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# **Investigating the Long-Run and Causal Relationship between GDP and Crime in Sweden**

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## **Abstract**

Crime is one of the most harmful social problems throughout the world suggesting that the topic of crime is one of the most important research areas within the field of economics. This thesis attempts to shed some new light on the relationship between crime and gross domestic product (GDP) in the Nordic countries. More specifically the aim of the paper is to look for the existence of a cointegration relationship between GDP and various categories of crime in Sweden using annual data from 1950 to 2012. It does this by means of the bounds-testing approach to cointegration and vector error correction models. It further tests for Granger causality.

The results differ depending on the crime category. They do, however, show that there indeed exists a long-run equilibrium relationship between GDP and some crime categories while not with others. Furthermore, Granger causality results imply that GDP is more often than not a determinant of crime rather than a result of crime.

Keywords: Crime, GDP, Bounds-testing approach, VECM, Granger causality

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# 1. Introduction

Crime constitutes a significant activity in most economies. On the one hand, it allows for the consumption of various illegal goods and services. On the other, criminal activity can be socially harmful, and the resulting cost may be substantial. Although estimates of the total costs of crime in a society are by the nature of the phenomenon not very accurate, the available estimates suggest that this cost is high (e.g. Anderson, 1999; Cohen *et al.*, 2004; Webber, 2010). No matter what the true cost is, it is undeniable that crime is one of the most harmful social problems throughout the world. Thus the implication is that the topic of crime is one of the most important research areas within the field of economics (Glaeser, 1999).

Although crime plays such a significant role in most economies the relationship between gross domestic product (GDP) and crime remains unclear. The theoretical relationship is vastly complex with both positive and negative bidirectional causality being possible. This not only suggests a problem regarding external validity of empirical work but also results in endogeneity being a major identification challenge.

This paper attempts to address the identification challenge by applying time-series and simultaneous equation models which reduces the probability of endogeneity bias (Brandt and Williams, 2007). More specifically the aim of the paper is to look for the existence of a cointegration relationship between GDP and various categories of crime in Sweden using yearly data from 1950 to 2012. Following Narayan and Smyth (2004) and Chen (2009) this is done by means of a bounds-testing approach to cointegration and vector error correction models (VECM). Furthermore, regardless of whether such a relationship exists, Granger causality tests will be employed to examine the direction of causality.

While the use of cointegration and Granger causality has been increasing when analysing the relationship between crime and macroeconomic indicators (see Masih and Masih, 1996; Narayan and Smyth, 2004; Chen, 2009; Detotto and Manuela, 2010), this kind of study has never been done within the Nordic Countries.

The Nordic countries are often specified as welfare-states with low prison populations, knowledge-based crime policies and an absence of serious punitive measures in the public debate (Estrada, Pettersson and Shannon, 2012). This makes the Nordic countries an interesting focal point for crime research. Especially so, since the GDP-crime relationship may differ in the Nordic countries from that of other countries. This thesis is limited to only one of the Nordic

countries, the choice being Sweden. Sweden has recorded crime statistics from as early as 1950, which are readily available, and span various categories of crime

Understanding the relationship between GDP and crime over time is crucial. It may reveal that GDP is one of the many determinants of crime, it further may affect crime in the short-run as well as the long-run. The subject of the determinants of crime has long been of interest to researchers (e.g. Becker, 1968; Ehrlich, 1975; Freeman, 1999; Levitt, 2004). The relationship may also reveal that crime affects GDP, either in the short-run, the long-run or both. If so, it provides important information when estimating the total cost of crime as well as when constructing crime-fighting policies. It can give an important indication of how much effort should be put into fighting crime and which categories of crime are the most harmful. It can thus imply what type of policies are the most efficient in reducing the social costs of crime.

This thesis is organized as follows. Section 2 reviews the previous empirical literature. Section 3 discusses the possible theoretical relationships between GDP and various criminal activities, paying special attention to the difficulties resulting from the complex theoretical relationships. Section 4 explains the main econometric methods used in the thesis. Section 5 presents the data used and its main drawbacks. Section 6 reports on the empirical results of the analysis along with a discussion of the main findings. Section 7 is the conclusion.

## 2. Previous Research

The relationship between crime and macroeconomic variables remains unclear. Previous economic research, both theoretical and empirical, has by large part focused on the relationship between crime and unemployment usually finding a positive correlation (see e.g. Freeman (1999) for a review of the earlier literature). In the last decade the literature on the empirical relationship between crime and economic growth has increased. Regardless of a complex theoretical relationship most results are in consensus of a negative association between economic performance and criminal activity.

One of the earlier studies on crime and growth was done by Mauro (1995). He used country-level panel data to investigate the relationship between corruption and growth in the early 1980s. The dataset included 67 countries from all over the world. Using both ordinary least squares (OLS) and two-stage least squares (2SLS) he finds a significant negative relationship.

Pellegrini and Gerlagh (2004) do a similar study where they use growth regression analysis on country-level panel data for 48 countries worldwide, for the period of 1975-1996. They also find a negative relationship between corruption and economic growth. Gaibulloev and Sandler (2008; 2009) use panel data to analyse the impact of terrorism on growth separately in West-Europe and in Asia. In both cases they find that terrorism has a significant negative effect on growth.

Regarding more conventional crimes, Arvanites and Defina (2006) use a fixed effects model for US states to estimate the effect of business cycles on street crime in the period of 1986-2001. They found that an improving economy has a significant negative effect on property crime and robberies. Cardenas (2007) using a vector autoregressive (VAR) model shows that crime has a negative impact on productivity thereby decreasing economic growth in Columbia. Detotto and Otranto (2010) use monthly Italian data and an autoregressive state space model to measure the impact of crime on economic growth. They conclude that crime has a negative effect on economic growth. Detotto and Manuela (2010) use quarterly Italian data between 1981 and 2005 to analyse the causal and temporal relationship between crime and economic indicators related to the aggregated demand function. Using Johansen method to cointegration and Granger causality they find that in the short run crime positively affects GDP and public spending while in the long run it negatively effects investment and public spending.

Narayan and Smyth (2004) and Chen (2009) use small samples to test for long-run and causal relationships between various types of crime, unemployment and income. Both do this by means of the bounds-testing approach to cointegration and Granger causality tests. Narayan and Smyth (2004) use annual data in Australia and found that fraud, homicide and motor vehicle theft are cointegrated with both unemployment and income. They further found some evidence that unemployment, homicide and vehicle theft Granger cause income in the long term, but that long-run income and unemployment Granger cause fraud. Chen (2009) uses annual data in Taiwan. He finds that there is a clear long-run equilibrium relationship between unemployment, income and total crime. He further finds that unemployment, theft and economic fraud Granger cause income.

Limited research on the relationship between crime and macroeconomic indicators has been done in the Nordic countries. Blomquist and Westerlund (2014) use Swedish county panel data from 1975-2010 to analyse cointegration between crime and unemployment. Their results do not support a long-run relationship. Krüger (2011) used a wavelet-based approach to analyse

the impact of economic fluctuations on crime in Sweden. He uses Swedish monthly crime data from the beginning of 1995 and finds that all crime rates share seasonal behaviour with aggregate economic activity. Furthermore he concludes that alcohol and drug related crimes as well as economic crimes are pro-cyclical while property crimes, violent crimes and sexual crimes move counter-cyclically with economic activity.

### 3. The Theoretical Relationship between GDP and Crime

The possible theoretical relationship between GDP and crime is quite complex. GDP can affect crime, both in a positive and a negative direction. Crime can also affect GDP, both positively and negatively. In order to fully comprehend the relationship between GDP and crime one must understand the concept of GDP. Hence this chapter is organized as follows. It starts with a brief explanation of the concept of GDP. It then moves on to discussing how GDP can affect crime followed by a discussion on how crime can affect GDP. Lastly, it discusses how this complex relationship may result in estimation difficulties.

