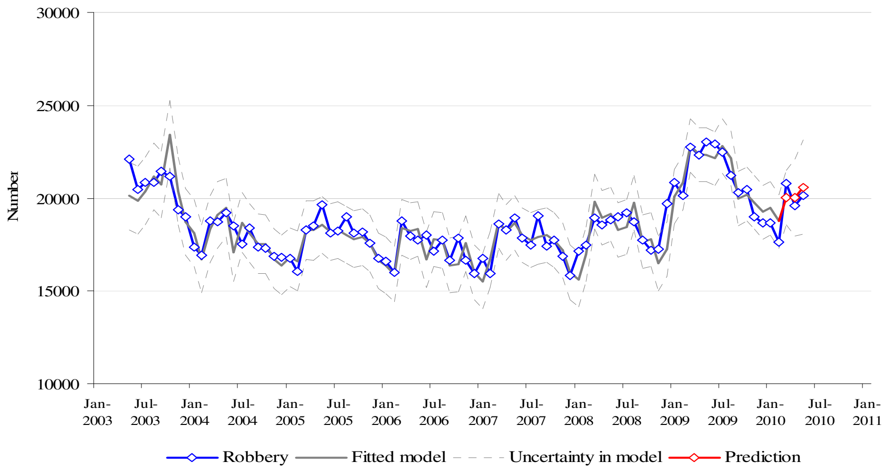
Buenos Aires, motor vehicle theft



Mexico, intentional homicide



São Paulo: robbery



As Figure 8 demonstrates, each example forecast shows a reasonable degree of accuracy when compared with the actual crime series. In two cases (Buenos Aires and São Paulo) the forecast matches the actual series extremely well, both in terms of direction and magnitude. Forecasts in Poland, Uruguay and Mexico, whilst correctly predicting the direction of the crime trend, do suffer somewhat from errors in the *magnitude* of crime changes. In all three countries, the forecasts underestimated a crime peak during the three month period of forecast. Underestimation of crime peaks by the model almost certainly points to the involvement of additional factors (not included in the model) that lead in practice to higher crime levels than predicted by the economic coefficient and seasonal changes alone.

The model and forecast for Buenos Aires is interesting as, although it includes a period of acute economic crisis in 2002, no particular impact on motor vehicle thefts was observed, *despite* the inclusion of an economic predictor. Using the economic predictor and crime trend history, the three month forecast continues to match very well the observed series. This could mean – in this particular context – that the crime response elasticity to economic change is valid only up until a certain limit, where after severe economic conditions do not have any further impact on crime. This may be due to the engagement of alternative coping mechanisms or specific state responses (such as increased police presence) in times of real crisis. Such mechanisms would have the effect of limiting the impact of economic crisis on crime. Of course, such results must be interpreted with caution. In addition to any impact on underlying crime levels, economic factors may impact on the police crime recording process itself. This may be either through a direct effect on levels of police resources, or through indirect effects, such as the level of motivation and diligence of police officers.

The case of Mexico is also interesting as analysis of the particular crime of intentional homicide in Mexico with respect to possible underlying economic factors may, at first glance, be somewhat surprising. Much has been reported in the media globally about the impact of drug-related violence on homicide rates in Mexico.[29] Data released by the Government of Mexico demonstrate that homicides linked with organized crime are largely responsible for an overall rise in homicide rates in Mexico in recent years.[30] With this additional factor to be taken into account, it may perhaps be expected that associations between homicide and economic factors are either not strong, or are concealed by changes in the level of conflict between drug-trafficking groups or in the level of anti-drug law enforcement activity.

Nonetheless, the best-fit ARIMA model suggests that there is some association between intentional homicide and at least one economic factor (male unemployment) in Mexico. Figure 8 confirms that the model is able to produce a reasonable forecast for the homicide trend in the last three months of the data series. It should of course be remembered that the economic factor is only *one component* of the model. Its inclusion in the best-fit, however, does indicate that it makes a significantly statistical contribution to the description of the homicide series.

A number of explanations may be advanced for this association. It is likely that the connections between homicide and male unemployment in Mexico are multi-directional and highly local. Data from the Government of Mexico indicate that some 8 municipalities were responsible for over 40 percent of organized-crime related homicides nationally in the first six months of 2010. Organized crime-related homicides, in turn accounted for almost 70 percent of *total* homicides in the country during the same period.[31] The average unemployment rate in the states containing these municipalities was around 20 percent higher than the national average during the year 2009.[32] Challenging economic conditions in these districts may be one reason why young men join groups involved in drug-trafficking. It may also be a driver of restructuring within criminal groups and resultant conflict over territory and drug routes, as individuals break away in a bid to make more profit. Perhaps almost as likely, however, is that extreme levels of drug violence in these particular districts are themselves responsible for reduced local investment, closure of shops and businesses, and subsequently higher levels of unemployment. At the national level, those homicides that are not linked with organized crime or drug activity (around 30 percent of total homicides) may be associated with higher unemployment in so far as economic stress can increase levels of tension and conflict within society in general.[33] As such, the association identified through statistical modelling may represent a complex interplay between homicide and unemployment in Mexico, where neither factor is clearly the *dependent* or *in*dependent variable.

[29] See for example, http://www.bbc.co.uk/news/world-latin-america-10681249
[30] http://www.presidencia.gob.mx/base-de-datos-de-fallecimientos/
[31] UNODC calculation from data provided by Presidencia, base de datos de fallecimientos, and INEGI.
[32] UNODC calculation from http://www.inegi.org.mx/Sistemas/temasV2/Default.aspx?s=est&c=25433&t=1
[33] See for example World Bank, World Development Report 2011, at p. 79

Assessing the impact of economic predictors

The examples demonstrate that where economic data is known and is included in a best-fit ARIMA model, this can be used (together with information from the historic crime series) to forecast possible evolutions in the crime trend. In the examples presented, the ARIMA model includes a lag of some 4 to 14 months between changes in economic and crime variables.

Where a lag of a few months or more exists, ARIMA modelling may be particularly useful for crime forecasting in practice as a forecast for the next month would not require economic data for that month. As long as crime data for the present month were available together with economic data up to the lag point, then the model could be used to forecast possible evolutions in crime in the next month. From a policy and law enforcement operational perspective, this could prove useful in decisions such as allocation of police resources or deployment of specific crime prevention measures. Such measures may include situational prevention through increased police patrols in identified crime 'hot-spots', intensive community work with known at-risk groups, or awareness raising amongst neighbourhood watch and business premises security cooperation schemes.

In addition to short-term forecasting for possible crime trend changes in the coming months, the development of long-term policies can also be informed by knowledge of *likely* crime responses *in the event of* certain economic changes. Where an economic variable is included in the ARIMA model, 'what if' analysis can be carried out to estimate the likely impact on a particular crime in response to, for example, an x percent increase or decrease in the economic predictor.

Figure 12 below shows an example using a context already presented in this report, that of motor vehicle theft in Buenos Aires. The best-fit ARIMA model for this context identified one economic variable – share price index – as representing a statistically significant improvement to the model. As discussed earlier in this report, this should not be interpreted to mean that there is a clear relationship (let alone a causal relationship) between changes in share price and motor vehicle theft in Buenos Aires. Rather, share price index likely functions as a generic proxy indicator for confidence in the economy and hence of overall economic health. When share prices fall substantially overall, it is possible that at least some of the enterprises comprising the index are experiencing possible reductions in the labour force and reduced output.

In order to model the effect of the economic predictor on motor vehicle theft, forecasts were generated based on a consecutive 5 point increase per month in share price index, and on a consecutive 5 point decrease per month in share price index. The ARIMA model for Buenos Aires includes a 4 month lag before the economic predictor influences the motor vehicle theft outcome variable.

Figure 12 – 'What if' analysis: Buenos Aires: motor vehicle theft

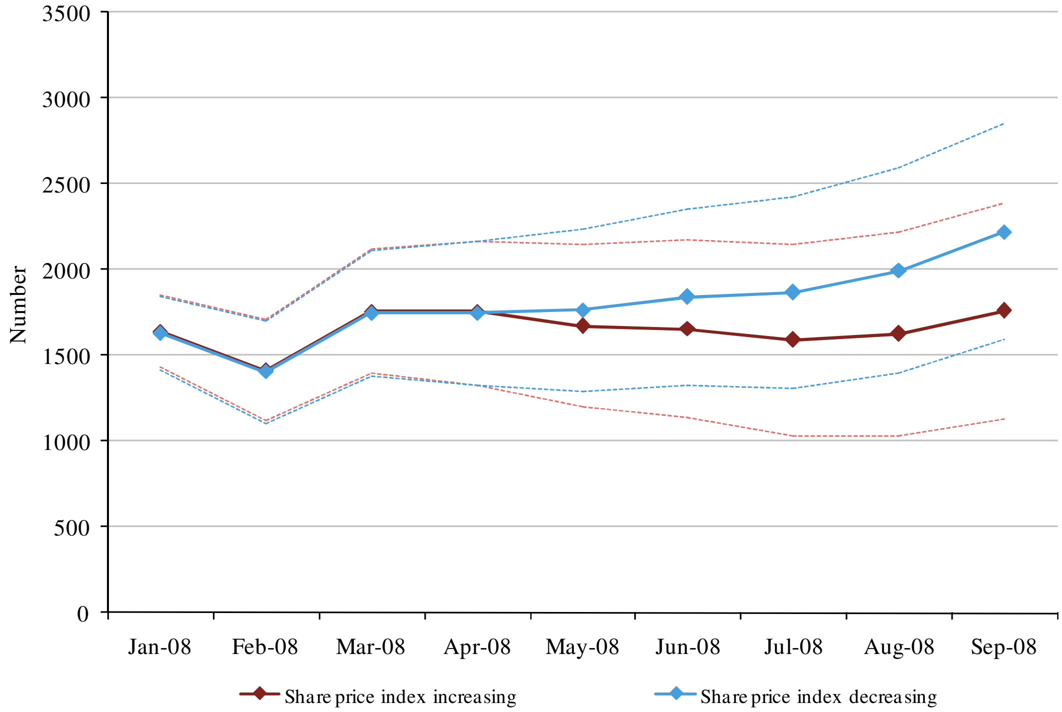


Figure 12 shows that the forecast for both increasing and decreasing share price index continues identically for four months until the lag time is complete. Thereafter, in the next month, the forecast for numbers of motor vehicle theft based on *decreasing* share price index is around 6 percent higher than for *increasing* share price index. After five months, the difference has risen to over 25 percent.

Such estimations can be useful for informing long-term policies that aim at making crime less sensitive to economic factors, through social, education, immigration and labour market improvement. In this respect, the ability to conduct such 'what if' analysis for a number of countries can also create opportunities for exchange of experience, ideas and policy strategies.

Conclusions and next steps

In light of the theoretical connections between economic stress and crime, the aims of this report were:

- to **identify** and **raise awareness** at global, regional and national level of the possible effects of economic stress on crime; and
- to work towards a **predictive capacity** for such effects at country level

To this end, the report described analysis undertaken on high frequency (monthly) police data for intentional homicide, robbery and motor vehicle theft, in 15 different country/city contexts.

Key findings

- Whether in times of economic crisis or non-crisis, economic factors may play an important role in the evolution of crime trends. Out of **fifteen** countries examined in total, a statistical model identified an economic predictor for at least one crime type in **twelve** countries, suggesting some overall association between economic changes and crime in these countries.

- Of the **fifteen** countries included in the analysis, visualization of data suggests that **eleven** countries showed significant changes in economic indictors during the period 2008/2009 that may tentatively be termed economic 'crisis'. Both visual inspection of data series and statistical modelling suggest that in **eight** of these eleven 'crisis' countries, changes in economic factors were associated with changes in crime, leading to identifiable increases in at least one crime type during the period of crisis.

- Violent property crime types such as robbery appeared most affected during times of crisis, with up to two-fold increases in some contexts during a period of economic stress. However, in some contexts, increases in homicide and motor vehicle theft were also observed. In no case where it was difficult to discern an increase in crime in response to crime was any *decrease* in crime observed. The available data do not therefore support a hypothesis that economic crisis can lead to crime downturns.
- Where an association between one or more economic variables is identified by statistical modelling, the model frequently indicates a **lag time** between changes in the economic variable and resultant impact on crime levels. The average lag time in the contexts examined was around **four and half months**.
- Statistical modelling at the national and city level proved useful for the generation of forecasts in crime trends up to around **3 months** in advance, using information from the previous crime trend and changes in economic variables. The accuracy of forecasts in many cases was suitable for use in practice.

Towards ongoing monitoring

The analysis presented in this report indicates that, across a range of country/city contexts, in different regions of the world, economic downturn has the potential to result in short term crime increases over and above prior long-running trends. Crime increases are not automatic, however, and in some countries that showed clear signs of economic stress in 2008/2009, there was no discernible impact on crime. There may be many reasons for this, including differing profiles of offenders and potential offenders for particular crime types in different contexts, and the existence of effective crime prevention strategies that are engaged as economic conditions worsen. In addition, it must be remembered that analyses carried out with police-recorded crime data are subject to the continued reporting and effective recording of crime events throughout times of economic crisis.

As may be expected from a criminological perspective, increases in violent acquisitive crime such as robbery are most often identified during times of economic stress. However, changes in levels of homicide and motor vehicle theft are also observed in some contexts. Statistical modelling confirms that changes in crime trends may be associated with changes in economic factors, whether during periods of economic crisis or in times of 'usual' economic activity. The statistical technique used for analysis, found some association in around 80 percent of countries examined. This finding should be sufficient to advocate for further research and analysis on the possible effects of economic crisis on crime. The particular statistical technique used should not be regarded as conclusive, however, as it suffers from a number of constraints on its application. These include challenges where data are non-stationary, and a sensitivity to the particular time series used for analysis. In addition, although the technique may be suitable for forecasting short-term changes in crime trends, it does not provide formal identification of a long running relationship between crime outcomes and economic factors.

Nonetheless, the methodology and analysis described here can represent a good starting point for the development of ongoing monitoring at national level. Early on in the analysis it became clear that the production of a global or regional model for monitoring the effect of economic change on crime would not be possible within the time and budget constraints of the project. However, the statistical approach has been demonstrated to function in many national and city contexts. The development of a cross-national early-warning monitoring system will require the establishment of regular (monthly) data reporting on crime types of interest by national authorities, together with the completion of time series analysis and forecasting using national/city datasets. Information on the evolution of crime trends and results of analysis would represent a valuable resource both at national level and when shared more widely with neighbouring countries or the international community at large.

The United Nations Office on Drugs and Crime has taken steps towards the development of an online data portal for such data reporting and is currently at the stage of portal testing with the countries for which data is presented in this report. In light of the often sensitive nature of police-recorded crime data, the portal will need to address concerns of data security and levels of data sharing. Country contacts for crime and criminal justice statistics often change and this can be one important obstacle to the exchange of information and international cooperation in this field. The establishment of a clear procedure for reporting of data through the portal using 'country' logins with different levels of access would assist in this respect through the provision of clear, sustainable, reporting channels. Once the mechanisms for data reporting is fully functioning, the challenge will be to further develop the statistical methodology and to develop a sustainable capacity of ongoing analysis, forecasting, and facilitation of results sharing amongst countries by the international community. Whilst the ARIMA methodology is suitable in many ways, further expert input will be required in order to refine the statistical approach and to maximize the quality of outputs. In addition, thought must be given to national capacity and training needs for conducting statistical analysis and to the policy-relevance and use of results.

The experience of data collection and analysis in the context of this project also highlights the need to build and further strengthen crime statistics management capacities to support the integration of crime statistics systems and to ensure a more efficient collection of crime statistics at the local, national and international level. In this respect, analysis and forecasting of the impact of crisis on crime is dependent upon the availability of timely, accurate and reliable, high frequency monthly data. Collecting, managing and analysis such data requires a high degree of specialisation and may pose a particular challenge to administrations facing resource constraints. The project demonstrates, however, that there is scope to use standard processes and analytical models that can be applied with comparatively little resources. The sharing of crime statistics with other countries and the international community can also provide a means to improving data comparability, increasing research activity, and to the development of evidence-led crime prevention policy.

In addition, the project experience points to a need to support the development and use of international standards for crime data collection and exchange. Alignment of national standards with the most commonly used international standards allows minimisation of costs related to reporting and enables countries to take advantage of cross-national exchange of data and best practices in the field of crime statistics analysis and crime prevention. Development and adoption of relevant international standards – such as data format standards – can greatly improve the value of analytical models insofar as they open up models to as wide a number of countries as possible.

Although the challenges remain significant, this report demonstrates that – with comparatively few resources – a lot may be learned from the application of analytical techniques to existing data. Continued methodological development, as well as the strengthening of exchange of information and experience, between countries, has the potential to lay the foundation of a strong 'early-warning' system. The analysis reported here does *not prove* the existence of relationships between economic factors and crime. It does provide strong indications that certain associations are present, and that much may be gained from further investigation. If the impact of economic stress on crime trends can be further understood, and even forecasted in the short-term, then there is the potential to gain much through policy development and crime prevention action.

Annex 1 – Crime series metadata

Challenges to cross-national analysis of crime data

The metadata below show that a number of differences in the content and recording methodology of crime data as between countries exist. In particular:

- Countries show significant variation as to the inclusion of 'assault leading to death', 'infanticide', and 'killings by police' in police-recorded intentional homicide statistics;
- At least two countries include acts of attempted robbery in data on recorded robbery;
- At least two countries include 'receiving/handling a stolen vehicle' in data on motor vehicle theft;
- Counting units differ between 'offence' and 'victim' for the crime of intentional homicide;
- At least four countries reported significant breaks in the time series due mostly to changes in police-recording rules; and
- The month in which an offence is recorded (whether the month of reporting or the month in which it was believed to have taken place) varied as between countries.

Such differences mean that direct cross-national comparison of police-recorded crime statistics from the different countries must be conducted with caution. The inclusion/non-inclusion of a range of distinct criminal acts (such as muggings, pick-pocketing, or extortion) in police-recorded 'robbery' for instance, may mean that figures for robbery are affected in different ways by the same underlying factor, or by different underlying factors, as between countries. Similarly, where the time delay between reporting of an offence and recording in statistics varies between countries, apparently simultaneous changes in crime levels may in fact be unrelated, even though such patterns could appear, at first glance, to be linked.

Differences in the content and methodology of data must, in particular, be considered carefully when conducting analysis at the *global* or *regional* level. Indeed, modelling of national crime and economic data at global or regional level already presents a significant challenge, even before data methodology differences are taken into account. During periods of 'global' or 'regional' economic crisis, different countries may be affected at different times, in different ways, and to different extents. The analytical challenge is heightened by the comparability difficulties of police-recorded crime data discussed above. Where differences in the content and methodology of crime data are present, 'like-for-like' are not directly compared. Upon aggregation of data from a number of countries, factors such as different time lags between a crime event and recording may either risk cancelling out real underlying trend changes, or even generating statistical artefacts that are not reflective of reality.

Nonetheless, as mentioned above, an understanding of data differences is an important first step in any piece of cross-national research. Any future work on a global, regional or cross-national comparative analysis of crime and economic stress will need to build on the metadata presented in Annex 1 with a view to generating data series that are further harmonized and more directly comparable.

Intentional Homicide

Means death deliberately inflicted on a person by another person, including infanticide and excluding attempts

		Brazil	Canada	Jamaica	Mauritius	Mexico	Philippines	Uruguay
Do data comply with the definition?		YES	YES	YES	YES	YES	NO[34]	YES
Included?	Attempts	NO	NO	NO	NO	NO	NO	NO
	Assault leading to death	NO[35]	YES	NO	NO	YES	YES	YES
	Euthanasia	NO	NO	YES	NO	NO	NO	YES
	Infanticide	NO	YES	YES	YES	YES	NO	YES
	Assistance with suicide	NO	NO	NO	NO	NO	NO	NO
	Killings by police	NO	NO	YES[36]	NO	YES	NO	YES
	Traffic deaths	NO	-	NO	-	NO	NO	NO
	Felony murder	NO	-	NO	-	YES	N/A	NO
	Manslaughter	NO	-	NO	-	NO	N/A	YES

Robbery

Means the theft of property from a person, overcoming resistance by force or threat of force. Where possible, the category "Robbery" should include muggings (bag-snatching) and theft with violence, but should exclude pick pocketing and extortion.

		Brazil	Canada	Jamaica	Mauritius	Mexico	Philippines	Uruguay
Do data comply with the definition?		YES	YES	YES	YES	YES	NO	YES
Included?	Attempts	NO	YES	NO	YES	NO	NO	NO
	Muggings	YES	YES	YES	YES	YES	YES	NO
	Theft	YES	NO	YES	YES	YES	YES	YES
	Pick- pocketing	NO	NO	NO	NO	NO	NO	NO
	Extortion	NO	NO	NO	NO	NO	YES	NO
	Blackmail	NO	NO	NO	NO	NO	YES	NO

34 The term 'murder' rather than intentional homicide is used in the Philippines

35 Assault leading to death and robbery leading to death are recorded separately in Brazil

36 Only killings declared not to be in the line of duty by the Director of Public Prosecutions in Jamaica are included

Motor vehicle theft

Means the removal of a motor vehicle without the consent of the owner of the vehicle. "Motor Vehicles" includes all land vehicles with an engine that run on the road, including cars, motorcycles, buses, lorries, construction and agricultural vehicles.

		Brazil	Canada	Jamaica	Mauritius	Mexico	Philippines	Uruguay
Do data comply with the definition?		YES	YES	YES	YES	YES	NO	YES
Included?	Attempts	NO	NO	NO	NO	NO	NO	NO
	Joyriding	YES	YES	NO	NO	YES	NO	NO
	Theft of motorboats	YES	YES	YES	YES	NO	YES	NO
	Theft of motorcycles	YES	YES	YES	YES	YES	YES	YES
	Theft of commercial vehicles	YES	-	YES	-	YES	YES	YES
	Receiving / handling a stolen vehicle	NO	NO	NO	NO	YES	NO	YES
Data coverage								
		Brazil	**Canada**	**Jamaica**	**Mauritius**	**Mexico**	**Philippines**	**Uruguay**
Do data cover the entire geographical area of the country?		YES[37]	YES	YES	NO[38]	YES	YES	NO[39]
Population of geographical area to which data relate		-	-	2,698,800	-	108,396,211	94,388,044	1,359,808
Number of individual police units (stations) reporting		-	-	164	-	32	1509	24
Do data include offences and suspects recorded by all police forces in the country?		NO[40]	YES	YES	YES	YES	NO[41]	YES
Do data include offences and suspects recorded at both federal and state level?		YES	YES	YES	N/A	NO[42]	NO[43]	YES

37 Data were received for Brazil at the national level and separately for Sao Paolo and Rio de Janeiro

38 Data exclude the island of Rodriques

39 Data relate to Montevideo only

40 Data from the military police of Brazil are excluded

41 Data from the National Bureau of Investigation in the Philippines are excluded

42 Data relate only to State level, but Federal offences are very limited and include only those related to Federal property or homicide of high level Federal public servants

43 Data correspond to those reported by regional to municipal level police units

Recording methods

		Brazil	Canada	Jamaica	Mauritius	Mexico	Philippines	Uruguay
Counting unit for:	**Intentional homicide**	VICTIM[44]	OFFENCE	VICTIM	OFFENCE	VICTIM	OFFENCE	CASE
	Robbery and motor vehicle theft	CASE	OFFENCE	OFFENCE	OFFENCE	OFFENCE	OFFENCE	CASE
Was there any significant break in the series from 1990-2010?		NO	YES	YES	YES	NO	YES	NO
From 1990-2010 was there any change in:	**Definitions of offences**	NO	NO	NO	NO	NO	NO	NO
	Police-recording rules	NO	YES[45]	NO	NO	YES[46]	YES[47]	NO
	Geographic units reporting the offences	NO	NO	NO	NO	NO	NO	NO
Is a principle offence rule applied?		YES	NO	YES	YES	YES	YES	YES
How are multiple (serial offences counted)?		UNCERTAIN	AS TWO OR MORE OFFENCES	AS TWO OR MORE OFFENCES	AS TWO OR MORE OFFENCES	AS TWO OR MORE OFFENCES	UNCERTAIN	AS TWO OR MORE OFFENCES
How are offences recorded?		An offence is recorded in data for the MONTH in which it was REPORTED to the POLICE	-	An offence is recorded in the data for the MONTH in which it was believed to have TAKEN PLACE	-	An offence is recorded in data for the MONTH in which it was REPORTED to the POLICE	An offence is recorded in data for the MONTH in which it was REPORTED to the POLICE	An offence is recorded in the data for the MONTH in which it was believed to have TAKEN PLACE
If offences are recorded in a month during or after the investigation, what is the average time delay between reporting and recording?		-	-	Less than 1 month	-	Less than 1 month	-	Less than 1 month
Are monthly figures corrected if necessary later?		YES	-	YES	-	NO	YES	YES
If so, how is this done?		OTHER	-	UNCERTAIN	-	-	UNCERTAIN	The offence is subtracted from the month to which it was originally assigned

44 Counting unit for homicide varies from state to state in Brazil

45 Prior to 1998, robbery was counted as the number of victims. After 1998, robbery was counted as the number of incidents

46 Each state has a different criminal code and different recording rules. It cannot be excluded that changes were made during the period

47 A new unit crime periodic reporting was introduced in 2009 resulting in an increase in the number of recorded offences from that date

Annex 2 – Detailed results of statistical modelling

A model of 'Simple Seasonal' or 'Winters' Multiplicative' indicates that the inclusion of economic variables did not sufficiently improve the model for it to be selected as the best-fit. Where the best-fit model *did* include one or more economic predictors, these are provided in the table in bold text.

Country or city	Crisis by visualization	Relationship by visualization	Intentional homicide		Robbery		Auto theft	
			Time series	Model (lag, months)	Time series	Model (lag, months)	Time series	Model (lag, months)
Brazil	✓	Insufficient data	Stationary	Simple Seasonal	-		Inconclusive	(1,1,0)(0,1,0) **Share price index (7)** and possibly **unemployment rate (2)**
Buenos Aires	✓ (in 2002)	-	Inconclusive	Winters' Additive	Inconclusive	Simple Seasonal	Inconclusive	(0,1,0)(0,1,0) **Share price index (4)**
Canada	✓	Insufficient data	Stationary	(0,0,6)(0,0,0) **Treasury bill rate (13) Unemployment rate (1)**	Inconclusive	(1,0,0)(0,1,1) **Share price (0) Unemployment rate (2)**	Inconclusive	(0,0,0)(0,0,0) **Share price (1) Deposit rate (15)**
Costa Rica	✓	R	Inconclusive	Simple Seasonal	-	Simple Seasonal	-	Simple Seasonal
El Salvador	✓	H	Stationary	Simple Seasonal	-		-	
Italy	✓	R, M	Inconclusive	(0,1,1)(0,0,0) **Real income (5)**	Stationary	Winters' Additive	Inconclusive	Simple Seasonal
Jamaica	✓	H, R	Inconclusive	Simple Seasonal	Inconclusive	Simple Seasonal	-	
Latvia	✓	R	Inconclusive	(1,0,1)(0,0,0) **Youth unemployment rate (1)**	Inconclusive	Winters' Additive	Inconclusive	Winters' Multiplicative
Mauritius	✓	-	Inconclusive	(0,0,0)(0,0,0) **Real income (8)**	Inconclusive	(0,0,2)(0,0,0) **Currency per SDR (0)**	Stationary	Simple Seasonal
Mexico	✓	R, M	Inconclusive	(0,1,0)(0,0,0) **Male unemployment (8)**	Inconclusive	(0,1,0)(0,1,0) **Male unemployment (0)**	Inconclusive	Simple Seasonal
Philippines	-	-	Inconclusive	Simple Seasonal	Inconclusive	(2,1,5)(0,1,1) **Deposit rate (5) Share price (5)**	Inconclusive	(0,1,0)(0,1,0) **Share price (9)**
Poland	-	-	Inconclusive	(0,0,0)(0,1,1) **Treasury bill rate (13)**	Inconclusive	(0,1,1)(0,1,0) **Treasury bill rate (5)**	Inconclusive	Winters' Multiplicative
Rio de Janeiro	✓	R, M	Inconclusive	Simple Seasonal	Inconclusive	Simple Seasonal	Stationary	(1,1,0)(0,0,0) **Treasury bill rate (8)**

Sao Paulo	✓	H, R	Inconclusive	(0,1,2)(1,1,0) **Male unemployment rate (1)**	Inconclusive	(0,1,0)(0,1,1) **Currency per SDR (3)** and possibly **treasury bill rate**	Inconclusive	(0,1,1)(0,1,0) **Currency per SDR (9)**
Thailand	✓	M	Inconclusive	Simple Seasonal	Inconclusive	(0,1,1)(0,0,0) **Unemployment rate (12)**	Inconclusive	(1,0,0)(1,0,1) **Real income (0)**
Trinidad and Tobago	✓	-	-	(0,0,0) non-seasonal **Real income (0)** **Lending rate (0)**	-	Winters' Additive	-	Simple Seasonal
Uruguay	-	-	Inconclusive	Simple Seasonal	Inconclusive	(2,1,0)(0,1,0) **GDP (2)**	Stationary	(0,1,0)(0,1,0) **GDP (0)**

Crime codes: H, Intentional homicide; R, Robbery; A, Auto theft

Highlighted squares correspond to specific crime-country/city contexts where a period of economic crisis *and* an impact on the specific crime type is apparent from visualization *and* the best-fit ARMA model includes at least one economic predictor

Stationarity was checked for crime time series data with a constant only and with constant plus time trend terms. Time series could be made stationary within an ARIMA model by seasonal differencing or transformation, but in this case stationarity was not formally tested. In such cases, stationarity is labelled as "inconclusive".

It is important to stress that the results presented in the table above are in no way intended to be definitive. The best-fitting model was found to be highly sensitive to the time period used in the identification of the model, including with respect to which economic variables were selected as significant, or even if any were. The instability of the model demonstrates that although ARIMA is an appropriate and accepted approach to forecasting, it is not necessarily always an optimal method for the clear identification of association between crime and economic factors. As noted in this report, a rigorous, formal proof of a time series relationship between non-stationary variables involves the application of cointegration analysis. Nonetheless, the models generated by ARIMA analysis, whether including economic indicators or not, do fit the evolution of the country/city crime series examined reasonably well and, as discussed below, can have some value for forecasting purposes. Annex 4 shows the observed crime series and the ARIMA model fit for each of the contexts included in the table above.

Annex 3 – Statistical methodology

The approach adopted has been one of developing (seasonal) ARIMA(X) models that attempt to describe the monthly variations in the crime indicators and that might provide some short-term predictive capabilities. An ARIMA model predicts the current value of a crime indicator based on the past observations of the crime series itself as well as past random errors. This model is extended (the X in ARIMA(X)) to allow for current and past observations in economic time series (predictors) to be included. Such an approach allows for an examination of the contribution of economic factors in describing the monthly variability in the crime series and may provide some predictive (forecasting) ability over the short term (say 3 months).

Exponential smoothing and (seasonal) ARIMA models that include potential economic factors as predictors are considered. The following models proved to be the most appropriate:

Simple Seasonal:
Appropriate for time series with no trend but a seasonal effect that is constant over time.

Winters' Additive:
Appropriate for series with a linear trend and a seasonal effect.

Winters' Multiplicative:
Appropriate for time series with a linear trend and a seasonal effect that depends on the level of the series.

ARIMA models:
Seasonal autoregressive integrated moving average (ARIMA) models, denoted by ARIMA $(p,d,q)(P,D,Q)_S$, with the inclusion of economic time series as predictors.

Where p, d and q are the orders of the autoregressive, integrated and moving average terms. The autoregressive term predicts the current value using the preceding values of the same time series. It reflects the lingering effects or memory of previous observations. The integrated part (or differencing) reflects the trend or "drift" in the time series (i.e. of order 1 for a linear trend; more than one for higher order polynomial trends). This term is used to render the time series stationary, if necessary. The moving average term predicts the current value from preceding random errors or "shocks".

In a seasonal ARIMA model the terms P, D and Q predict the current value in the time series using observations and errors at times with lags that are multiples of the seasonality s (in this case s=12 corresponding to monthly data).

Economic time series are also added to the ARIMA model as potential predictors so that, for example, past or present values of relevant economic factors might be used to help explain some additional (i.e. beyond that accounted for by ARIMA alone) monthly variability in the crime series and so provide a greater predictive (forecasting) capacity to the model.

Stationarity and unit root tests

ARIMA models assume that the time series are stationary (such that, for example, the mean and variance do not change over time). Stationarity is tested using the Kwiatkowski–Phillips–Schmidt–

Shin (KPSS) test.[48] This test assesses the null hypothesis that a univariate time series is trend stationary against the alternative that it is a non-stationary unit-root process. Results reported are based on the autoregressive model with constant only and with constant plus time trend terms.

If the time series are non-stationary it is possible to apply an ARIMA model with a certain order of differencing (the integrated term in ARIMA) to make the time series stationary, but this might be a less than optimal modelling approach. If a cointegration relationship exists then valuable information would be lost concerning the long-run equilibrium forces present in the levels of the data. In this case a superior modelling technique to ARIMA would be an Error Correction Model.

The examination of stationarity in the time series has not been exhaustive in this study but in some instances non-stationary or inconclusive results have emerged. However, even if the times series appeared to be non-stationary an ARIMA model is still presented. In such cases, caution should be taken regarding the validity of the ARIMA model.

Selecting the best-fitting model

SPSS version 16.0 Expert Modeler was used to determine the best-fitting ARIMA model (or exponential smoothing) including statistically significant economic time series. The R-squared and adjusted R-squared values were used to differentiate between the various models.

[48] D. Kwiatkowski, P. C. B. Phillips, P. Schmidt, and Y. Shin (1992): Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. Journal of Econometrics 54, 159–178.

Annex 4 – Best-fit ARIMA models for each context

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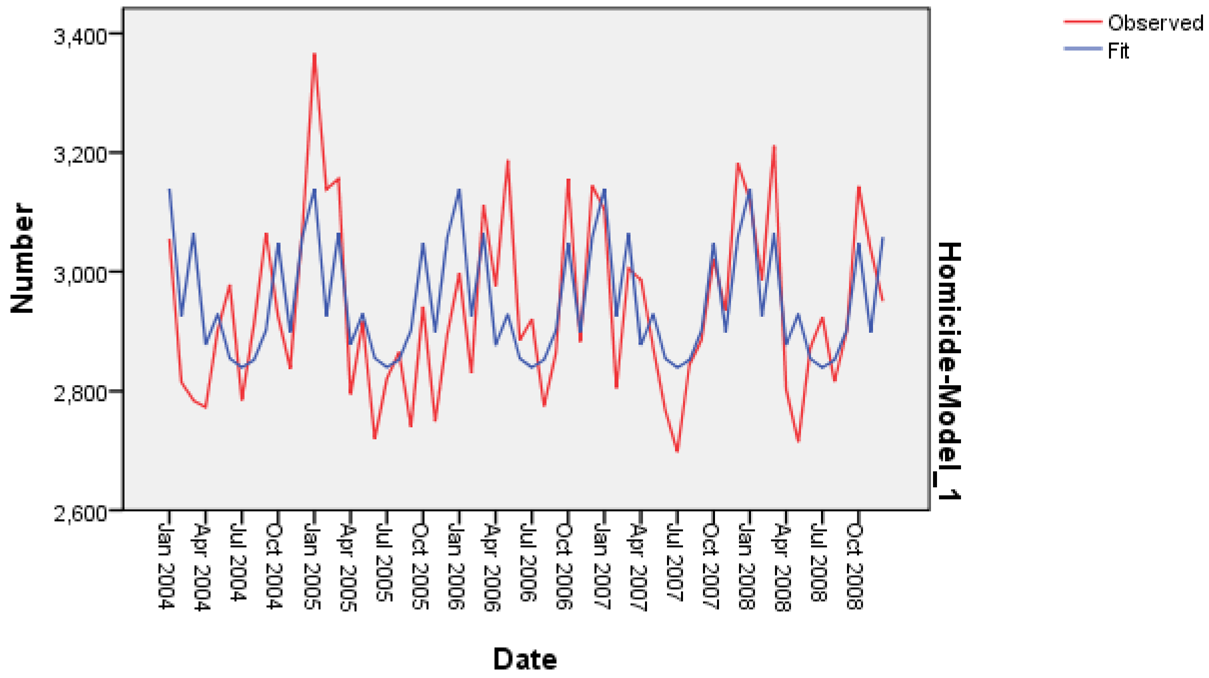

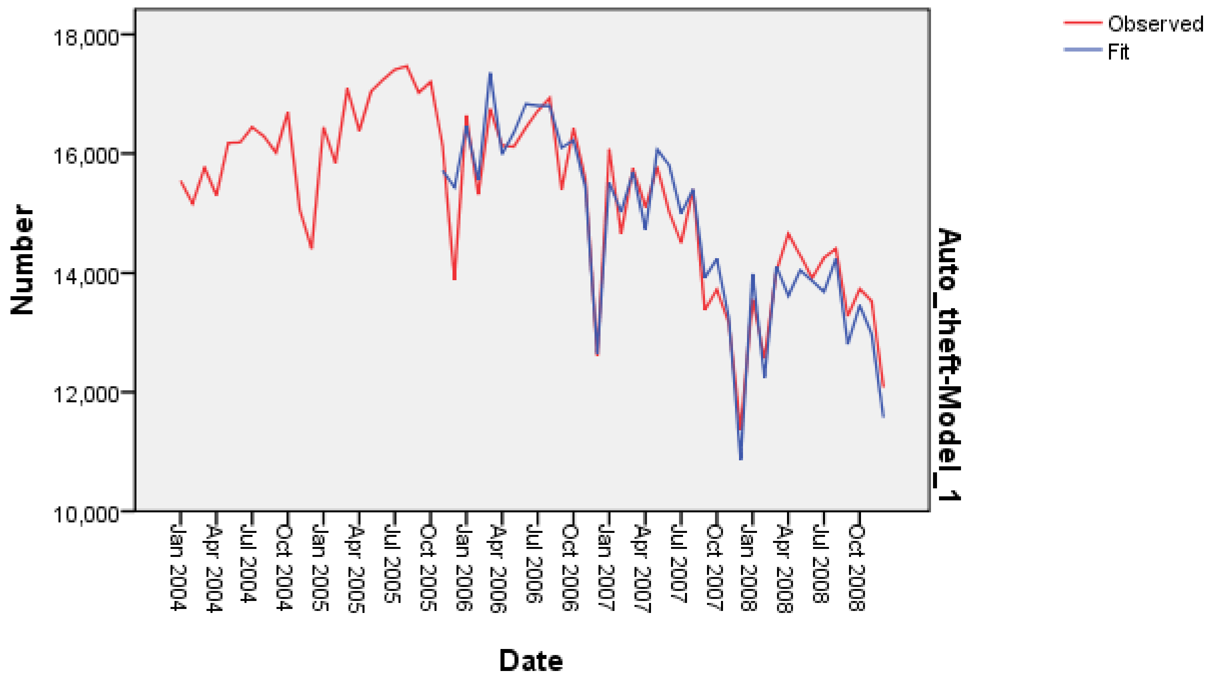

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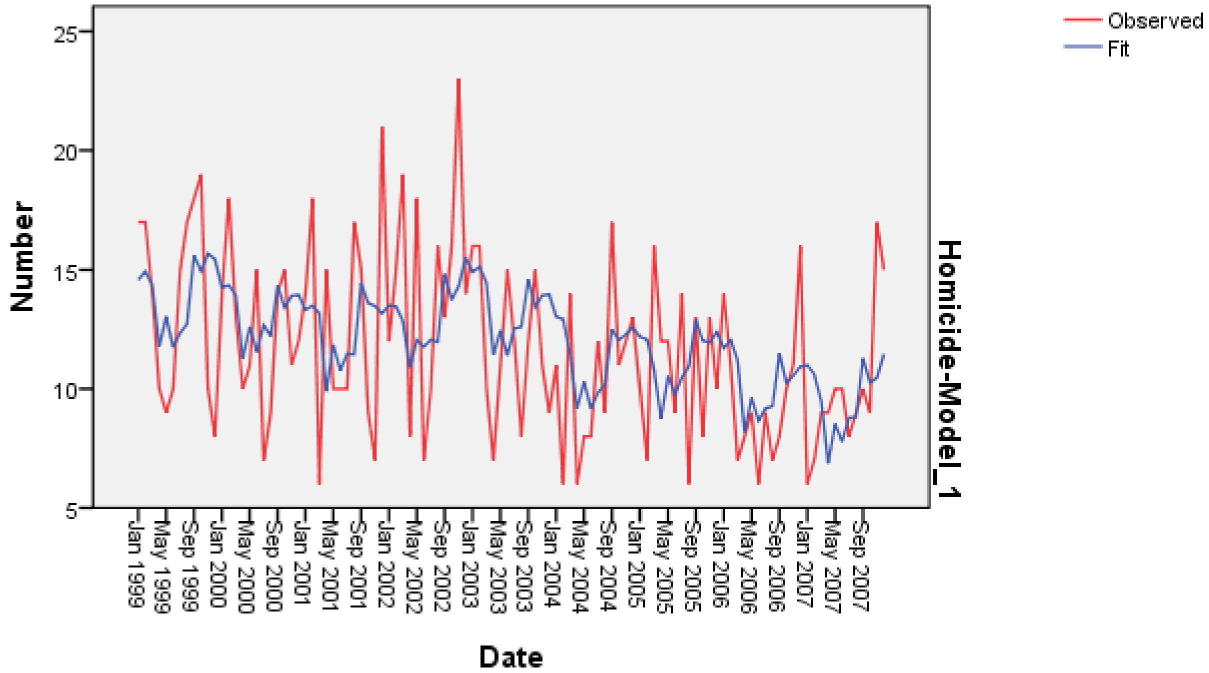