#### 3.1 *The Concept of GDP*

The aim of economic organization is to maximize the availability of goods and services to the members of society (e.g. Varian, 1992). GDP is designed to measure the market value of all final goods and services produced within an economy during a given time period, usually a year (e.g. Mankiw and Taylor, 2006). The GDP measure is essentially the sum of all the value-added (wages and profits) produced within the economy during the period in question.<sup>1</sup>

GDP is a production concept but may also be viewed from the expenditure side and the income side employing the following identities (e.g. Rowan, 1968):

$$Y(K, L) \equiv C + G + I + X - M \equiv w_L \cdot L + w_K \cdot K \quad (1)$$

where the first expression on the left hand side is the economy wide (net) production function, the middle expression represents how the production is allocated to various uses (expenditure account) and the right hand side views GDP from the income side. In the production function

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<sup>1</sup> Note that deterioration in the (real) value of capital, natural resources etc. is essentially negative production and value added.

$K$  stands for capital and  $L$  labour used in the production. In the expenditure account,  $C$  stands for private consumption,  $G$  for public consumption,  $I$  for investment,  $X$  for exports and  $M$  for imports. In the income account,  $w_L$  represents the remuneration of labour and  $w_K$  the remuneration of capital per unit. Expression (1) is an accounting identity (Rowan, 1968).

While the measure of GDP is meant to incorporate the value of all final production within an economy it fails to do so in various ways, one of them being that GDP typically fails to include income generated in an underground economy (United Nations, 2008). The main reason for this is that in practice GDP is typically measured on the basis of data on market trade and production collected by the statistical authorities (Landefeld, Seskin and Fraumeni, 2008). Activities within the underground economy are illegal (typically do not move along the usual marketing channels) and hence are generally not reported to the official data collection agencies or easily measured by them.

Assuming that illegal activities in the underground economy result in the production of some valuable goods and/or services<sup>2</sup> then GDP, as traditionally measured, underestimates the total value of production in the economy. For example, in Sweden the underground market production was estimated to be approximately 10-17% of the gross national product (GNP) around the 1990s using indirect methods, while around 4-5% of GDP in 2005 using a survey (Schneider and Enste, 2002; Davis and Henrekson, 2010).<sup>3</sup> Thus, although illegal production should positively affect GDP it usually does not.

Examples of illegal production of goods and services that GDP fails to embody are the production and sale of illegal drugs and prostitution. These can involve voluntary trade between two individuals and are therefore not only contributing to total production but are also utility-enhancing to both individuals as well as socially beneficial to the extent that the exchange generates more benefits to the users than external disutility to others.

### *3.2 From Crime to GDP*

While all crime is aimed at increasing the offender's utility and all crime seemingly involves some risk to the offender of being apprehended and possibly penalised. These crimes additionally involve one or more victims which suffer additional costs as a result of the crime

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<sup>2</sup> If one believes in the rational individual this must be true in the long run, since one would not go into production of goods or services which would not pay off in the long run.

<sup>3</sup> Andersson (1999) puts the annual aggregate cost of crime in the US at well over 1 trillion US\$ or some 8-10% of the US GDP. In the UK the total cost of *only* violent crime was estimated to be approximately £124 billion in 2012 or approximately 8% of GDP (Institute for Economics & Peace, 2013).



(Ehrlich, 1975). These include property crimes, vandalism, violent crimes, sexual crimes and fraud.

Crime against property undermines property rights and thus has a negative impact on both trade and accumulation (see e.g. Árnason, 2000; Pellegrini and Gerlagh, 2004). More specifically, the risk of having one's property stolen, destroyed or vandalised has a negative impact on investment. Individuals and firms will be less inclined to invest if there is a risk that instead of themselves, others reap the benefits of the investment. Since trade is an exchange of property rights, clearly with weaker property rights there will be less trade leading to less specialization and greater inefficiencies.

All crimes that result in an unexpected cost to one or more individuals (victims) have the potential to further result in a reduction in social trust. This reduction in trust simply reflects the risk of being a victim of a crime. Lower levels of trust, in turn, decrease the efficiency of trade via e.g. additional transaction costs (e.g. Burchell and Wilkinson, 1996). The unexpected costs to victims may also be in the form of emotional and/or physical costs (e.g. Glaeser, 1999). They can be exceptionally large in relation to violent and sexual crimes. They do not only lower the quality of life but can also lead to efficiency losses through a reduction in working hours and a decline in labour productivity (Farmer and Tiefenthaler, 2004). Thus all crimes, that include one or more victims, have the potential to negatively affect GDP.

All individuals face a time constraint and criminals are no exception (e.g. Glaeser, 1999). Criminals may hence resort to sacrificing legal work for illegal work. The trade-off between legal and illegal work results in an opportunity cost of producing crime, which is clearly a social cost and leads to a decrease in measured GDP. The trade-off may further result in loss of taxation since generally there are no taxes paid on criminal activity. This may lead to increased taxation on legal activity with the associated efficiency loss and decrease in GDP (e.g. Mankiw and Taylor, 2006).

On the other hand, crime may have a positive effect on GDP through expression (1). Governments and individuals tend to spend resources on ways to prevent crime, for example police, judicial systems, prisons and private security. This kind of private and public consumption and investment can have a positive effect on GDP as traditionally measured.<sup>4</sup>

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<sup>4</sup> It is important to keep in mind that in a crime-free economy these institutions would be unnecessary and the resources used by them could be used in a more efficient manner.

### *3.3 From GDP to Crime*

The economic approach to crime, first developed by Becker (1968), explains how criminals (like all individuals) are opportunistic rational beings who compare the expected costs of committing a crime to the expected benefits. If they find that the expected benefits outweigh the expected costs they will commit the crime, while if they find that the expected costs exceed the expected benefits, they will not.

With this in mind it is easy to see that as GDP increases so do opportunities for some types of crime. For example, increased wealth means greater expected benefits from property crime. Increased wealth leading to increased investment also increases vandalism opportunities and thus decreases the cost of vandalism. Hence, both property crime and vandalism can increase. Increased wealth, further, can result in increased demand for illegal goods and services. In return an increased demand either results in increased supply or higher prices, both of which may lead to more violence and corruption (United Nations Office on Drug and Crime, 2009). Additionally, some research has found that an increase in income may result in an abusive husband to become more violent (Tauchen, Witte and Long, 1991). Hence, GDP could positively affect crime rates.

On the other hand, as GDP decreases, people become poorer with the associated increase in the need for money, resulting in a possible increase in certain crimes. For example property crime could increase, as the expected costs of property crimes go down, and the supply of illegal goods and services could increase. It is also possible that as GDP decreases, psychological stress increases resulting in increased violence (e.g. Gavrilova *et al.*, 2000). Hence, GDP could negatively affect crime. Furthermore, one of the most popular theories is the one concerning the relationship between unemployment and crime (Freeman, 1999; Becker, 1968). When GDP falls unemployment tends to rise leading to an increase in various crime rates. So GDP could both directly and indirectly affect crime.

### *3.4 Issues*

It is evident that the relationship between GDP and crime is complex. GDP can affect crime and crime can affect GDP, they can further affect each other both negatively and positively. This makes it difficult, if not impossible, to know what type of relationship to expect a priori. An identification challenge arises because of the probability of both GDP and crime being endogenous. This leads to an endogeneity bias, resulting in difficulties with estimating the true

relationship (Verbeek, 2012). It can, for example, lead to a result of cointegration when in fact there is none, implying a spurious regression (Blomquist and Westerlund, 2014). Furthermore, endogeneity makes it almost impossible to estimate the true causal relationship without having the benefit of an exogenous shock (and even then it is difficult) (Verbeek, 2012). By applying time-series models and simultaneous equation models it is possible to reduce the probability of the endogeneity bias (Brandt and Williams, 2007).