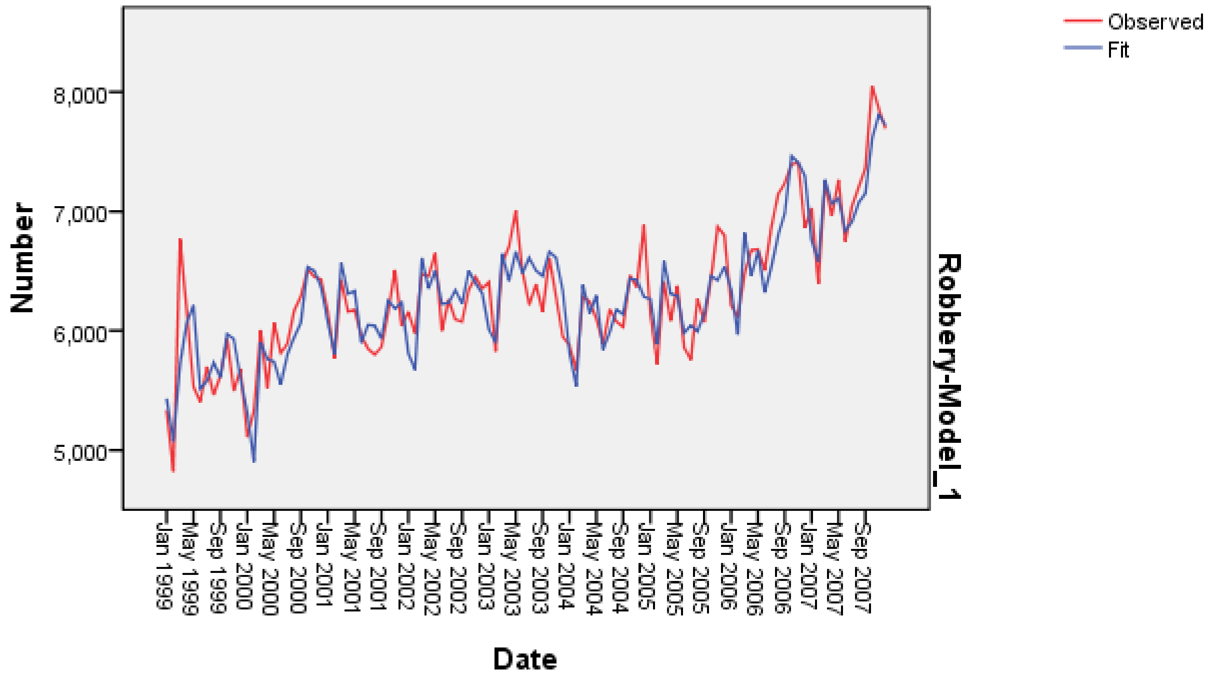

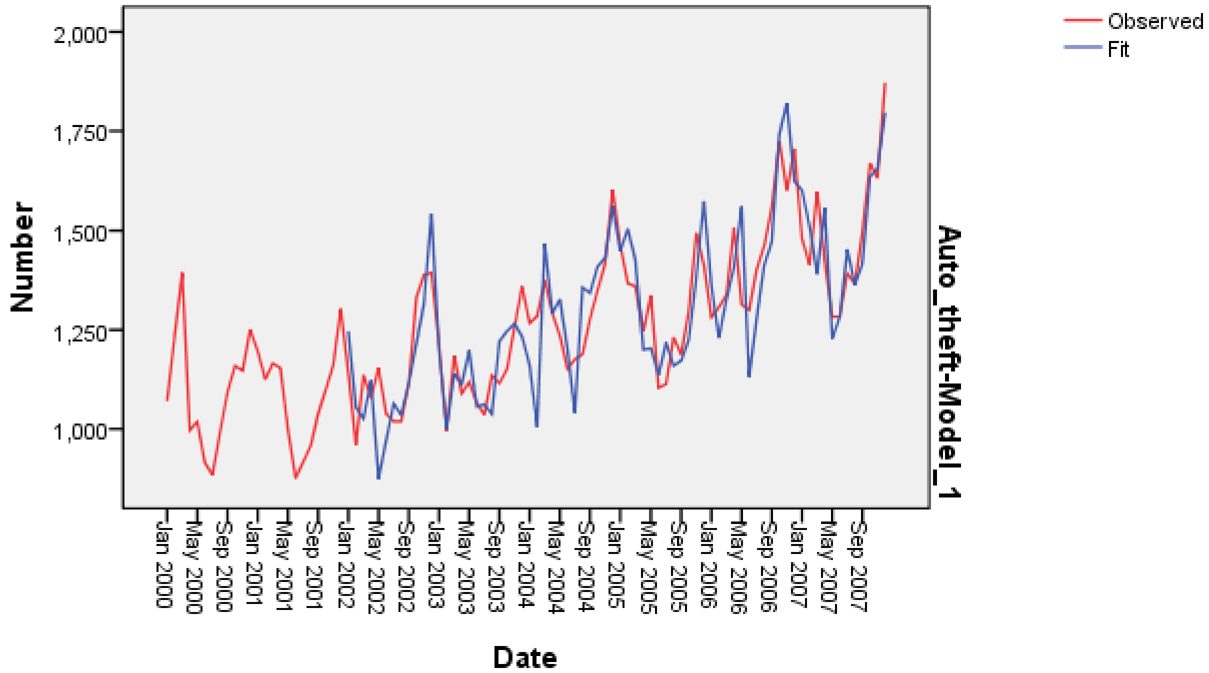
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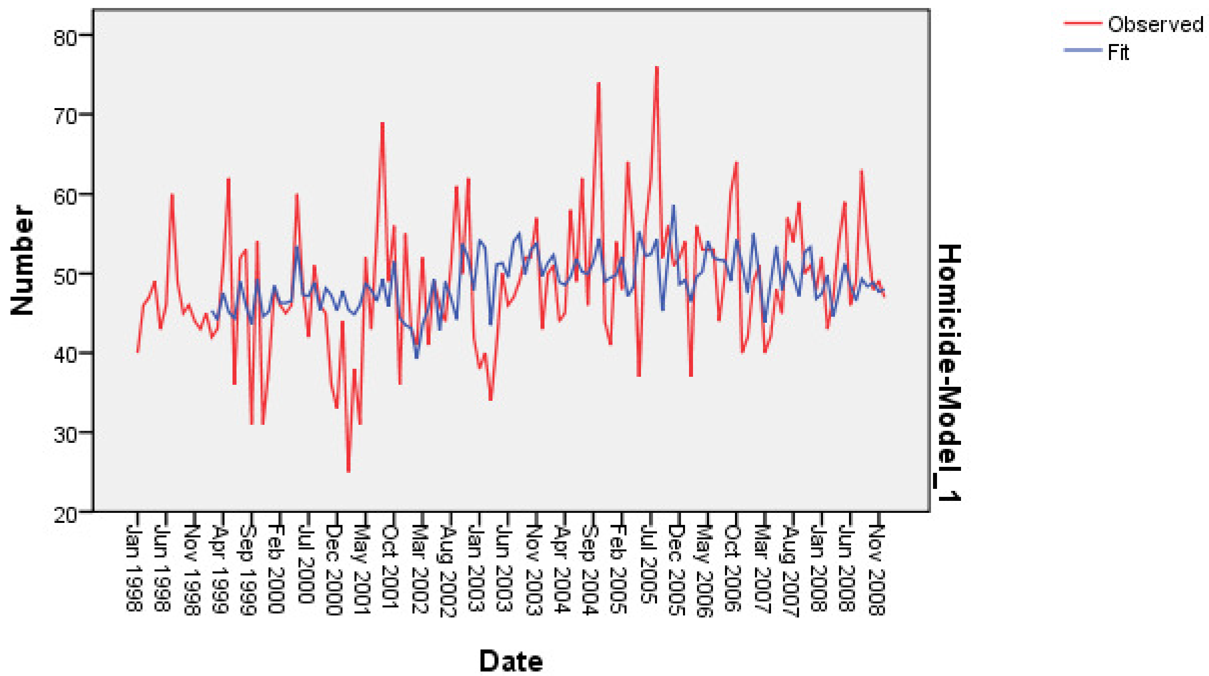
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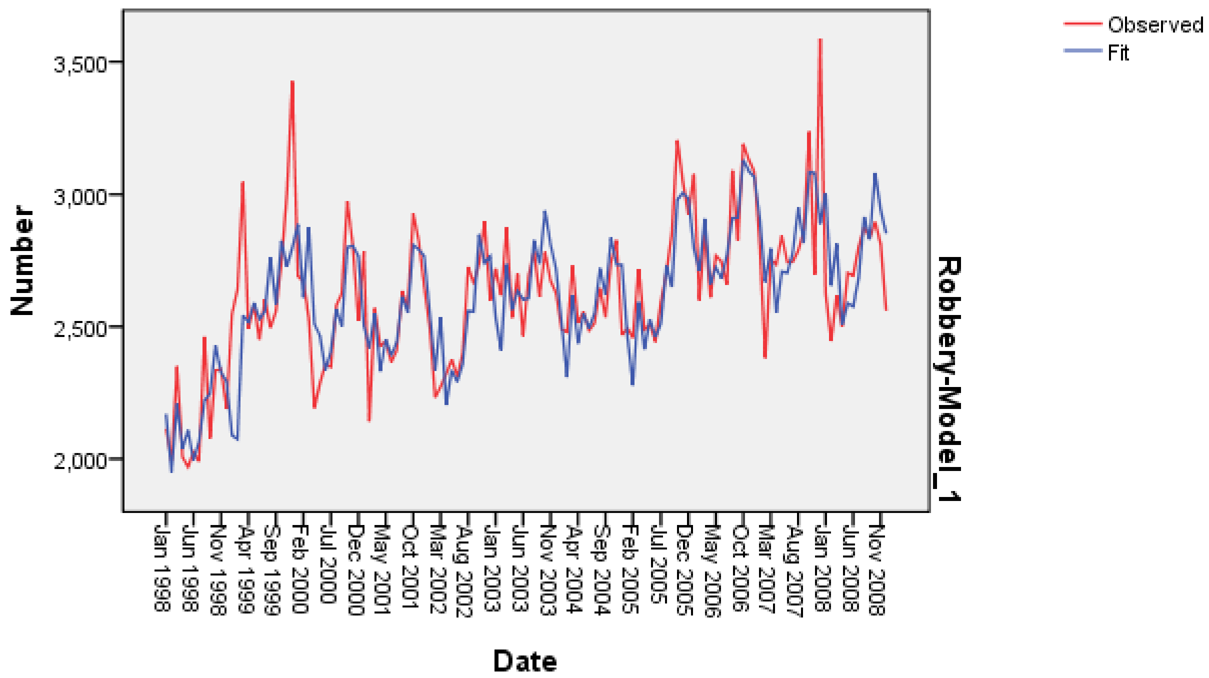
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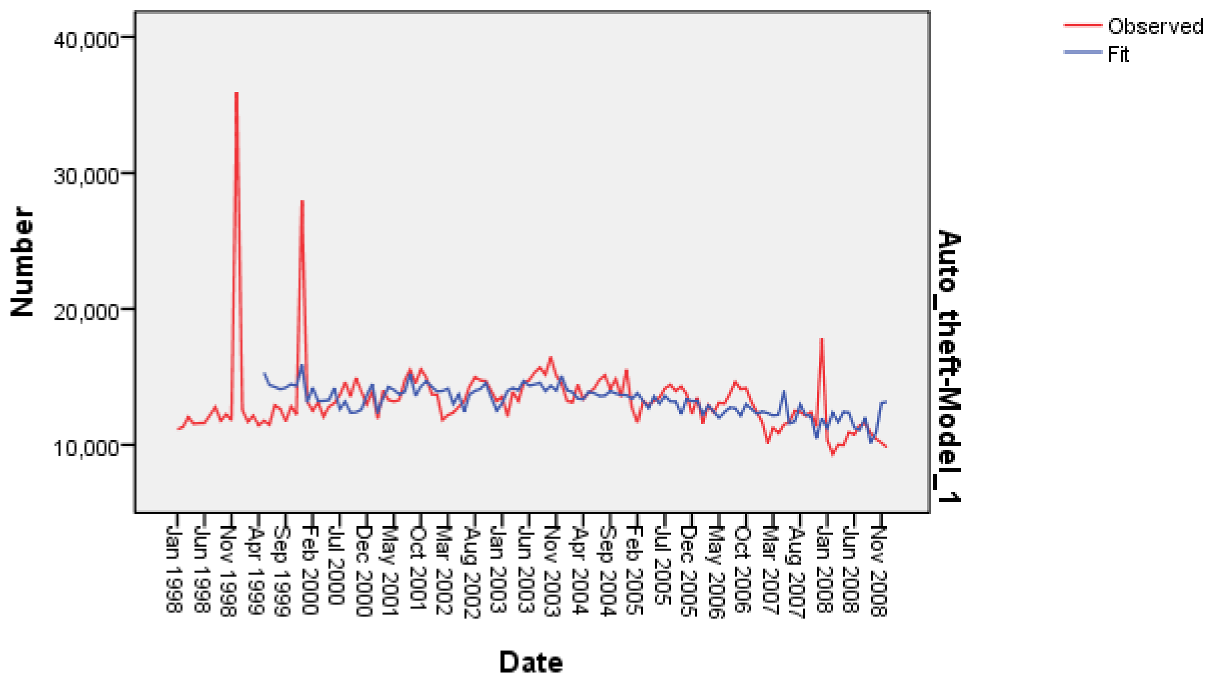
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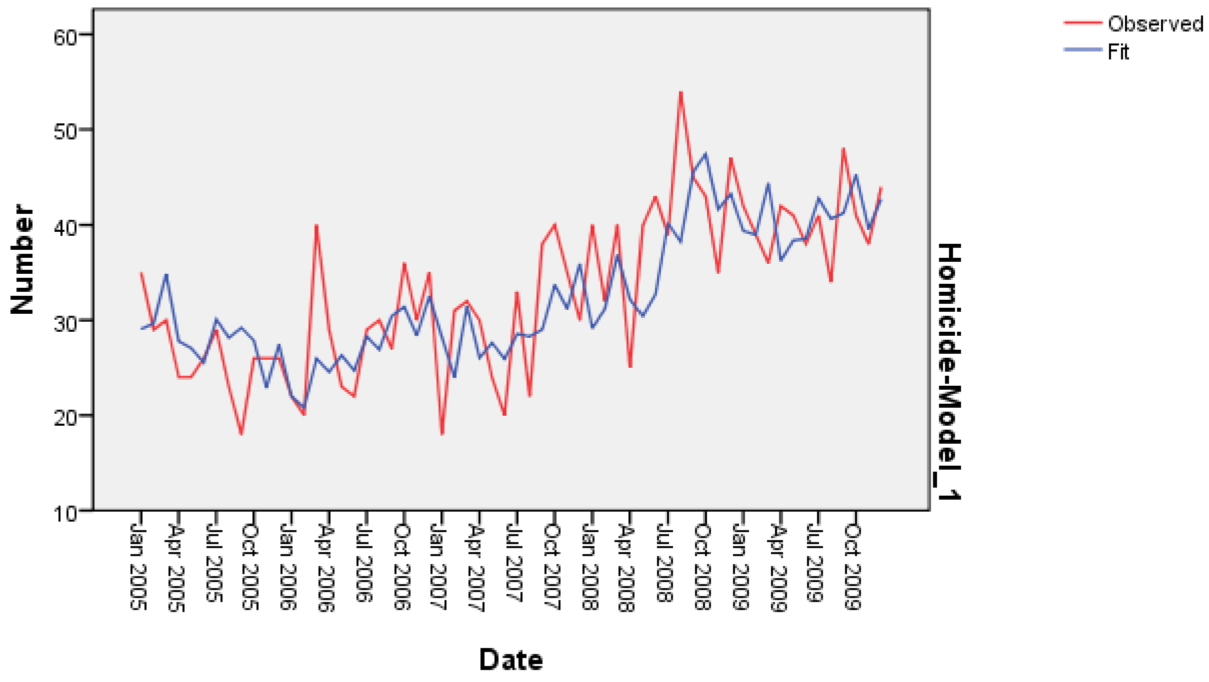
Costa Rica



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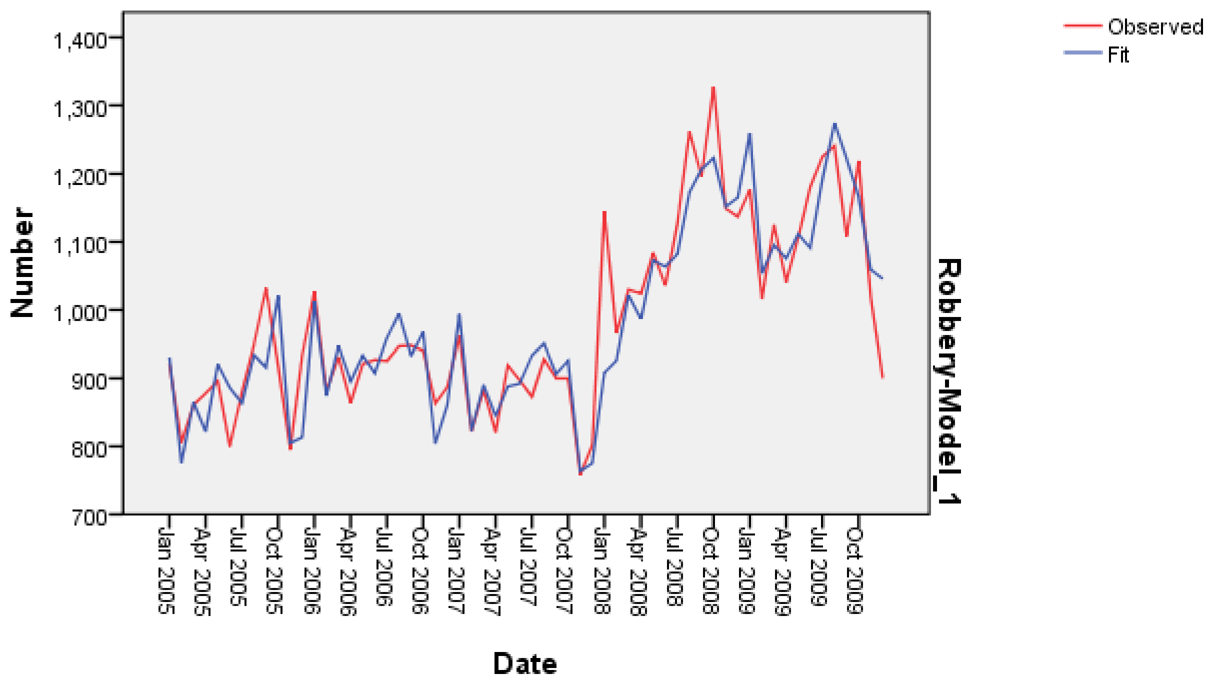

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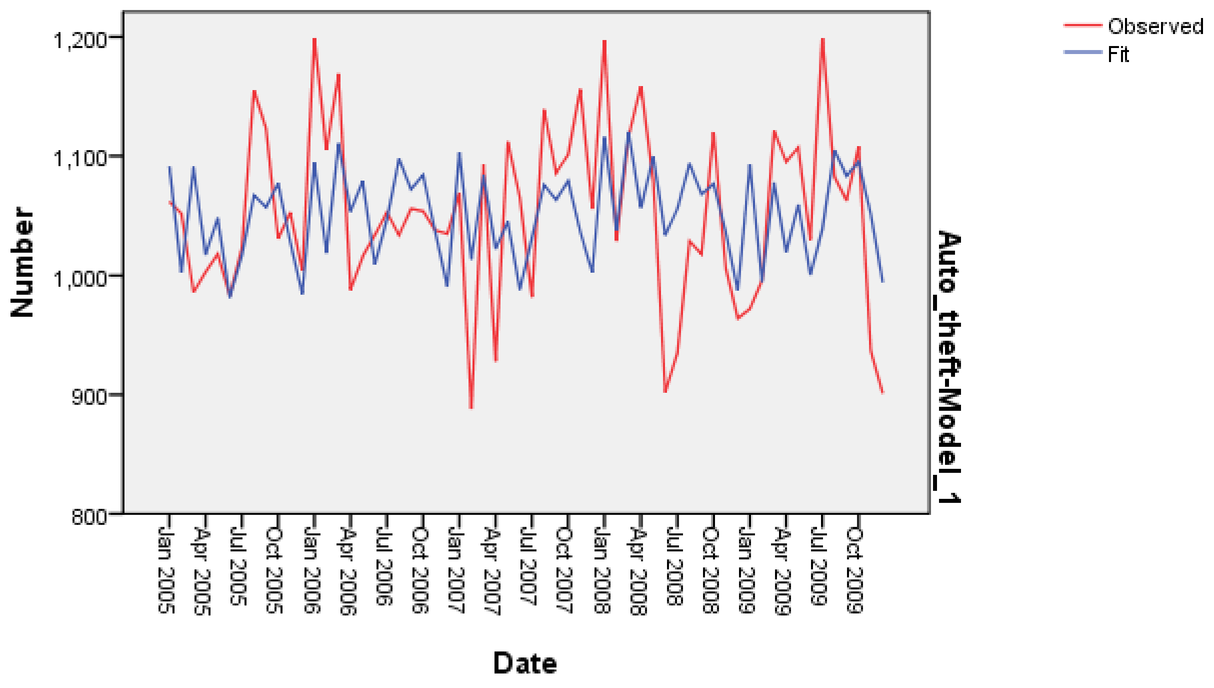
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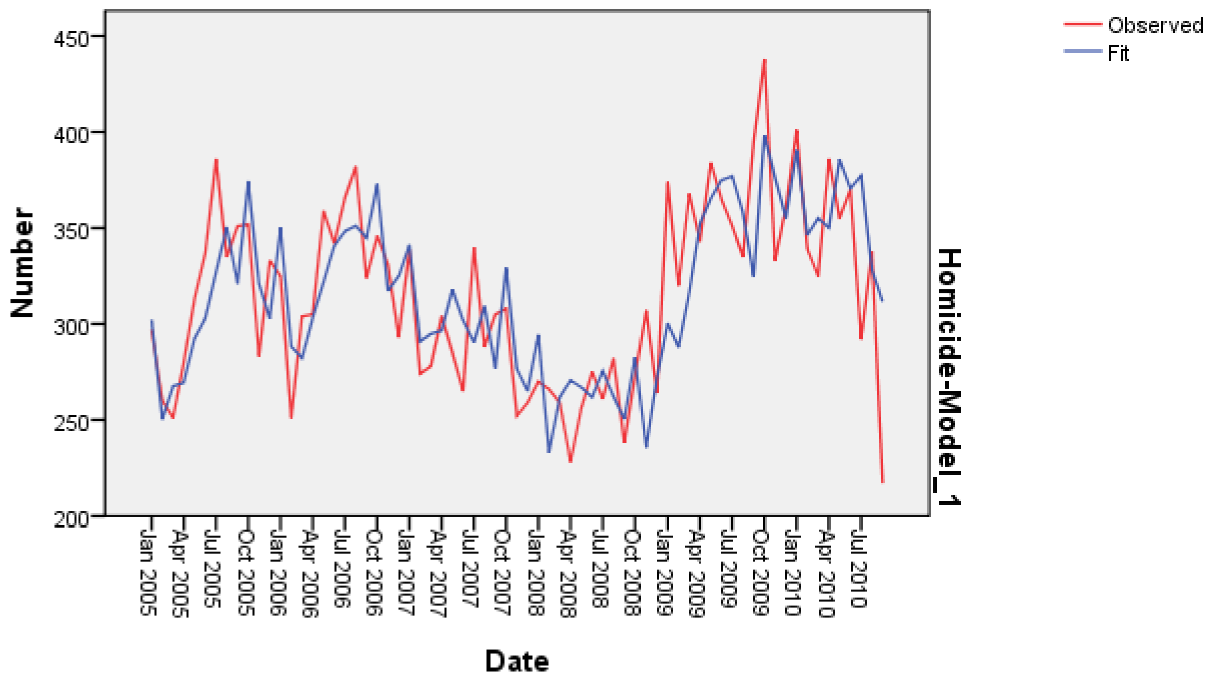
El Salvador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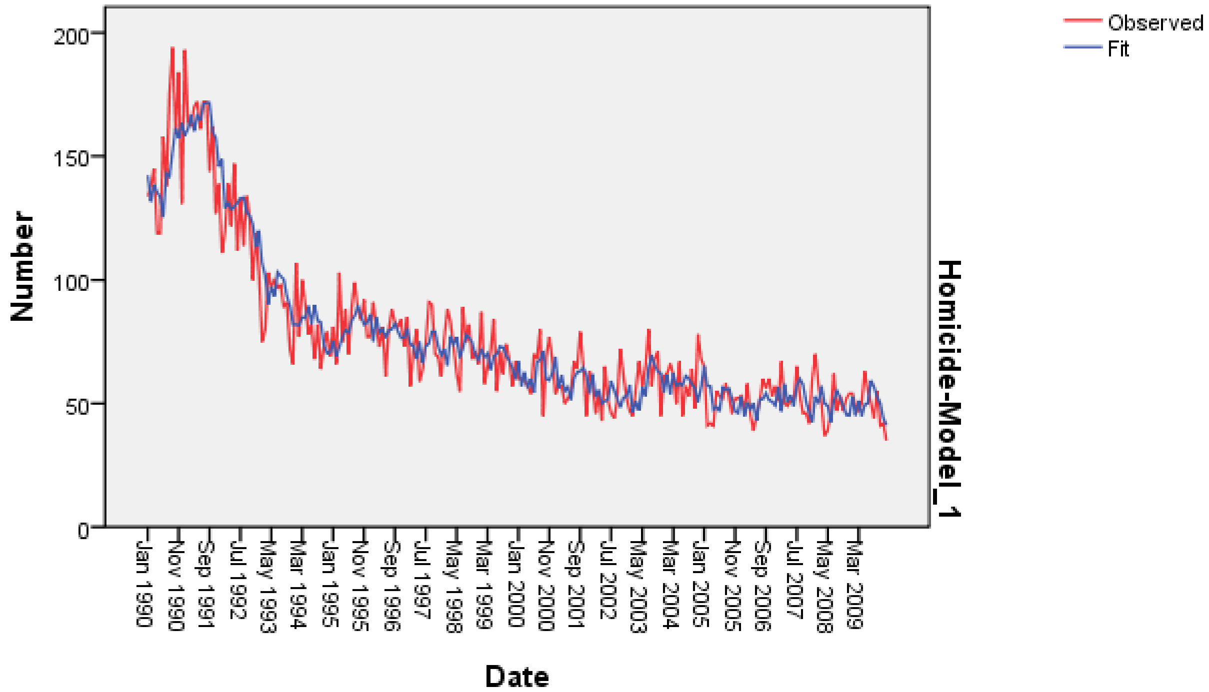
Italy



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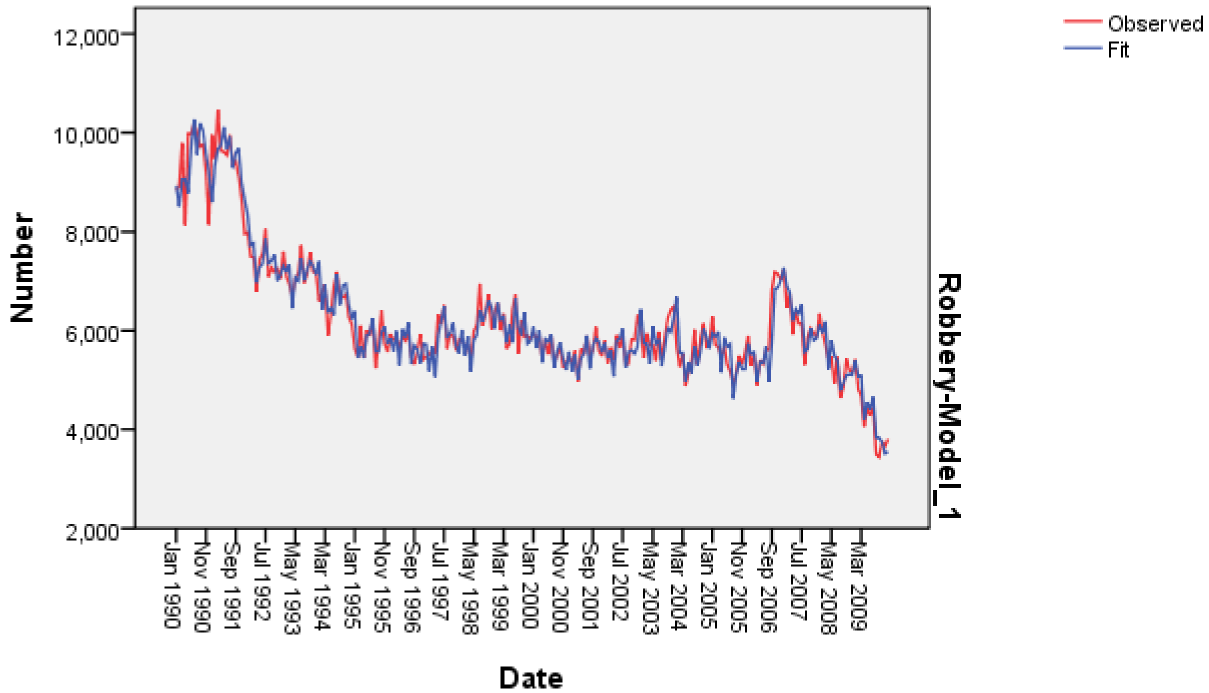