The complex theoretical relationship also threatens the external validity of empirical results. This is because the relationship between the two may differ between various countries for numerous reasons. However, since Sweden is one of the Nordic countries which are often grouped together in terms of government involvement as well as in terms of crime rates and crime management it is likely that these results can be generalized over all the Nordic countries.

## 4. Methodology

This chapter discusses the main econometric methods applied. The bounds-testing approach to cointegration, which will be used to identify a long-run relationship between GDP and various crime variables is explained in detail. Following, is a description of the Toda-Yamamoto approach to Granger causality which will be used to identify the direction of causality between GDP and the various crime variables.

### 4.1 Cointegration

There are several methods available for cointegration testing. The conventional methods include the Engle-Granger two step method and the Johansen method (e.g. Enders, 2010; Greene, 2008). However, this thesis applies the bounds-testing approach to cointegration developed by Pesaran *et al.* (Pesaran and Pesaran, 1997; Pesaran and Shin, 1999; Pesaran, Shin and Smith, 2001). It has several advantages over the other methods mentioned. First and foremost, it can be applied irrespective of whether the variables are integrated of order zero,  $I(0)$ , or of order one,  $I(1)$ . This is a major advantage as it is quite common that the order of integration is not fully known (e.g. Elliott and Stock, 1994). It is, nevertheless, important to note that the approach fails if a variable is  $I(2)$ . The second advantage of the bounds-testing approach is that it has superior properties in small samples to the Engle-Granger and Johansen

methods (Narayan and Smith, 2004).<sup>5</sup> More specifically, when written in the error correction framework the model is less vulnerable to spurious regression (Chen, 2009). As the sample applied here only contains 63 observations this is indeed a valuable feature. Last but not least the approach is simple to understand, implement and interpret.

The bounds-testing approach consists of two main steps.<sup>6</sup> The first one involves estimating a conditional (or unrestricted) error-correction model (ECM) on the form:

$$\Delta y_t = \alpha_0 + \alpha_1 \cdot t + \beta_y \cdot y_{t-1} + \beta_x \cdot x_{t-1} + \sum_{i=1}^p \gamma_{1,i} \cdot \Delta y_{t-i} + \sum_{j=0}^q \gamma_{2,j} \cdot \Delta x_{t-j} + \varepsilon_t \quad (2)$$

where  $y_t$  represents the dependent variable and  $x_t$  the independent variables.  $\alpha_0$  is a drift term and  $t$  is a time trend, both of which do not necessarily need to be incorporated in the model.  $\varepsilon_t$  is the error term to be estimated and all  $\alpha$ ,  $\beta$  and  $\gamma$  are parameters to be estimated. The lag lengths  $p$  and  $q$  are determined by minimizing information criteria. A key assumption of the methodology is that the errors are serially uncorrelated. Hence, when the appropriate model is believed to be found it is necessary to test for autocorrelation in residuals. If autocorrelation is detected the number of lags in the model should be increased until the residuals are serially independent. The lagged values of  $\Delta y_t$  and the current and lagged values of  $\Delta x_t$  model the short-run dynamics while the levels  $y_{t-1}$  and  $x_{t-1}$  model the long-term relationship between  $y$  and  $x$ .

The estimation results from equation (2) are used to conduct an  $F$ -test where the null hypothesis of no long-term relationship is tested against a general alternative, that is:

$$H_0: \beta_y = \beta_x = 0$$

$$H_1: \beta_y \neq 0, \beta_x \neq 0 \text{ or } \beta_y \neq 0, \beta_x = 0 \text{ or } \beta_y = 0, \beta_x \neq 0.$$

This test follows a non-standard distribution which depends on (i) whether the variables in equation (2) are  $I(0)$  or  $I(1)$ , (ii) the number of regressors and (iii) whether the conditional ECM in equation (2) contains an intercept and/or a trend. Pesaran, Shin and Smith (2001) report some critical values which are based on a sample size of 1000 observations. Narayan (2005) calculates critical values for 30-80 observations. As the current sample size is only of 63

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<sup>5</sup> The OLS estimators of both the short-run and long-run parameters are consistent in small samples, within the bounds-testing framework.

<sup>6</sup> Before applying the bounds-test it is recommended to test for all the variables' order of integration. This both provides information on the data as well as makes sure that none of the variables are  $I(2)$ .

observations Narayan's critical values will be used. The critical values are in the form of a lower bound (where all variables are assumed to be I(0)) and an upper bound (where all variables are assumed to be I(1)). If the calculated  $F$ -statistic falls below the lower bound the null hypothesis of no cointegration cannot be rejected. If the calculated  $F$ -statistic exceeds the upper bound the null hypothesis of no cointegration is rejected. If the calculated  $F$ -statistic falls between the two bounds the test is inconclusive.

If the null hypothesis of no long-run relationship is rejected it is possible to move on to the second part of the bounds-testing approach where the long-run and short-run parameters are estimated using a regular (restricted) ECM on the form:

$$\Delta y_t = \beta_0 + \beta_1 \cdot t + \sum_{i=1}^p \theta_{1,i} \cdot \Delta y_{t-i} + \sum_{j=0}^q \theta_{2,j} \cdot \Delta x_{t-j} + \phi ECM_{t-1} + \varepsilon_t \quad (3)$$

where  $y_t$  is the dependent variable and  $x_t$  represents the independent variables.  $\beta$ ,  $\theta$  and  $\phi$  are parameters to be estimated. Again, the model does not need to include an intercept nor a trend.  $p$  and  $q$  are determined via information criteria.  $\varepsilon_t$  is a white noise disturbance term. The ECM term is obtained through the estimation of the long-run equilibrium:  $y_t = a_0 + a_1 \cdot t + a_2 \cdot x_t + u_t$  and  $ECM_{t-1} = y_{t-1} - \hat{a}_0 - \hat{a}_1 \cdot t - \hat{a}_2 \cdot x_{t-1}$ .<sup>7</sup> The estimated coefficients,  $\hat{\theta}_{1,i}$  and  $\hat{\theta}_{2,i}$  show the short-run dynamics of the relationship.  $\phi$  is the speed of adjustment parameter which shows how fast any deviations from the long-run equilibrium are corrected.

## 4.2 Granger Causality

If two variables are cointegrated there must exist Granger causality between them, either unidirectional or bidirectional (Granger, 1988). Furthermore, the non-existence of a cointegration relationship does not exclude the possibility of a short-run relationship and Granger causality. Hence, whatever the results of the cointegration tests it is possible to test for Granger causality between GDP and various crimes.

It is important to keep in mind that Granger causality tests do not provide evidence of the traditional meaning of causality:  $x_t$  is said to Granger cause  $y_t$  if  $y_t$  is better predicted using the lagged values of both  $x_t$  and  $y_t$  than if only lagged values of  $y_t$  are used (Granger, 1988). Granger causality does not exclude the possibility of the effect being through another variable, i.e. the

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<sup>7</sup> As before, the constant and the trend do not need to be included in the model.

relationship to be spurious (e.g. He and Maekawa, 2001). So when looking at the results of the causality tests one should be cautious with over-interpreting the meaning.

The usual way of testing for Granger causality is through a VAR model or a VECM depending on if the variables are cointegrated or not. This method assumes that the researcher can safely determine if the variables are integrated, cointegrated or stationary. Furthermore the legitimacy of the results is dependent upon this information being accurate (Toda and Yamamoto, 1995). But traditional unit root tests (e.g. the augmented Dickey-Fuller test) are known to suffer both from low power and distorted size in the sense that they over-reject the null (e.g. DeJong, 1992; Schwert, 1989; Enders, 2010).

While this thesis will partly apply these conventional Granger causality methods, the focus will be on a more robust approach, the Toda-Yamamoto Granger causality approach. The Toda-Yamamoto approach is independent of whether the variables are integrated, cointegrated or trend stationary (Toda and Yamamoto, 1995). The basic idea of the procedure is to estimate a simple VAR model on the form:

$$y_t = \alpha_y + \sum_{i=1}^{p+m} \beta_i \cdot y_{t-i} + \sum_{j=1}^{p+m} \gamma_j \cdot x_{t-j} + \varepsilon_t$$

$$x_t = \alpha_x + \sum_{i=1}^{p+m} \delta_i \cdot x_{t-i} + \sum_{j=1}^{p+m} \theta_j \cdot y_{t-j} + u_t$$

Where  $y_t$  and  $x_t$  are the variables of interest,  $\alpha_y$  and  $\alpha_x$  are constants,  $\beta_i$ ,  $\gamma_j$ ,  $\delta_i$  and  $\theta_j$  are parameters to be estimated.  $\varepsilon_t$  and  $u_t$  are white noise processes.  $p$  is the optimal lag length of the model (the number of lags that minimizes information criteria) and  $m$  is the maximum order of integration of the variables of interest.<sup>8</sup> The VAR model is estimated with OLS.

To test if  $x_t$  Granger causes  $y_t$  one can use an  $F$ -test to test the null hypothesis  $H_0 : \gamma_1 = \gamma_2 = \dots = \gamma_p = 0$  against a general alternative. If the null hypothesis is rejected one can conclude that  $x_t$  Granger causes  $y_t$ . Similarly to test if  $y_t$  Granger causes  $x_t$  one can test the null hypothesis  $H_0 : \theta_1 = \theta_2 = \dots = \theta_p = 0$  against a general alternative.

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<sup>8</sup> For example, if one of the variables is I(0) and the other is I(1) then  $m = 1$ .

## 5. Data

The data used are two categories of time series; GDP and crime variables. All series are annual and span the years 1950-2012, resulting in a small sample of only 63 observations. Data on current price GDP is retrieved from Statistics Sweden (2014) and is transformed into fixed priced GDP ( $Y_t$ ) with base year 2012. The crime data constitutes reported crime rates collected from the Swedish National Council for Crime Prevention (Brottsförebyggande rådet, Brå) (Brå, 2013a). The data is then categorized into six groups: (i) total crime ( $TC_t$ ), (ii) violent and sexual crime, ( $VS_t$ ); (iii) property crime ( $P_t$ ), (iv) fraud ( $F_t$ ), (v) vandalism ( $Va_t$ ) and (vi) drug crimes ( $D_t$ ). Total crime includes all incidents reported as crime by the police, customs or prosecutors in the country. Crimes are recorded in the time period they are reported in irrespective of whether the crime was committed in the same period or not. Furthermore, the reported crime statistics also includes crime reported in Sweden but committed abroad (Brå, n.d.a). Brå categorizes violent crime to include crime against life and health as well as sexual offenses. Property crime includes all reported thefts, robberies and stealing. Fraud includes all reported acts of fraud and other acts of dishonesty. Drug crime is defined as crimes against the narcotics drug act (Brå, n.d.a).

It is important to realise that reported crime data only includes a fraction of the actual crime rate. The gap between the reported crime rate and the true crime rate is often referred to as the *dark figure of crime* (Bidermann and Reiss, 1967). If the dark figure of crime were constant over time it would not pose a big problem when looking at the long-run relationship between crime and GDP (or other variables for that matter). It could affect the coefficient estimates resulting in a downward bias since the reported crime rate, in most cases, underestimates the true level of crime. The statistical significance should, however, remain unbiased. But as is pointed out by Biderman and Reiss (1967) the gap varies between types of crimes and over time and space. Hence fluctuations in reported crime may be due to changes in reporting rather than changes in the true crime rate. This difference in volatility results in a measurement bias when estimating the relationship between GDP and crime.

Although this is highly disadvantageous, it is in general difficult to get around it when analysing crime. One option is to use data from victimization surveys, which have recently started to be conducted in Sweden. While these could give more accurate crime rates they would still be faulty as surveys typically suffer from various biases (see e.g. Choi and Pak, 2005). Perhaps the ideal solution would be to structure a kind of crime index by combining the

reported crime rate with the crime rate stated in victimization surveys. However, this is not a feasible possibility for this thesis since victimization surveys have only been conducted in Sweden since 2006 (Brå, 2006). Furthermore, the surveys purely focus on crimes against the person which fall into the categories of violent crime, property crime and fraud. Hence, they provide no information on the true number of total crimes, vandalism nor drug crime. But it is interesting that they indicate that in 2012 only 33% of total crimes against the person were reported to the police, but in 2005 this number was even lower, at 21% (Brå, 2013b; Brå 2006). If the report rate is increasing over time then the measurement bias should be decreasing.

### 5.1 Descriptive statistics

Table 1 shows the mean, standard deviation, maximum and minimum of the seven time series. GDP is measured as GDP per capita while the crime variables are measured as crime per 100,000 capita.<sup>9</sup> Figures 1 and 2 show the evolution of the variables from 1950 to 2012. Note that GDP is measured on the right-hand axis while the crime trends are measured on the left axis.

**Table 1:** Descriptive statistics.

	<b>Mean</b>	<b>Std. Dev.</b>	<b>Max.</b>	<b>Min.</b>
<b>GDP</b>	211,866	85,241	372,361	88,478
<b>Total crime</b>	9,834	4,179	15,048	2,771
<b>Violent crime</b>	498	321	1,181	157
<b>Property crime</b>	5,573	2,139	8,618	1,570
<b>Fraud</b>	685	343	1,351	208
<b>Vandalism</b>	840	590	2,167	72
<b>Drug crime</b>	333	286	990	0

Source: Statistics Sweden (2013) and Brå (2013a) and author's calculations.

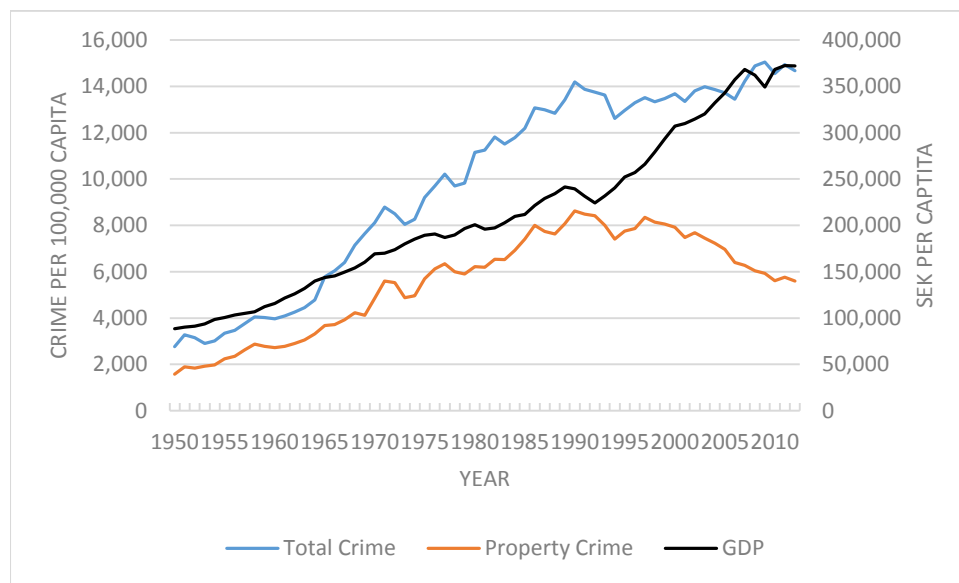
Table 1 and figures 1 and 2 show that real GDP per capita has been continuously increasing with the exceptions of the early 1990s and the crisis starting in 2008. Despite the crisis, real GDP was at its all-time high in 2011 with over 372 thousand SEK per capita and it was only slightly lower in 2012. Average GDP per capita in Sweden was approximately 212 thousand SEK annually in the period from 1950 to 2012.