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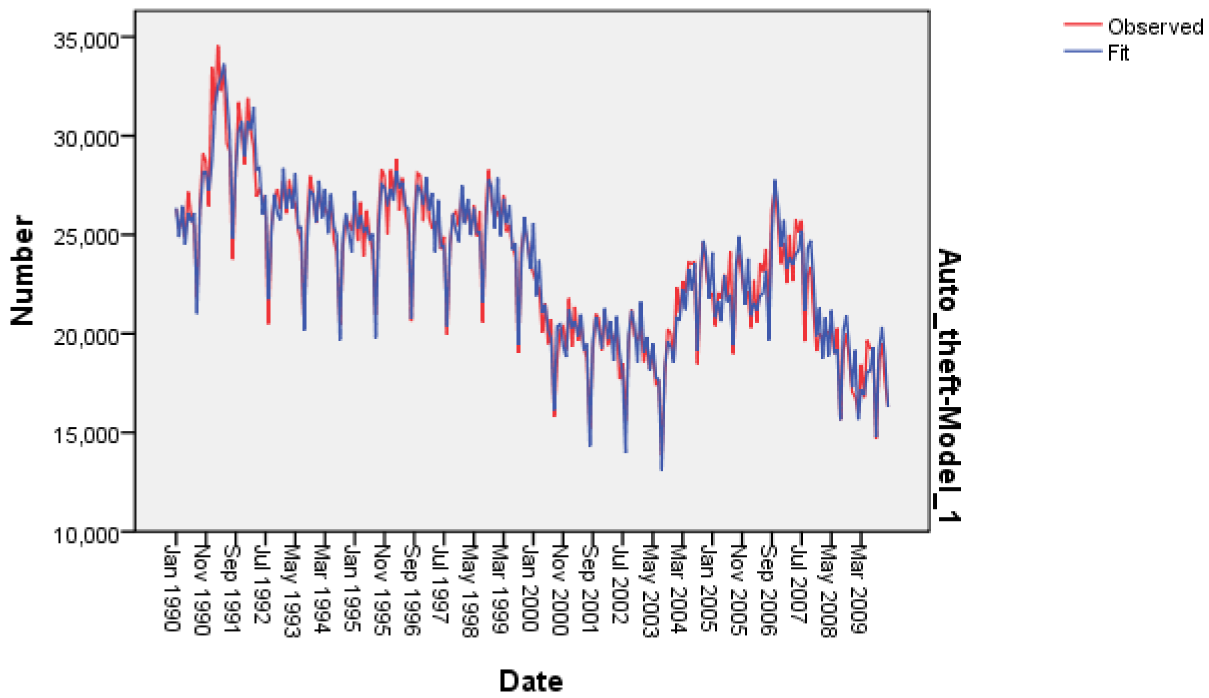
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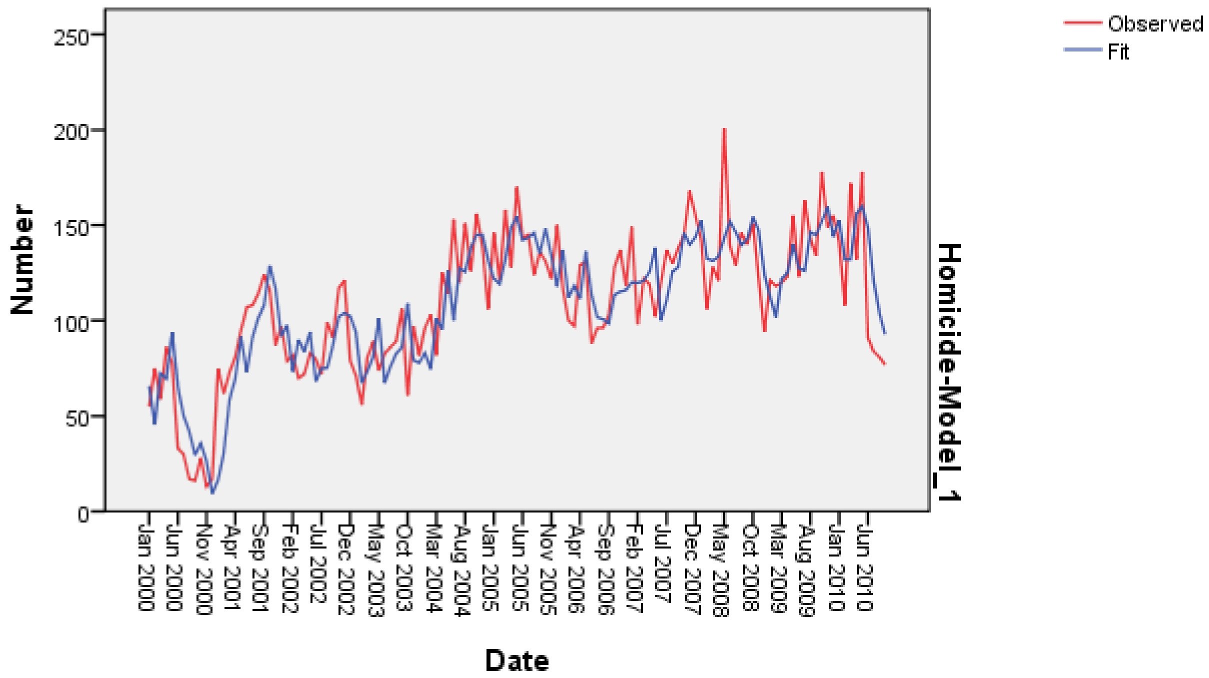
Jamaica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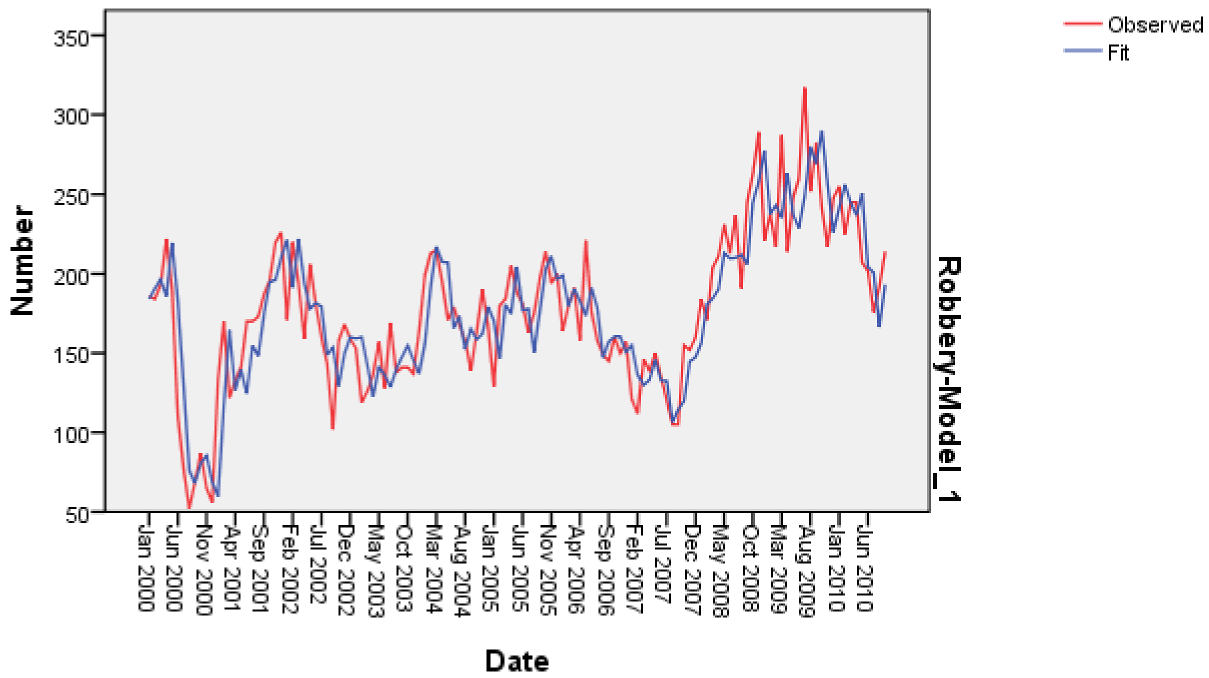
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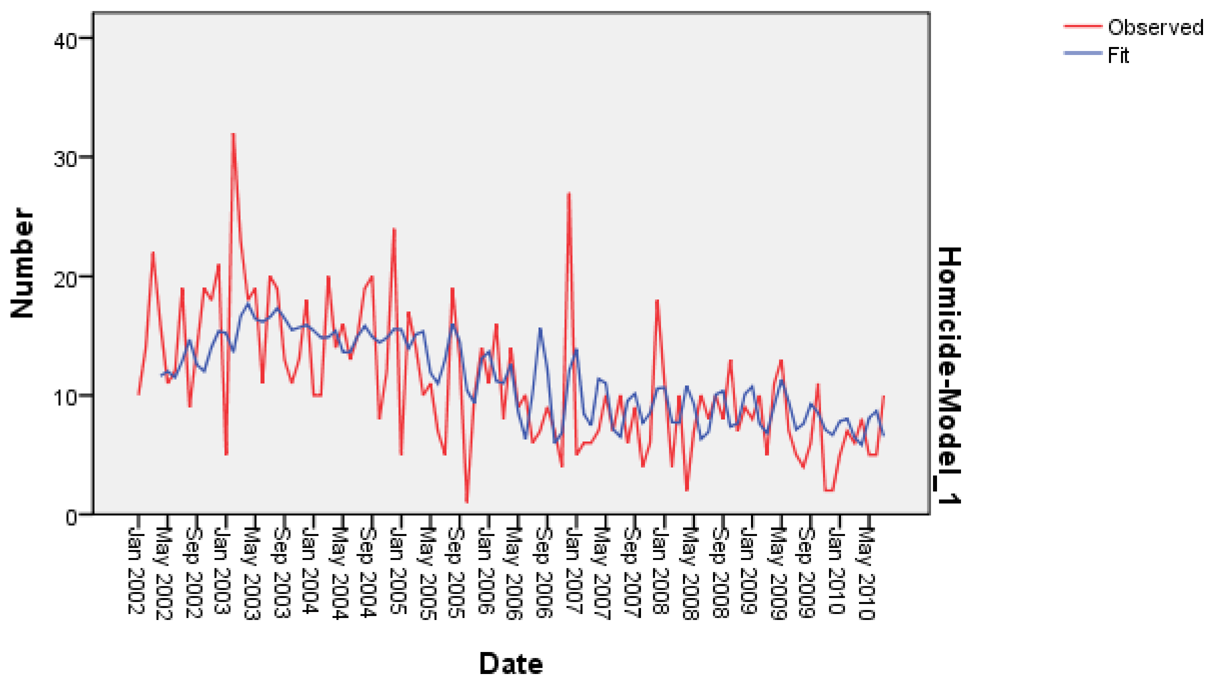
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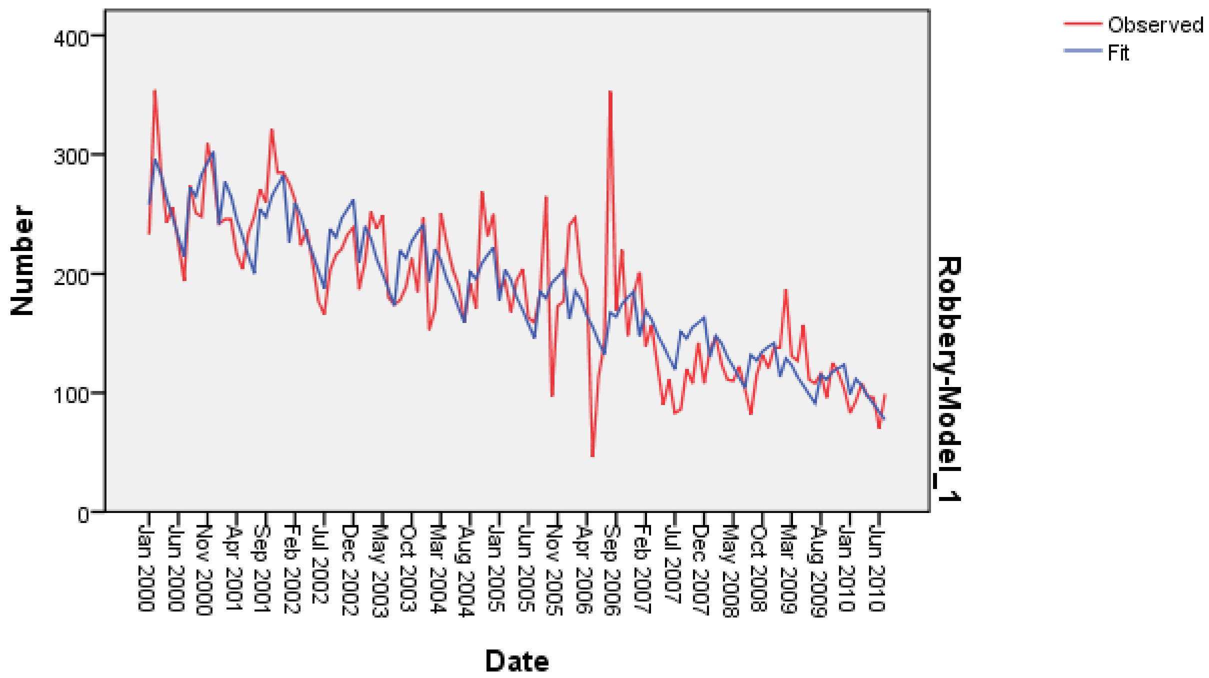
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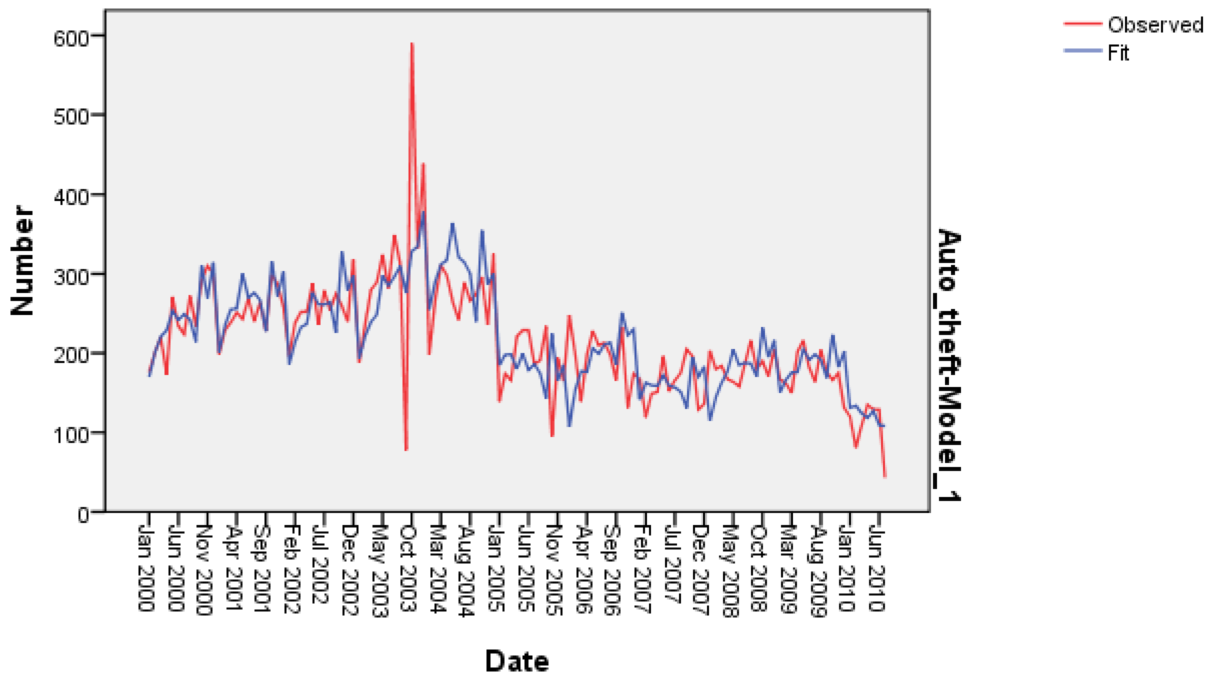
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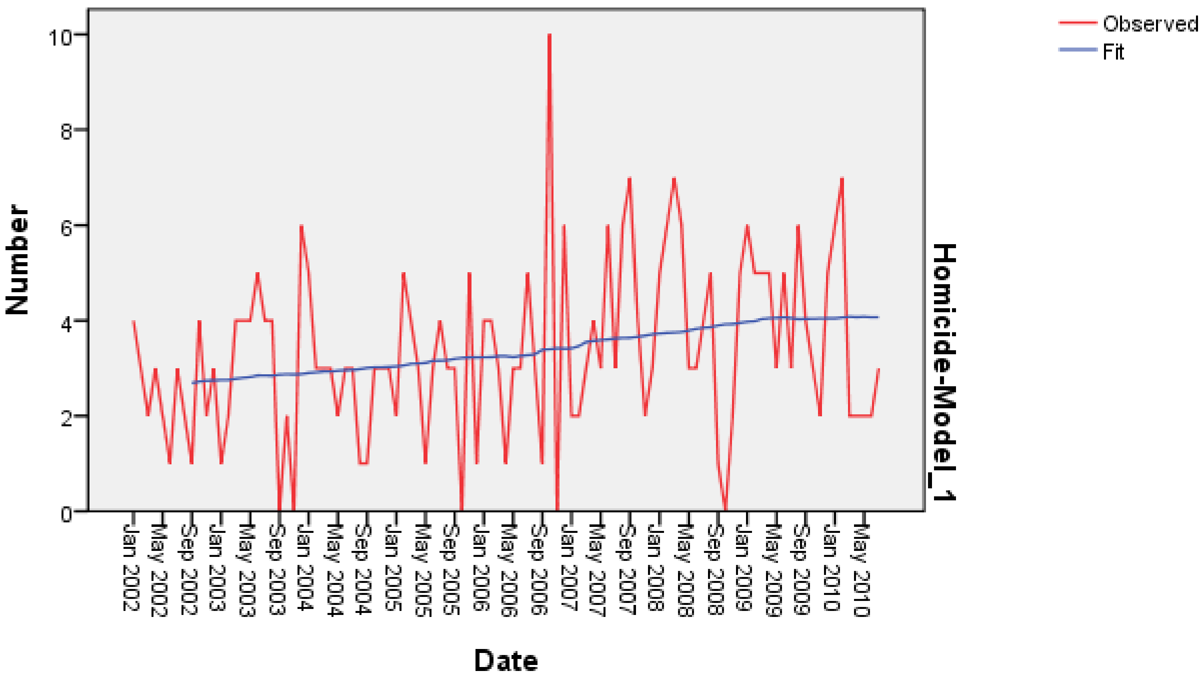
Mauritius



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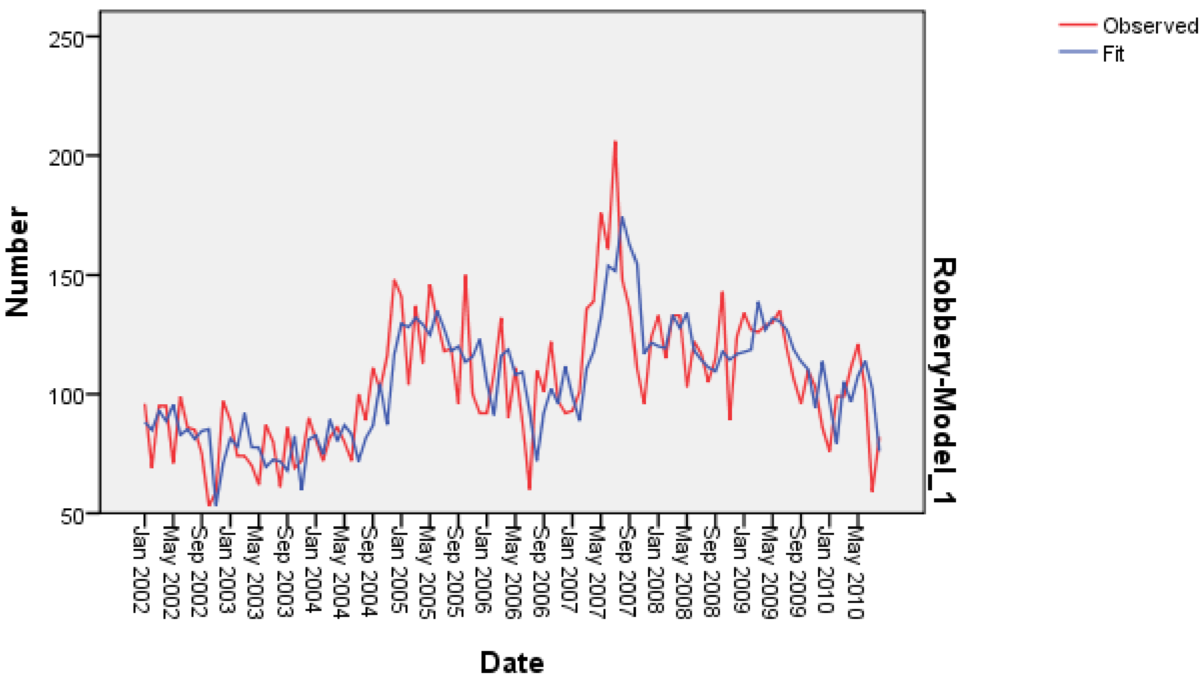