Reported total crime rates have been rising steadily since 1950. They were at their lowest in 1950 at almost 2,800 reported crimes per 100,000 capita. Interestingly, they reached their

<sup>9</sup> When doing the statistical analysis all variables will be measured in per 100,000 capita to simplify interpretation of results.



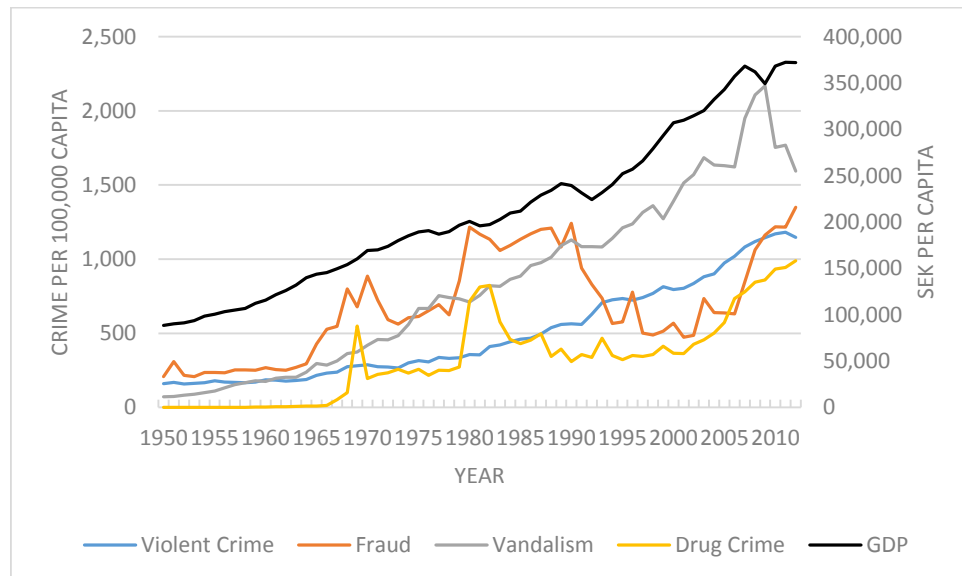
maximum in 2009 when the recent financial crisis was at its peak. Total reported offences increased dramatically between 1950 and 1990. Like can be seen on figure 1, this trend is primarily driven by an increase in property crime, more specifically theft (Estrada, Pettersson and Shannon, 2012). Since 1990, property crime has been decreasing. Despite this decrease total crime has continued to increase. This is partly due to a substantial increase in reported vandalism which between 2007 and 2009 had a sharp increase reaching a maximum of 2,169 reported incidents per 100,000 capita in 2009. Between 2009 and 2010 reported vandalism fell by approximately 20%.



**Figure 1:** Evolution of GDP, total crime and property crime, 1950-2012.  
Source: Statistics Sweden (2013) and Brå (2013a)

Violent crime has been increasing steadily since 1950, although not as fast as vandalism. The trend has an average of 498 reported incidents per 100,000 capita, ranging from a minimum of 157 in 1952 to a maximum of 1,181 in 2011. Fraud has had some fluctuations. It increased until the 1990s when an extensive change was made in the Swedish tax system (Regeringskansliet, 2010). It then decreased until around 2002 where it started to increase again reaching its maximum in 2012 with 1,351 frauds being reported per 100,000 capita. Reported drug crimes in Sweden were almost non-existent until in the late 1960s. Since then they have increased to around 990 reports per 100,000 population. They still remain quite infrequent compared to other crimes, being less than 7% of total crimes. However, as has been mentioned some types of crime tend to be less reported than others. According to Brå, drug crimes are systematically underreported and constitute a much larger part of the true crime rate than is recorded.

Moreover, drug crimes are believed to be the most common form of criminal activity in Sweden (Brå, n.d.b).



**Figure 2:** Evolution of GDP, violent crime, fraud, vandalism and drug crime, 1950-2012.

Source: Statistics Sweden (2013) and Brå (2013a)

Table 2 shows the calculated correlation between all the variables. The first row shows a very strong positive correlation between GDP and violent crime and GDP and vandalism with correlation coefficients of approximately 0.98. The correlation between GDP and total crime is 0.91 while it is 0.83 between GDP and drug crimes, and 0.73 between GDP and property crime. The correlation is the weakest between GDP and fraud where the coefficient is 0.59. The correlation between different types of crimes is also fairly strong, ranging from 0.51 to 0.97.

**Table 2:** Correlation coefficients.

	GDP	Total	Violent	Property	Fraud	Vandalism	Drug
GDP	1.000	0.911	0.975	0.726	0.585	0.982	0.831
Total		1.000	0.860	0.927	0.746	0.924	0.820
Violent			1.000	0.645	0.515	0.972	0.804
Property				1.000	0.642	0.751	0.597
Fraud					1.000	0.585	0.795
Vandalism						1.000	0.818
Drug							1.000

Source: Statistics Sweden (2013) and Brå (2013a) and author's calculations.

## 6. Empirical Results

This chapter shows the results from an econometric analysis using, among other, the methods discussed in chapter 4. The chapter is organized as follows. It starts with testing for stationarity. It then moves on to the bounds-testing approach to cointegration to investigate the existence of a long-run relationship between GDP and crime. Following this, VECM will be estimated to obtain the long-run equilibrium and short-run dynamics. Finally, Toda-Yamamoto method is used to test for Granger causality to get implications of the direction of causality between GDP and crime. The chapter concludes with a discussion on the empirical findings.

### 6.1 Stationarity

The data is tested for its order of integration using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The ADF and PP tests have a null hypothesis of a unit root while the KPSS test tests the null of stationarity. The results for the tests are shown in table 3.

The results of the tests are somewhat unexpected. In figures 1 and 2, most if not all of the series seem non-stationary. This is only partially confirmed by the tests. All three tests indicate this in the case of GDP ( $Y_t$ ), violent and sexual crime ( $VS_t$ ) and fraud ( $F_t$ ). However, when the model contains an intercept, the null of a unit root is rejected for property crime ( $P_t$ ), drug crime ( $D_t$ ) and vandalism ( $Va_t$ ) at the 5% level, according to the ADF and PP tests. The null is also rejected for total crime at the 5% level according to the PP but at the 10% level according to the ADF. The KPSS test rejects the null of stationarity for all variables when the model contains an intercept. Hence, the results from the ADF, PP and KPSS tests are to a certain extent conflicting. When the models contain an intercept and a trend the null is not rejected for any variables according to the ADF and PP tests. The same results are found by the KPSS test except for violent and sexual crimes where it is not possible to reject the null.

After taking first differences, the null hypothesis of a unit root is rejected for all series according to the ADF and PP tests, regardless of whether the model contains an intercept or an intercept and a trend. However, when the model contains an intercept the KPSS test results are that for four out of seven variables, i.e. total crime, property crime, drug crime and vandalism, the null hypothesis of stationarity is rejected, suggesting that these four variables may be integrated of order 2. When including both an intercept and a trend the null is not rejected for any variables except property crime.