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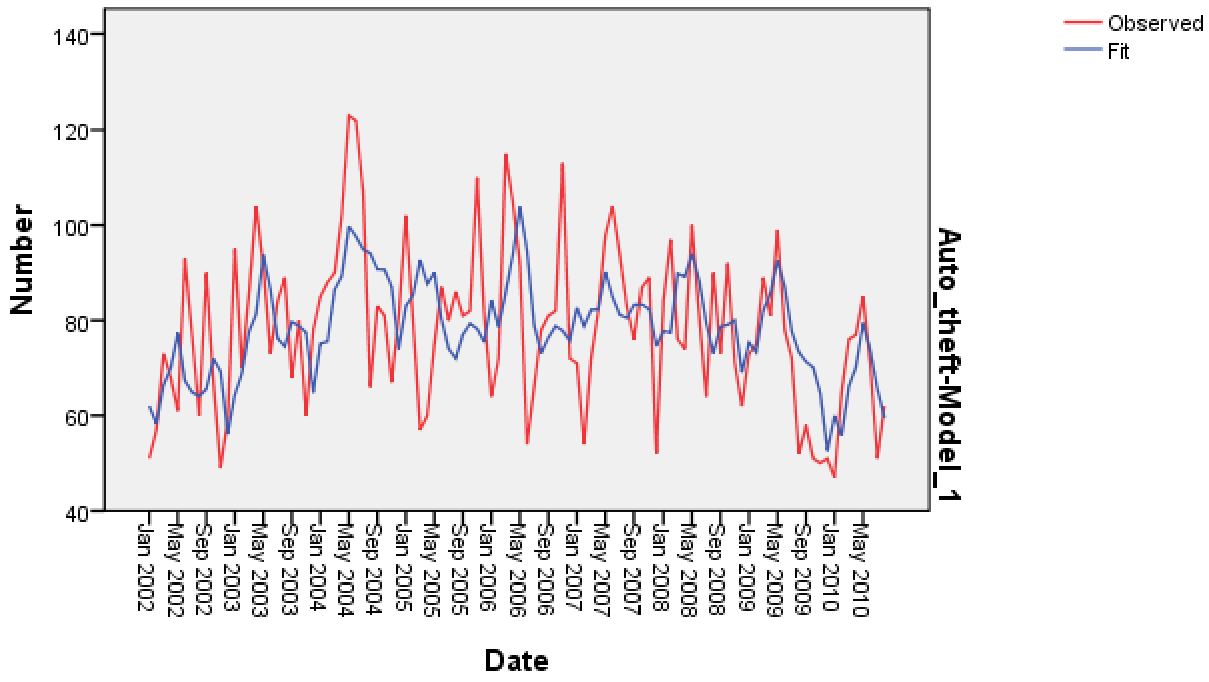
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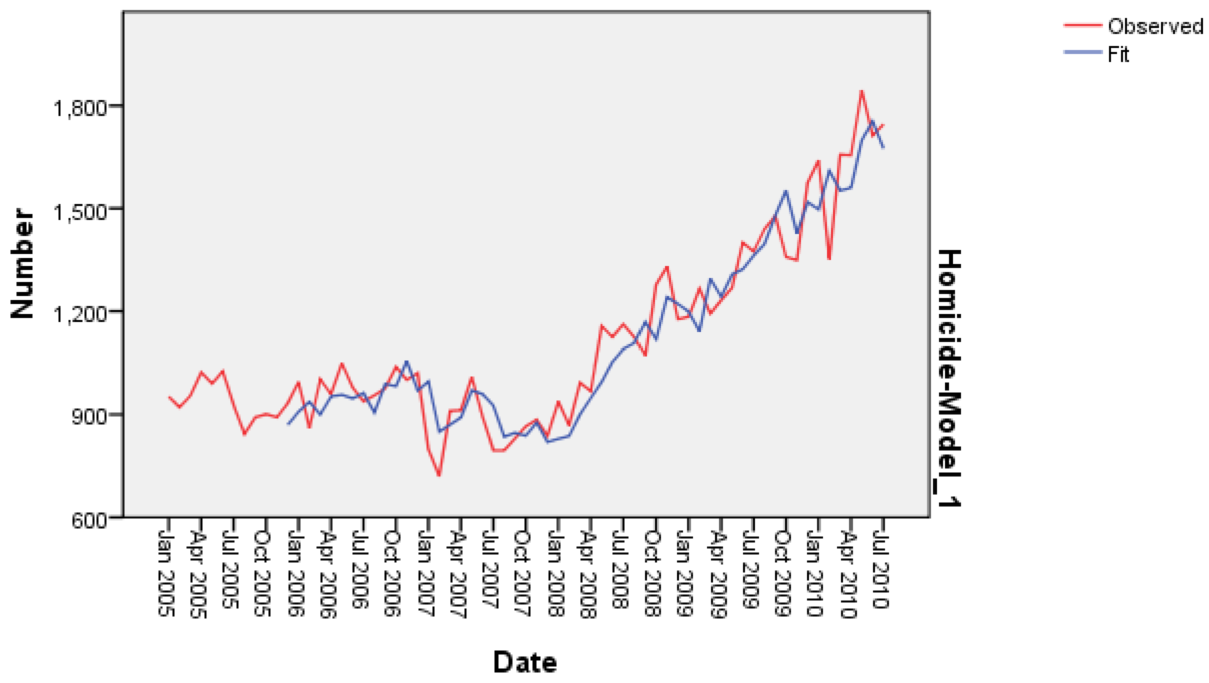
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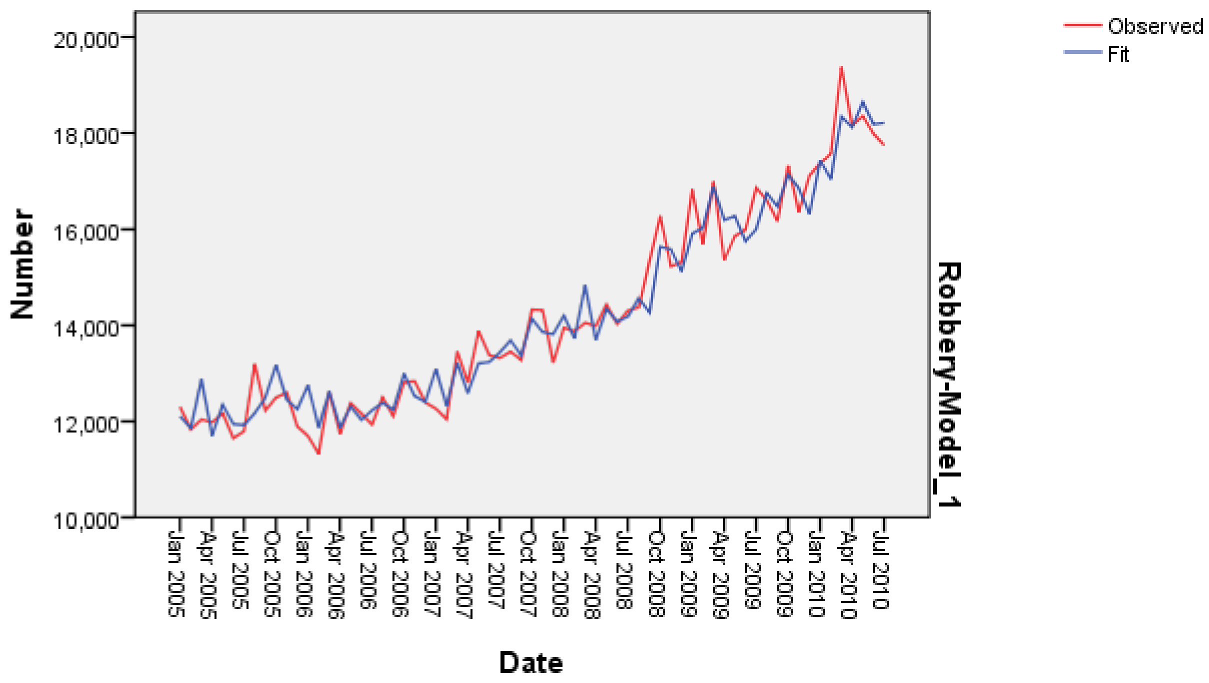
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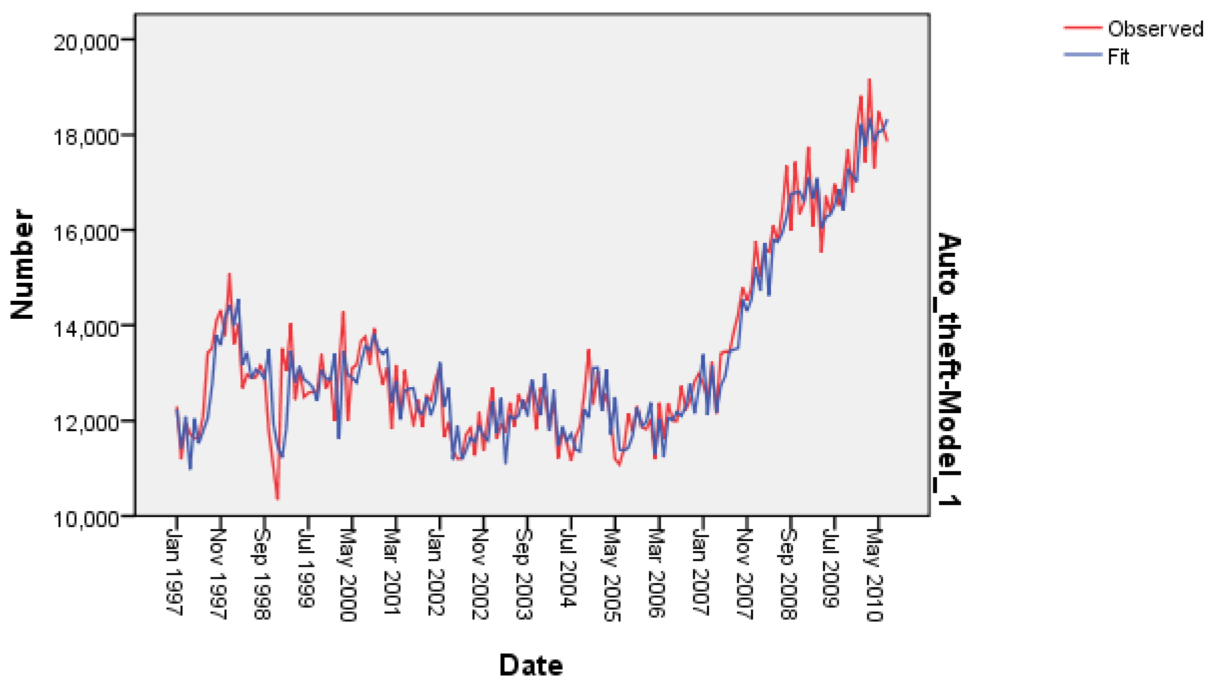
Oct 2009
Jan 2010
Apr 2010
Jul 2010
Date
Robbery-Model_1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Fit
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14,000
12,000
10,000
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Nov 1997
Sep 1998
Jul 1999
May 2000
Mar 2001
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May 2005
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Jan 2007
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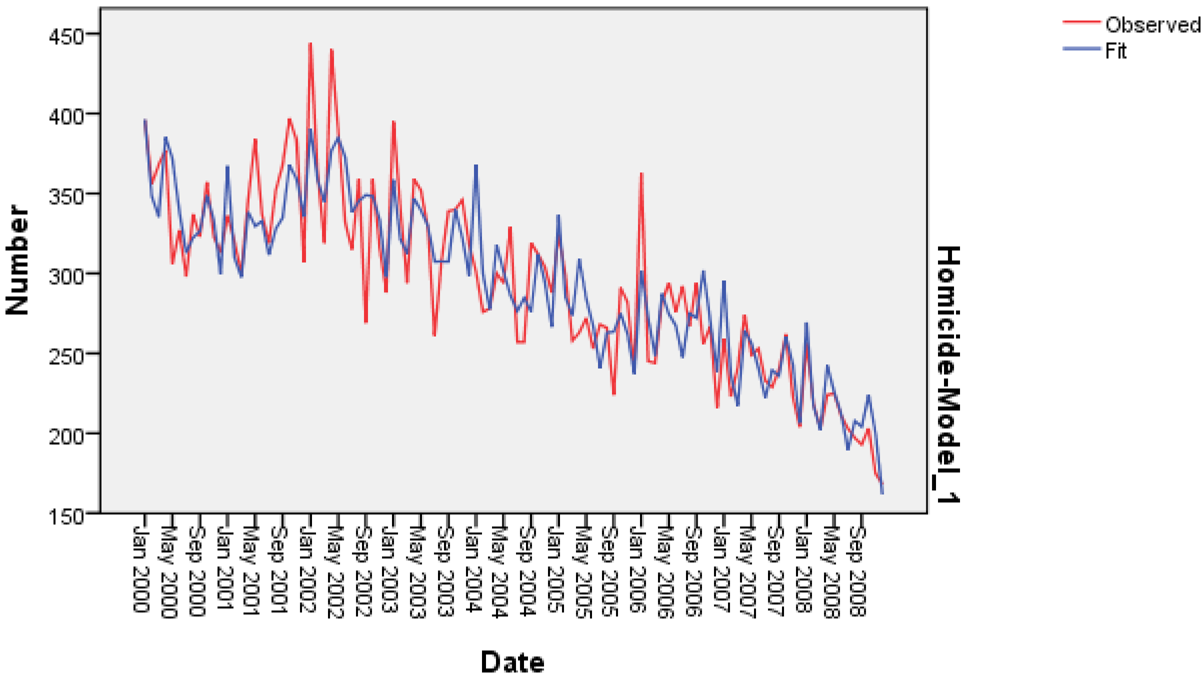
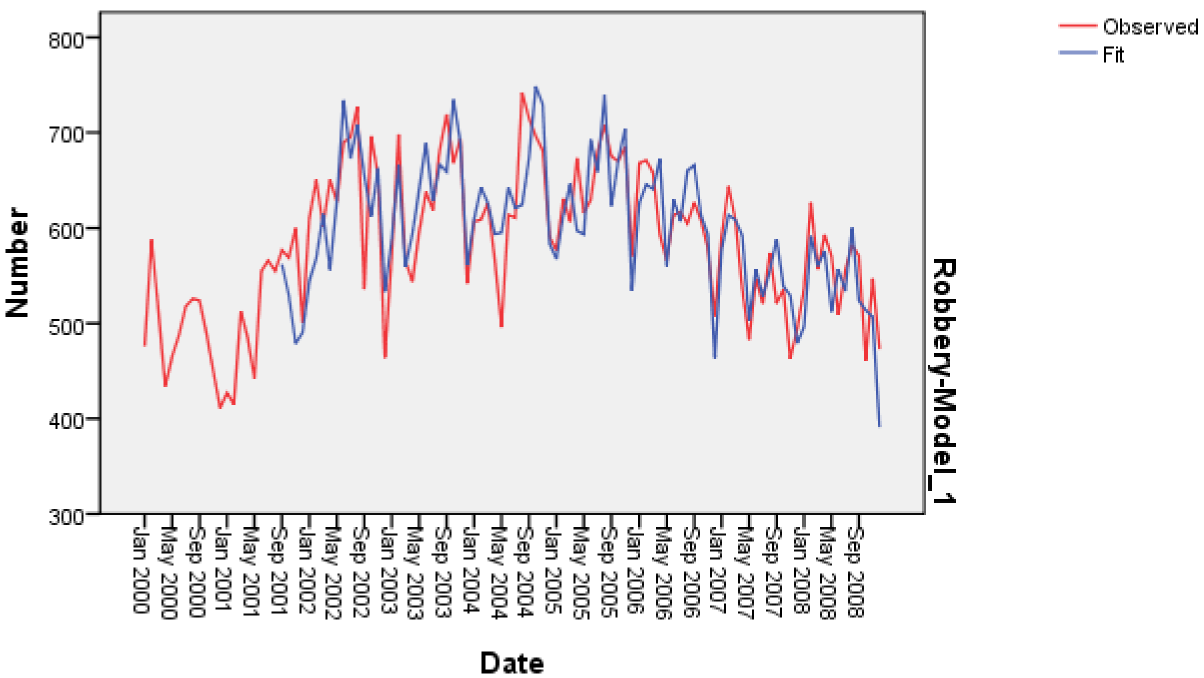
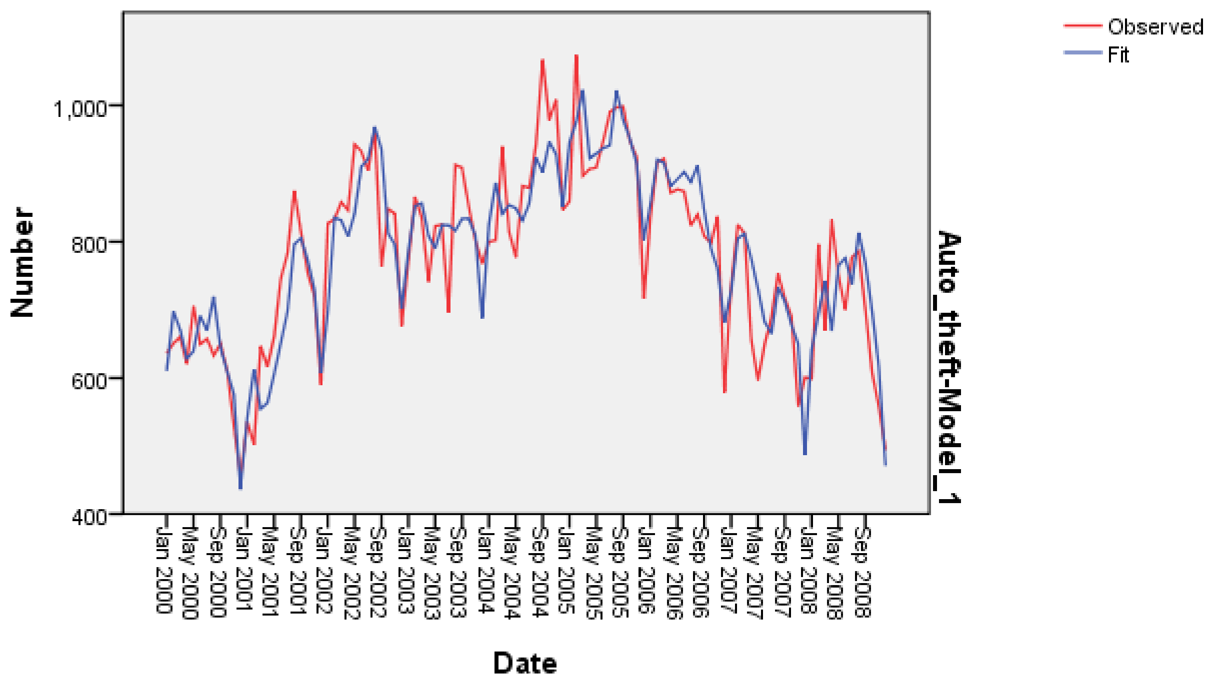
Jul 2009
May 2010
Date
Auto_theft-Model_1

Philippines







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Jan 2000
May 2000
Sep 2000
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Jan 2005
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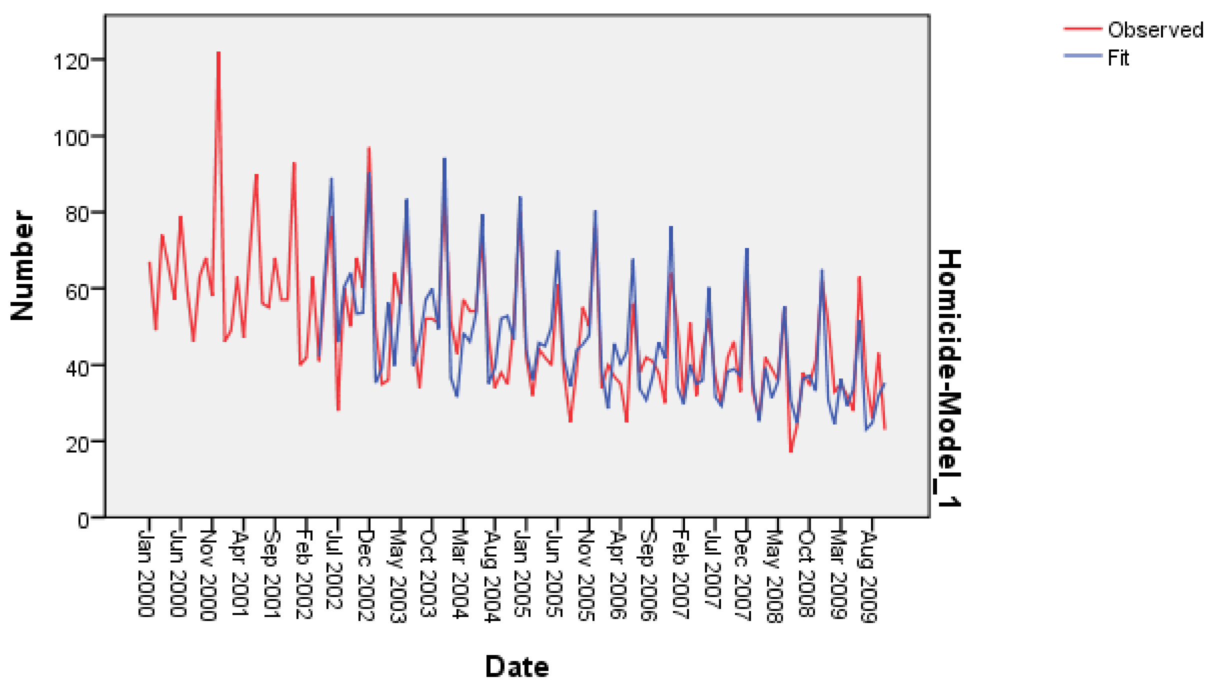
Jan 2008
May 2008
Sep 2008
Date
Auto_theft-Model_1