**Table 3:** Unit root test results.

	ADF tests		Phillips-Perron		KPSS <sup>1</sup>	
	Intercept	Intercept + trend	Intercept	Intercept + trend	Intercept	Intercept + trend
$\ln(Y_t)$	-1.448 (0.553)	-2.194 (0.484)	-1.487 (0.533)	-1.750 (0.717)	0.986	0.156
$\ln(TC_t)$	-2.869 (0.055)	-0.757 (0.964)	-3.030 (0.038)	-0.645 (0.973)	0.903	0.250
$\ln(P_t)$	-3.794 (0.005)	-0.429 (0.984)	-3.571 (0.009)	1.142 (1.000)	0.803	0.254
$\ln(VS_t)$	0.208 (0.971)	-3.170 (0.100)	0.299 (0.977)	-3.165 (0.101)	0.997	0.135
$\ln(D_t)$	-3.150 (0.028)	-1.809 (0.688)	-3.216 (0.024)	-1.805 (0.690)	0.774	0.234
$\ln(F_t)$	-1.504 (0.525)	-1.814 (0.686)	-1.499 (0.528)	-1.851 (0.668)	0.608	0.176
$\ln(Va_t)$	-3.657 (0.007)	-0.673 (0.971)	-4.767 (0.000)	-0.228 (0.991)	0.960	0.258
$\Delta \ln(Y_t)$	-5.301 (0.000)	-5.428 (0.000)	-5.157 (0.000)	-5.207 (0.000)	0.293	0.067
$\Delta \ln(TC_t)$	-6.744 (0.000)	-7.126 (0.000)	-6.744 (0.000)	-7.123 (0.000)	0.827	0.078
$\Delta \ln(P_t)$	-6.358 (0.000)	-6.911 (0.000)	-6.359 (0.000)	-13.110 (0.000)	1.202	0.414
$\Delta \ln(VS_t)$	-7.622 (0.000)	-7.618 (0.000)	-7.626 (0.000)	-7.624 (0.000)	0.137	0.101
$\Delta \ln(D_t)$	-4.589 (0.000)	-8.151 (0.000)	-7.549 (0.000)	-8.151 (0.000)	0.612	0.097
$\Delta \ln(F_t)$	-8.637 (0.000)	-8.548 (0.000)	-8.577 (0.000)	-8.494 (0.000)	0.119	0.098
$\Delta \ln(Va_t)$	-6.350 (0.000)	-7.807 (0.000)	-6.384 (0.000)	-8.108 (0.000)	0.879	0.062

$p$ -values for the tests are in parentheses.  $\Delta$  represents the first difference.

<sup>1</sup> Critical values for the KPSS test are (i) with intercept; 1% 0.739 (ii) with intercept and trend; 1% 0.216  
5% 0.463 5% 0.146  
10% 0.347 10% 0.119

This inconsistency between the different stationarity tests creates a certain uncertainty about the variables' true order of integration. This can be problematic for the analysis that follows. While the bounds-testing approach is not dependent on whether the variables are I(0) or I(1), the KPSS results indicating a possibility of I(2) variables is worrisome.

The inconsistencies may be explained by the tests' limitations. It is widely acknowledged that unit root tests generally suffer from low power as well as distorted size. That is, the tests are known to suffer from both type I and type II errors (e.g. DeJong, 1992; Schwert, 1989; Enders, 2010). Thus, the tests are prone to yield incorrect conclusions. Another possible reason for the contradictory results of the stationarity tests is the existence of structural breaks in the data (Enders, 2010).

In order to investigate this possibility further Perron unit root tests for data with a structural break are conducted for all the variables. The Perron test tests the null hypothesis of a unit root and a structural break either in the intercept or in the intercept and in the trend, depending on the specification of the test.

The main results of the Perron tests show that a structural break in the series may be the cause of the non-rejection of the unit root null hypothesis in the ADF and PP tests.<sup>10</sup> However, when looking at figures 1 and 2 it is apparent that property crime is the only series that shows a clear structural break in the trend; having a positive slope until the late 1990s and a negative slope thereafter. While total crime has a fairly stable upward trend both vandalism and drug crime show fluctuations, but none of the three show an obvious structural break in the long-run trend. Hence, it is considered more probable that the contradictory results of the unit root tests are simply a consequence of the lower power of the tests, except in the case of property crime.

To further look into the possibility of a structural break in property crime a Quandt-Andrews unknown breakpoint test is used. It tests for a structural break in the data when the breakpoint is unknown.<sup>11</sup> The test results show that a breakpoint is found in property crime in the year 1997, which corresponds well with what was expected from analysing figure 1. On this basis, the following analysis will include a structural break dummy when the property crime series is used.<sup>12</sup>

Even though the KPSS results indicate the possibility of I(2) variables both the ADF, PP and Perron tests indicate otherwise. This allows us to continue as all the series are I(1). However, this is still an important issue to keep in mind as the properties of the bounds-tests fail if one of the variables is I(2).

## 6.2 Cointegration

Following Narayan and Smyth (2004), bounds-tests for cointegration are conducted employing a model including an intercept but no trend:

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<sup>10</sup> Since most of the results of the Perron tests do not directly affect the continuation of the study the detailed results are reported in Appendix 1 along with a short discussion.

<sup>11</sup> This is done by implementing a Chow test for every date within the sample period except for the first and last 7.5% of the total sample period. The Chow test statistics are then summarized into one statistic for testing the null hypothesis of no breakpoint (EViews, 2009).

<sup>12</sup> The dummy is defined so it is equal to 1 until 1997 and 0 thereafter. This assumes a constant relationship between GDP and property crime over time but that the change in trend is because of some exogenous change.

$$\Delta \ln(Y_t) = \alpha_0 + \beta_y \cdot \ln(Y_{t-1}) + \beta_{x_i} \cdot \ln(C_{it-1}) + \sum_{h=1}^p \gamma_{1i} \cdot \Delta \ln(Y_{t-h}) + \sum_{j=0}^q \gamma_{2j} \cdot \Delta \ln(C_{it-j}) + \varepsilon_t$$

$$\Delta \ln(C_{it}) = \alpha_0 + \beta_y \cdot \ln(C_{it-1}) + \beta_{x_i} \cdot \ln(Y_{t-1}) + \sum_{h=1}^p \gamma_{1i} \cdot \Delta \ln(C_{it-h}) + \sum_{j=0}^q \gamma_{2j} \cdot \Delta \ln(Y_{t-j}) + \varepsilon_t$$

where  $Y_t$  represents GDP per 100.000 capita and  $C_{it}$  crimes per 100.000 capita. The subscript  $i$  is used to represent the different types of crimes. It is important that the coefficients in the models remain unrestricted when testing for a long-run relationship in order to prevent pre-testing problems. Thus the number of lags included in the models ( $p$  and  $q$ ) is determined using the Schwartz-Bayesian information criterion (SBC), and statistically insignificant coefficients are kept in the model. To test for autocorrelation Breusch-Godfrey tests are applied to all models. Should the model show any signs of serial correlation the number of lags in the model is increased until no autocorrelation is detected.

The key results of the bounds-testing approach are reported in table 4.<sup>13</sup> The table shows the 90% and 95% critical values for the bounds-tests assuming an unrestricted intercept and no trend (Narayan, 2005).<sup>14</sup>

When GDP is modelled with (i) total crime, (ii) violent and sexual crime and (iii) fraud, the corresponding  $F$ -statistics are found to be lower than the 95% lower critical value. This is irrespective of which variable is used as the dependent one. This implies no cointegration and hence no long-run relationship between the variables. However, this does not exclude a possible short-run relationship.

When property crime and GDP are modelled together with GDP as the dependent variable, the  $F$ -statistic is found to be higher than the 95% upper critical value. This implies the existence of a long-run relationship between GDP and property crime. However, the same result is not found when property crime is modelled as the dependent variable.

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<sup>13</sup> For more detailed estimation results the reader can turn to Appendix.

<sup>14</sup> Including a trend in the models where it could be suitable did not change the results of the cointegration test.

When drug crime is modelled as the dependent variable with GDP as the independent variable the corresponding  $F$ -statistic implies a long-run relationship between drug crime and GDP.

**Table 4:** Bounds-test results

<b>Critical values<sup>1</sup></b>		
	I(0)	I(1)
<b>95%</b>	5.125	6.000
<b>90%</b>	4.145	4.950
<b>Bounds-test Results</b>		
$F(Y_t TC_t) = 3.126$	$F(TC_t Y_t) = 4.113$	
$F(Y_t P_t) = 6.711$	$F(P_t Y_t) = 2.635$	
$F(Y_t VS_t) = 2.445$	$F(VS_t Y_t) = 2.151$	
$F(Y_t D_t) = 0.571$	$F(D_t Y_t) = 7.287$	
$F(Y_t Fr_t) = 2.196$	$F(Fr_t Y_t) = 1.148$	
$F(Y_t Va_t) = 2.478$	$F(Va_t Y_t) = 6.444$	

<sup>1</sup> Source: Narayan (2005).

$F(Y_t/TC_t)$  gives the  $F$ -value when  $Y_t$  is modelled as the dependent variable and  $TC_t$  as the independent variable.

However, if GDP is modelled as the dependent variable then the  $F$ -statistic is lower than the 95% lower critical bound implying no cointegration. When vandalism is modelled as the dependent variable with GDP, the calculated  $F$ -statistic exceeds the 95% upper bound critical value implying a long-term relationship between GDP and vandalism. If GDP is modelled as the dependent variable the estimated  $F$ -statistic is found to be lower than the 95% lower critical value, implying no

cointegration.

Theoretically, results of cointegration tests should be invariant of which variable is used as the dependent one (e.g. Enders, 2010). The fact that the results of the bounds-testing approach depend on which variable is the dependent one is a very undesirable property which makes it harder to get clear conclusions. However, the next step of the bounds-testing approach involves estimating VECMs which will either strengthen the evidence for cointegration or undermine it. Hence, at this point, we conclude that a long-term relationship *may* exist between property crime and GDP, vandalism and GDP and drug crime and GDP. Other crime categories show no signs of a long-term relationship with GDP.

### 6.3 Error Correction Models

For those models that exhibit evidence of cointegration, it is now possible to move onto the second step of the bounds-testing approach, which involves estimating a long-run equilibrium relationship and short-run dynamics (Pesaran, Shin and Smith, 2001). This is done by estimating a long-run equilibrium and a corresponding VECM for each relationship.

Table 5 shows the preferred VECMs<sup>15</sup> along with their cointegration relationships and traditional Granger causality results. The cointegration relationships show the long-run equilibrium relationship between the variables; they show a linear combination of the variables that is stationary. They are normalized so that the coefficient for the dependent variable from the bounds-tests results is one. The three equilibria imply a positive long-run correlation between GDP and property crime, GDP and vandalism and GDP and drug crime. This implies that if GDP grows over time, which most find desirable, these crimes will also increase unless something breaks up the equilibrium.

**Table 5:** VECM results.

	<b>GDP-Property</b>		<b>GDP-Vandalism</b>		<b>GDP-Drug</b>	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Dep.</b>	$\Delta \ln(Y_t)$	$\Delta \ln(P_t)$	$\Delta \ln(Y_t)$	$\Delta \ln(Va_t)$	$\Delta \ln(Y_t)$	$\Delta \ln(D_t)$
<b>Const.</b>	0.042*** (4.434)	-0.037 (-1.392)	0.019*** (4.143)	0.028** (2.013)	0.015*** (3.604)	0.175** (2.233)
$\Delta \ln(C_{it-1})$	-0.128*** (-2.866)	0.118 (0.934)	-0.052 (-1.326)	0.003 (0.022)	0.006 (0.870)	-0.053 (-0.425)
$\Delta \ln(Y_{t-1})$	0.281** (2.493)	0.747** (2.346)	0.303** (2.422)	0.936** (2.413)	0.317** (2.524)	-0.838 (-0.351)
<b>Dummy</b>	-0.031*** (-2.758)	0.047 (1.499)				
$ECT_{t-1}$	-0.076*** (-3.721)	-0.000 (0.002)	-0.006* (-1.678)	-0.039*** (-3.390)	-0.001 (-0.951)	-0.066*** (-2.955)
<b>Adj. R<sup>2</sup></b>	0.272	0.191	0.124	0.293	0.104	0.088
<b>SBC</b>	-4.838	-2.759	-4.702	-2.436	-4.680	1.211
<b>Cointegration relationships</b>						
<b>GDP-Property:</b>	$\ln(Y_{t-1}) = 19.968 + 0.436 \cdot \ln(P_{t-1}) + \hat{\varepsilon}_{P_{t-1}}^{***}$					
<b>GDP-Vandalism:</b>	$\ln(Va_{t-1}) = -2.685 + 0.383 \cdot \ln(Y_{t-1}) + \hat{\varepsilon}_{Va_{t-1}}$					
<b>GDP-Drug:</b>	$\ln(D_{t-1}) = -14.606 + 0.804 \cdot \ln(Y_{t-1}) + \hat{\varepsilon}_{D_{t-1}}$					
<b>Granger Causality</b>						
<b>GDP-property:</b>	$F(Y_t P_t) = 8.212^{***}$ [0.004]		$F(P_t Y_t) = 5.502^{**}$ [0.019]			
<b>GDP-vandalism:</b>	$F(Y_t Va_t) = 1.758$ [0.185]		$F(Va_t Y_t) = 5.820^{**}$ [0.016]			
<b>GDP-drug:</b>	$F(Y_t D_t) = 0.758$ [0.384]		$F(D_t Y_t) = 0.123$ [0.725]			

\*, \*\*, \*\*\* note statistical significance at the 10%, 5% and 1% levels respectively.

$t$ -statistics are in parentheses.  $p$ -values are in squared brackets.

The  $ECT_{t-1}$  term in the VECM represents the corresponding estimated residuals from the cointegration relationships.

<sup>15</sup> For the estimation of long-run effects and short-run dynamics a more parsimonious model is advisable than when testing for the existence of long-run relationship (Pesaran, Shin and Smith, 2001). It is still important that the models include enough lags not to suffer from serial correlation.



Models (1) and (2) in table 5 show the VECM for GDP and property crime. As already noted there is an equilibrium relationship between GDP and property crime defined by the first cointegration relationship. The speed of adjustment parameter to this equilibrium, estimated to be -0.076, is significant at the 1% level in model (1). This implies that GDP reacts to correct any deviations from the long-run equilibrium between GDP and property crime by approximately 7.6% annually, a sluggish adjustment. A change in property crime however, does not react to any disequilibrium. This can be seen from the insignificance of the speed of adjustment parameter in model (2) as well as that the coefficient is approximately zero.