Poland



Observed
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100
80
60
40
20
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Jan 2000
Jun 2000
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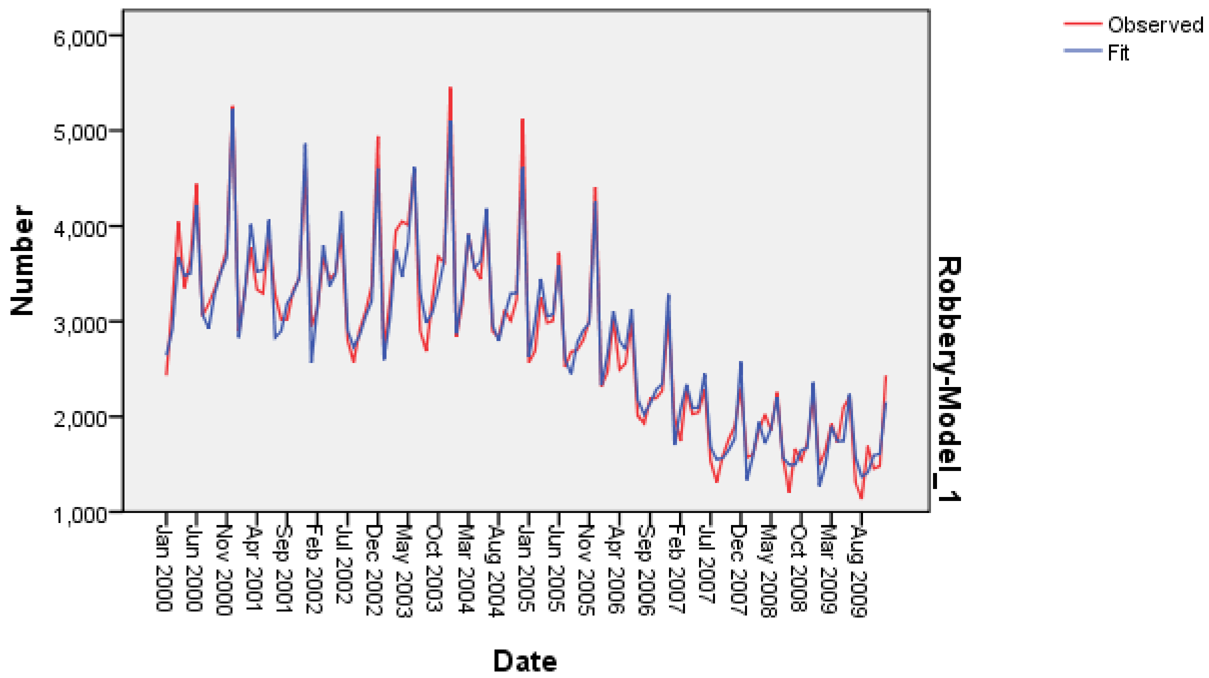
Mar 2009
Aug 2009
Date
Homicide-Model_1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3,000
2,000
1,000
Number
Robbery-Model_1
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Jun 2000
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May 2003
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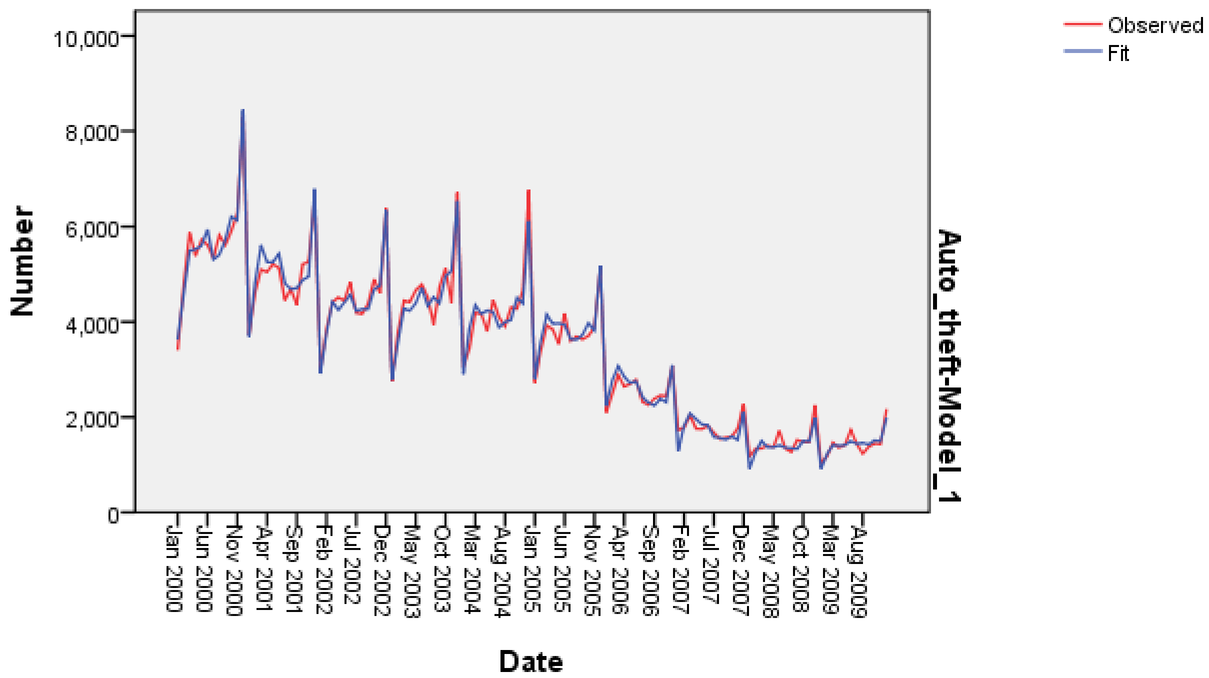
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6,000
4,000
2,000
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Number
Auto_theft-Model_1
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May 2003
Oct 2003
Mar 2004
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Nov 2005
Apr 2006
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Feb 2007
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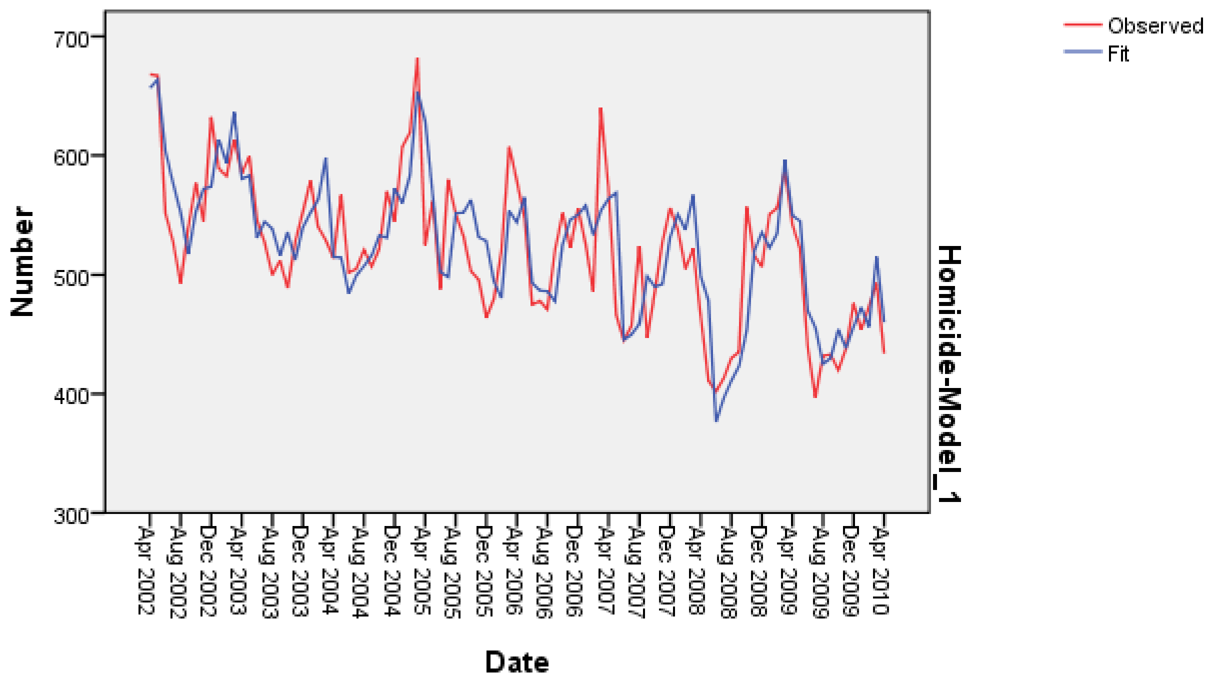
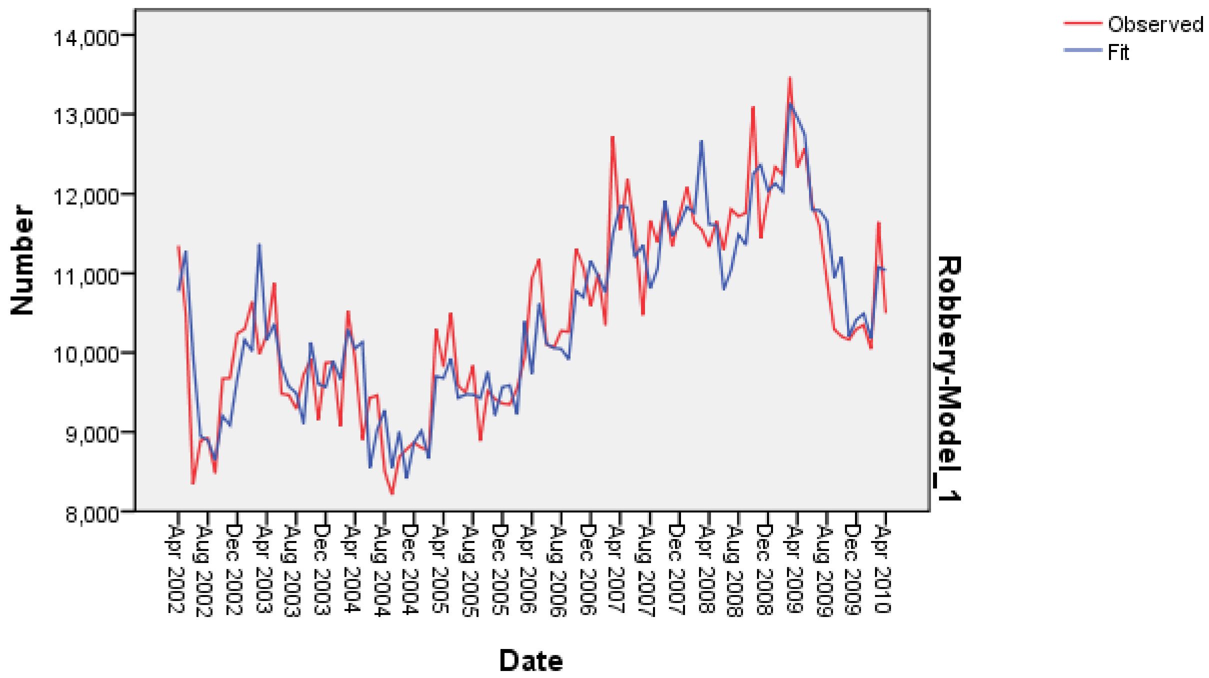
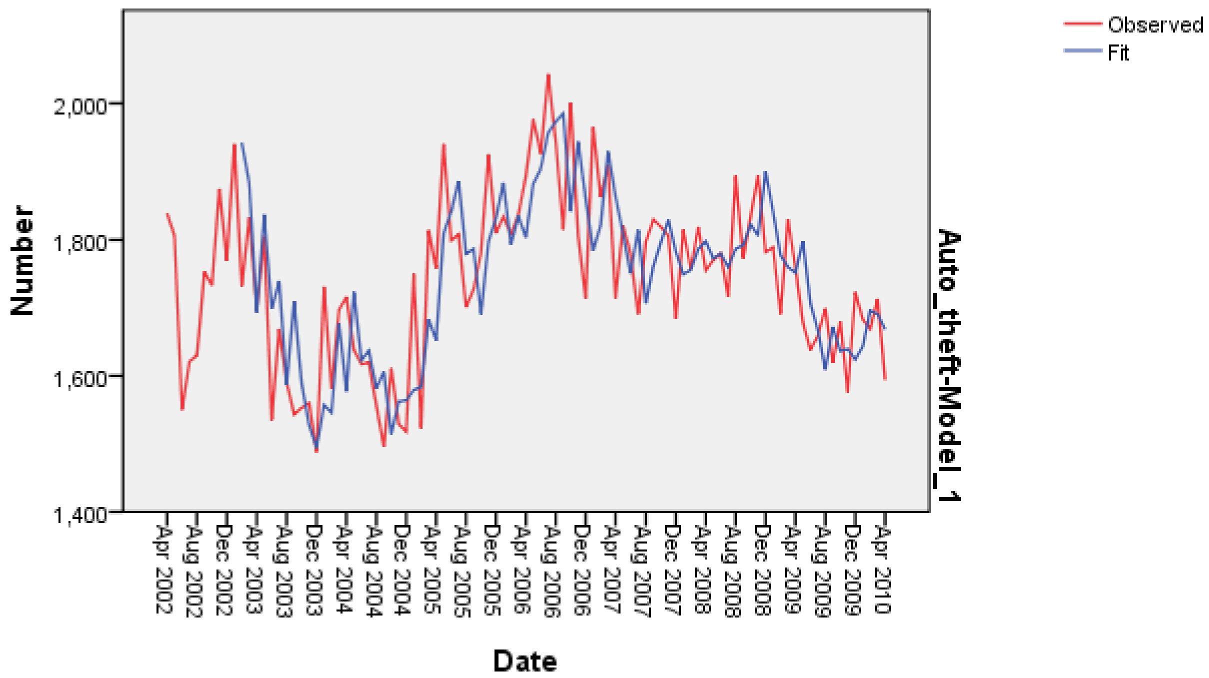
May 2008
Oct 2008
Mar 2009
Aug 2009
Date

Rio de Janeiro



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Number
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1,800
1,600
1,400
Auto_theft-Model_1
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Aug 2002
Dec 2002
Apr 2003
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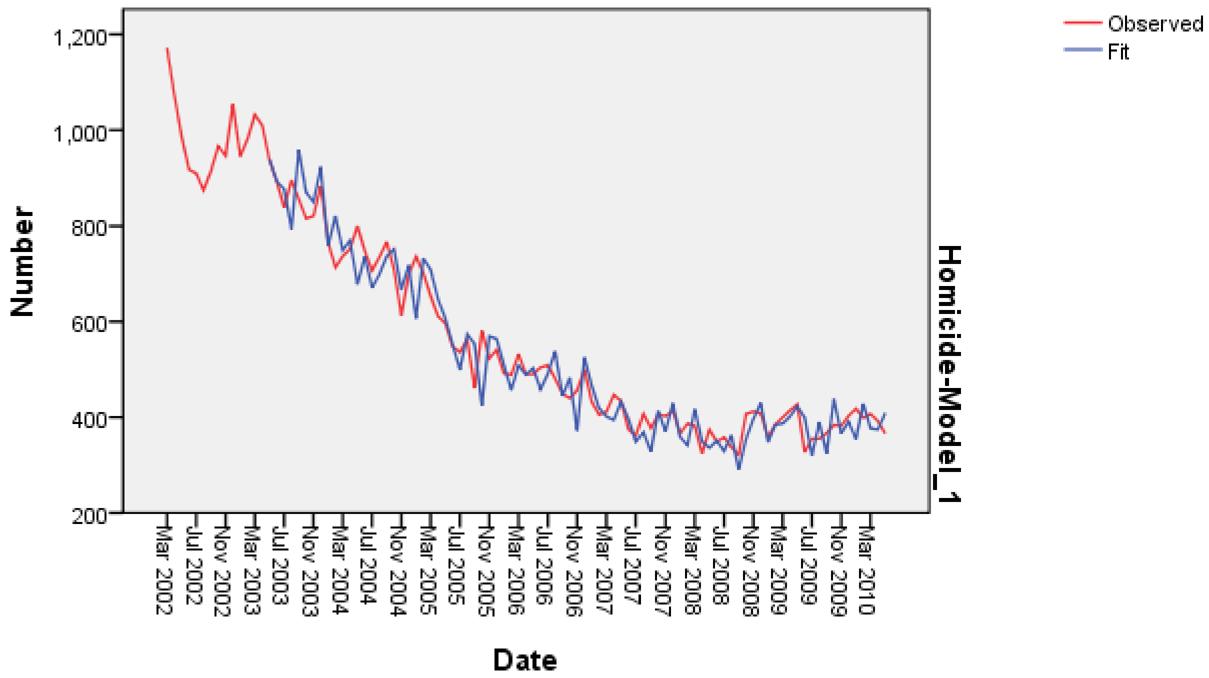
Aug 2009
Dec 2009
Apr 2010
Date

Sao Paulo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1,000
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600
400
200
Homicide-Model_1
Mar 2002
Jul 2002
Nov 2002
Mar 2003
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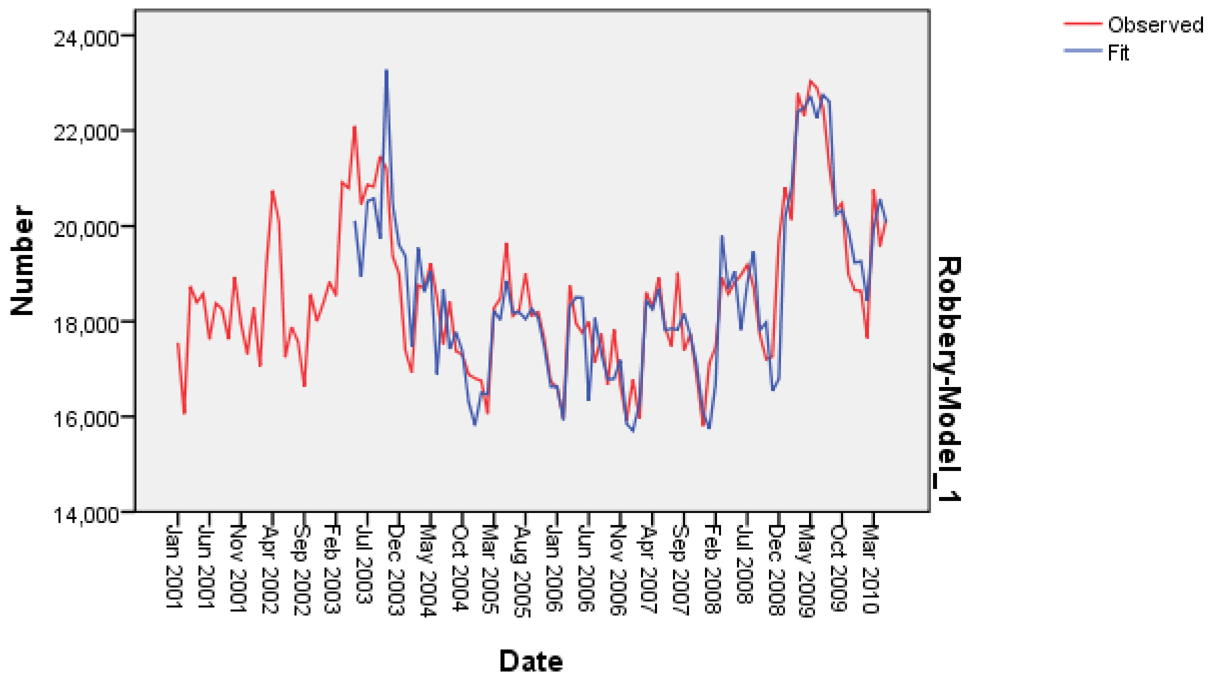
Date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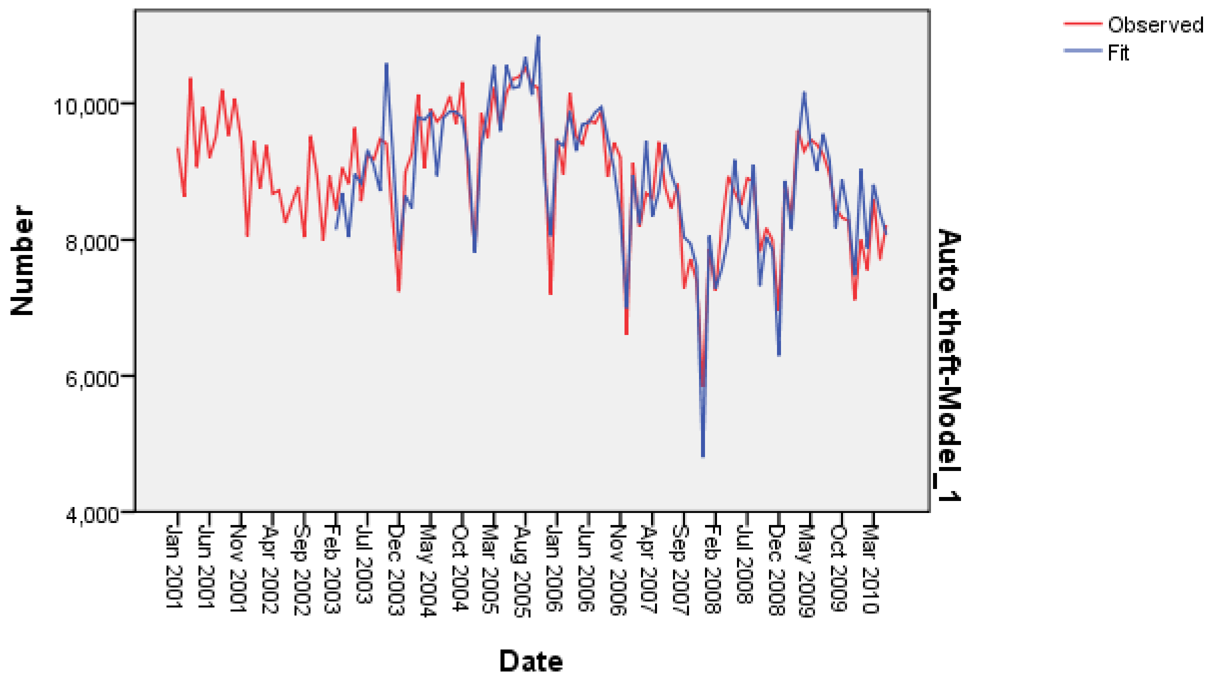
Date
Robbery-Model_1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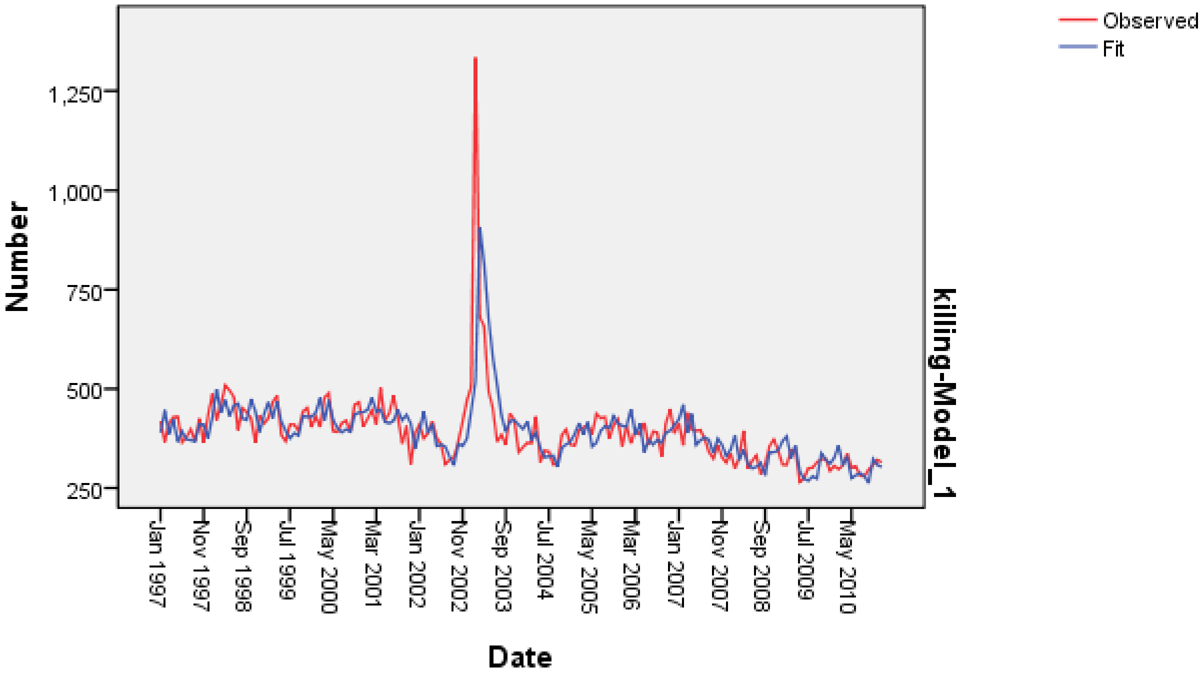
Date
Auto_theft-Model_1

Thailand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500
250
killing-Model_1
Jan 1997
Nov 1997
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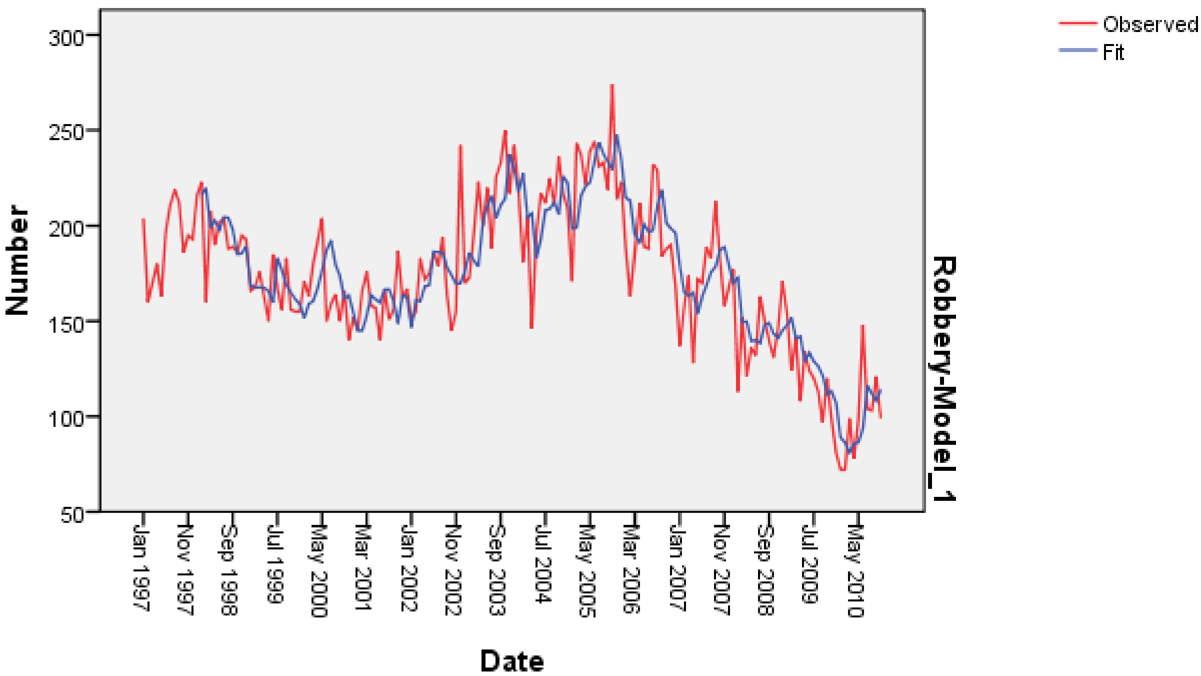
Date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Robbery-Model_1
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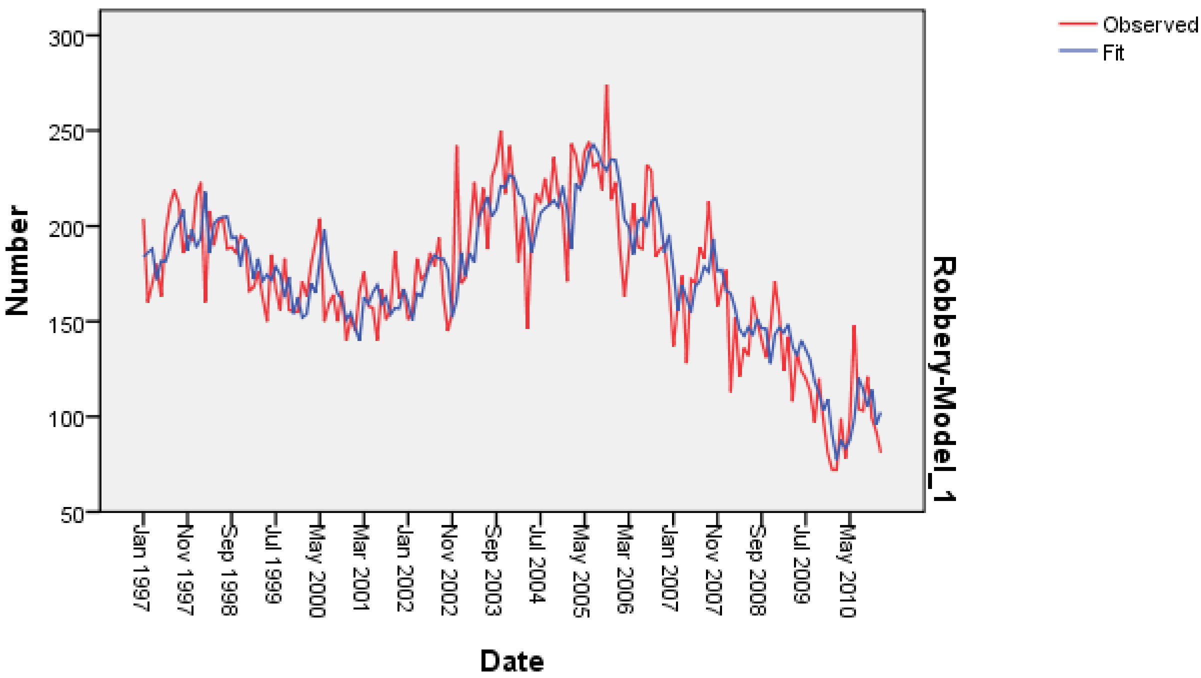
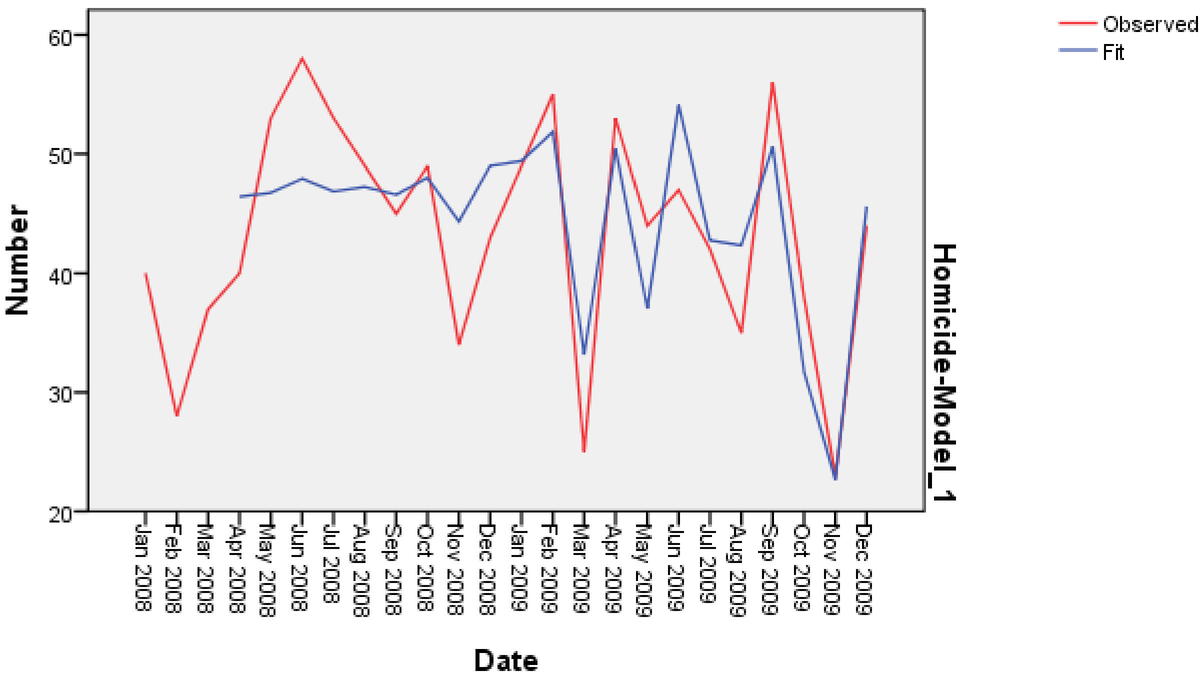
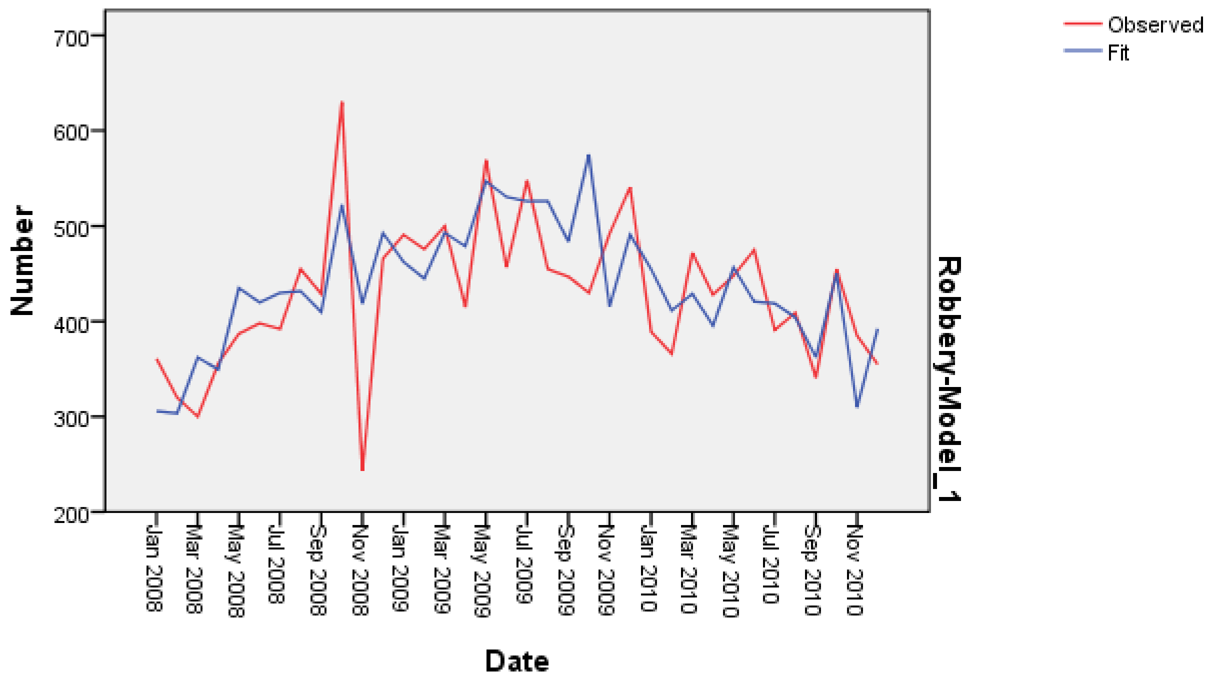
Date



Trinidad and Tobago

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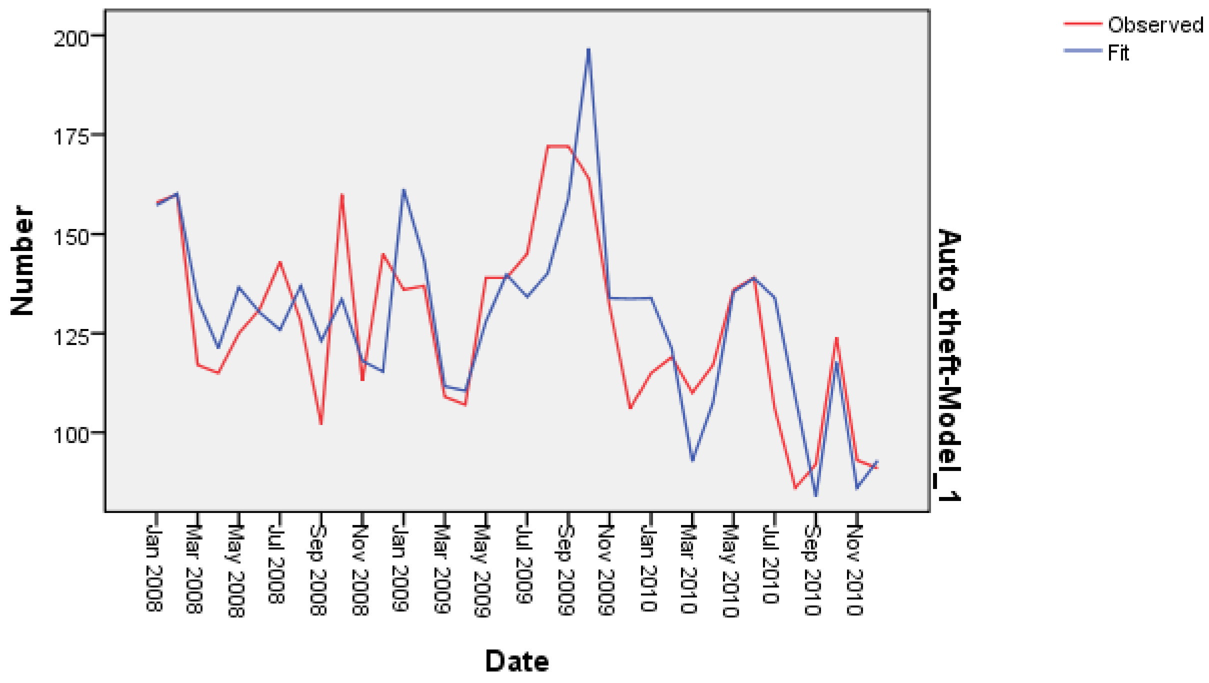
Date
Robbery-Model_1


Observed
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Number
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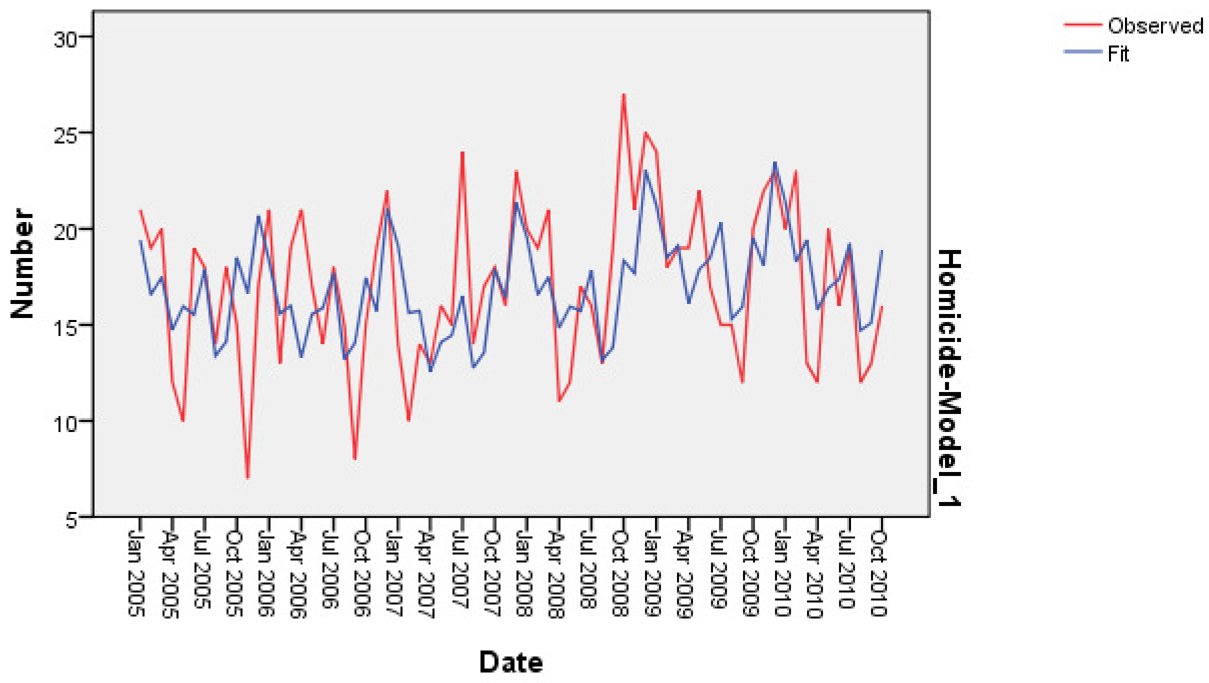
Nov 2010
Date
Auto_theft-Model_1

Uruguay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Apr 2005
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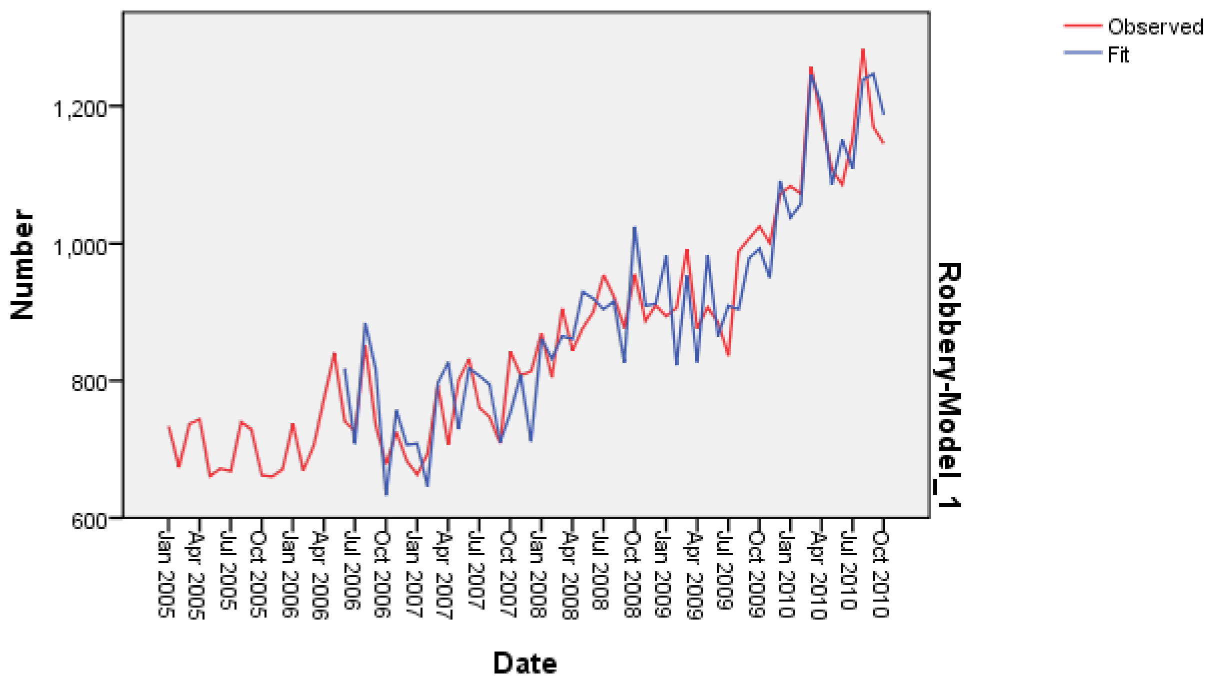
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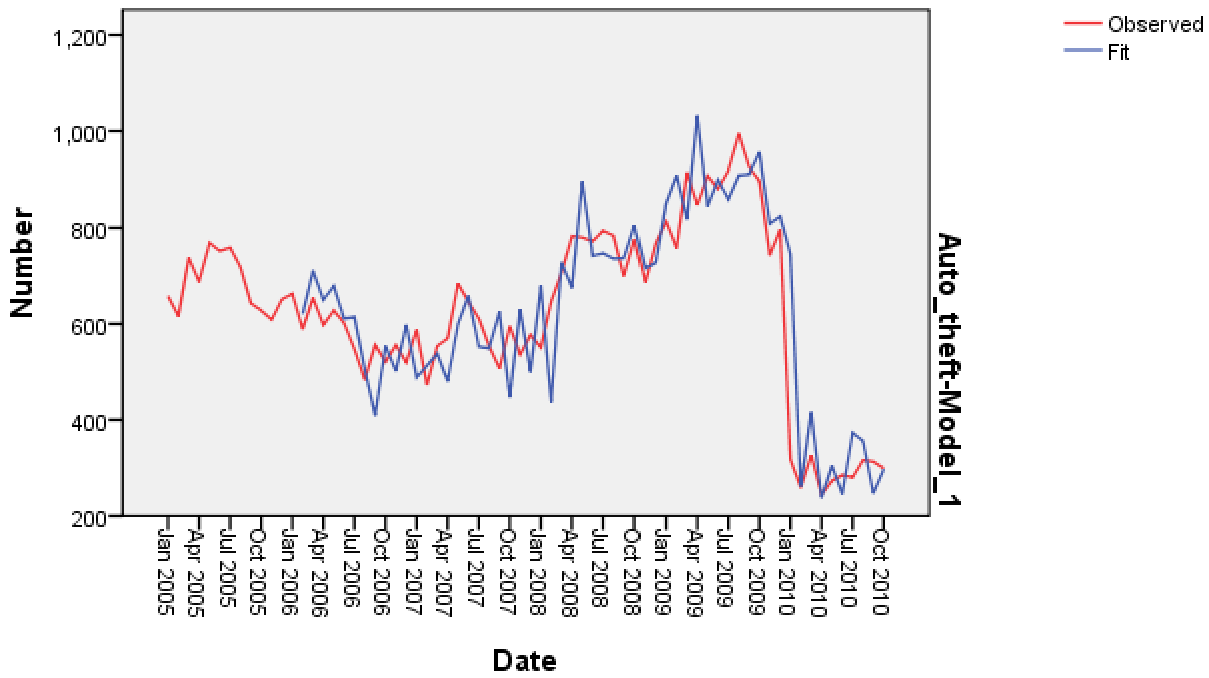
Observed
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