The short-run parameters in model (1) are both significant at the 5% level.<sup>16</sup> The coefficient for the lagged value of GDP ( $\Delta \ln(Y_{t-1})$ ) shows that a previous increase in GDP leads to a continuing but a smaller increase in the present period. The coefficient for the lagged value of property crime ( $\Delta \ln(C_{it-1})$ ) in model (1) shows that an increase in property crime significantly reduces GDP in the short run. More specifically, as property crime increases by 1% GDP decreases by almost 0.13% in the short run. Although 0.13% of GDP does not seem as much it is still a significant amount. For example, it equals around 484 million SEK per 100.000 capita in 2012. In model (2) the short-run parameter for lagged GDP has a statistically significant effect on property crime showing that as GDP increases by 1% then in the short-run property crime increases by 0.75%. However, it is important to remember that these parameter estimates are only short-run estimates. Furthermore, parameter estimates are rarely accurate and one should not over-interpret them.

The statistically significant speed of adjustment parameter in model (1) indicates that property crime Granger causes GDP in the long run. Furthermore, the significant short-run parameters in models (1) and (2) imply that GDP Granger causes property crime and property crime Granger-Causes GDP in the short run. Conducting simple Granger causality tests (last portion of table 5) verifies this hypothesis.

Models (3) and (4) represent the VECM for GDP and vandalism. The speed of adjustment parameter in model (3) is significant at the 10% level while the one in model (4) is significant at the 1% level. This implies that both GDP and vandalism respond to deviations from the long-run equilibrium. According to the parameter estimates, GDP responds to a positive disequilibrium by decreasing by 0.6% annually while vandalism decreases by 3.9%.

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<sup>16</sup> The short-run parameters are the coefficients for  $\Delta \ln(C_{it-1})$  and  $\Delta \ln(Y_{t-1})$ , as is explained in section 4.1.

Both speed of adjustment parameters in models (3) and (4) are statistically significant which implies that GDP Granger causes vandalism and vandalism Granger causes GDP in the long run. However, while the short-run parameters corresponding with vandalism are insignificant in both models the parameters for GDP are significant and indicate a positive effect. This further indicates that GDP positively Granger-causes vandalism in the short run but not vice-versa. Again, this is supported by the results of the direct Granger causality tests in the last part of table 5.

Models (5) and (6) show the VECM for GDP and drug crime. The speed of adjustment parameter is only statistically significant in model (6). It implies that in response to any positive deviations from the long-run equilibrium between GDP and drug crime, drug crime decreases by 6.6% annually. This further implies that GDP Granger causes drug crime in the long run. However, the change in GDP does not respond to any long-run disequilibrium. The short-run parameters show that GDP does not significantly affect drug crime nor drug crime GDP. This implies that there is no short-run Granger-causality between the variables. This is further shown by the traditional Granger causality tests reported in the bottom of table 5.

The power of the traditional Granger causality test is not very high (Enders, 2010). Hence, the results from the Granger tests can be misleading. A more robust method for testing for Granger causality is applied in the next section.

#### 6.4 More on Granger causality

Toda-Yamamoto Granger causality tests are implemented for GDP along with all crime categories. The Toda-Yamamoto Granger causality tests are improved versions of the standard Granger causality tests reported in table 5 (Toda and Yamamoto, 1995). The following VAR models are estimated

$$Y_t = \alpha_Y + \sum_{h=1}^{p+m} \beta_h \cdot Y_{t-h} + \sum_{j=1}^{p+m} \gamma_j \cdot C_{it-j} + \varepsilon_t$$

$$C_{it} = \alpha_{C_i} + \sum_{h=1}^{p+m} \delta_h \cdot C_{it-h} + \sum_{j=1}^{p+m} \theta_j \cdot Y_{t-j} + u_t$$

Where  $Y_t$  is GDP and  $C_{it}$  is crime  $i$  with  $i$  being an index for the six crime categories.  $p$  is chosen by minimizing the SBC information criterion, while still maintaining no autocorrelation.  $m$  represents the maximum order of integration for the two time series in each model;  $m = 1$  in all

cases.  $C_{it}$  is said to Granger cause  $Y_t$  if the  $H_0 : \gamma_1 = \gamma_2 = \dots = \gamma_p = 0$  is rejected. Similarly  $Y_t$  is said to Granger cause  $C_{it}$  if  $H_0 : \theta_1 = \theta_2 = \dots = \theta_p = 0$  is rejected. The results are shown in table 6.

**Table 6:** Granger causality results.

<b>F-test results w/o structural break</b>			
$F(Y_t TC_t) =$	6.105** (0.047)	$F(TC_t Y_t) =$	4.106 (0.128)
$F(Y_t P_t) =$	1.740 (0.419)	$F(P_t Y_t) =$	6.258** (0.043)
$F(Y_t VS_t) =$	1.612 (0.447)	$F(VS_t Y_t) =$	1.709 (0.426)
$F(Y_t D_t) =$	0.471 (0.493)	$F(D_t Y_t) =$	0.097 (0.756)
$F(Y_t Fr_t) =$	7.625*** (0.006)	$F(Fr_t Y_t) =$	2.662* (0.103)
$F(Y_t Va_t) =$	1.132 (0.568)	$F(Va_t Y_t) =$	6.453** (0.040)

\*, \*\*, \*\*\* note statistical significance at the 10%, 5% and 1% levels respectively.  

$p$ -values are shown in parentheses.  
 $F(Y_t/TC_t)$  gives the F-value when  $Y_t$  is modelled as the depend variable and  $TC_t$  as the independent variable.

While it is not possible to reject the null that GDP does not Granger cause total crime, it is possible to reject the null that total crime does not Granger cause GDP. As the previous analysis did not imply a long-run relationship it seems reasonable to infer that total crime Granger causes GDP but only in the short run.

While the more traditional Granger causality tests indicated bidirectional causality between GDP and property

crime, the Toda-Yamamoto method implies a unidirectional causation, running from GDP to property crime.

No Granger causality is found between GDP and violent and sexual crimes. On the other hand, a significant causality is found between fraud and GDP. More precisely, the results imply that fraud Granger causes GDP at the 1% level and that GDP Granger causes fraud at approximately the 10% level. This, along with cointegration results, implies a bidirectional causality in the short run.

It is found that vandalism does not Granger cause GDP but that GDP Granger causes vandalism at the 5% level. The results further indicate no short-run causality between GDP and drug crime. These results corresponds with the results from the traditional Granger causality tests shown in table 5.

The results from the Toda-Yamamoto method correspond to the results of the traditional Granger causality test by the most part as they suggests that GDP Granger causes vandalism in the short run but vandalism does not Granger cause GDP. Furthermore, they confirm that there is no short-run Granger causality between GDP and drug crime. However, although the traditional Granger tests indicated bidirectional causality between GDP and property crime the

Toda-Yamamoto method simply implies that GDP Granger causes property crime but not vice versa. Hence, the causal relationship between GDP and property crime remains unclear.

### *6.5 Main Results and Theoretical Implications*

The main results from the empirical analysis imply long-term equilibriums between GDP and property crime, drug crime and vandalism. These equilibriums all show a positive relationship. No long-run relationship was found between GDP and total crime, violent and sexual crime and fraud. Furthermore, short-run Granger causality is found between GDP and all crime categories except for violent and sexual crime and drug crime. This implies that although there is some kind of a relationship between GDP and five out of six crime categories analysed in this thesis, there is no relationship between GDP and violent and sexual crimes. Following is a more detailed discussion of the findings along with theoretical implications.

As has been stated, GDP is found to have a long-run equilibrium relationship with property crime. While in the long run they are positively correlated, in the short-run property crime negatively affects GDP but GDP positively affects property crime, according to the VECM results. However, these results are somewhat ambiguous as the Toda-Yamamoto method concludes that GDP Granger causes property crime but not vice versa. Hence, there is evidence supporting that the positive effect of GDP on property crime is stronger than the negative effect of property crime on GDP. This is the opposite of Krüger's (2011) results but he found that in the short run economic activity and property crime move counter-cyclically. Taking that into account the results are consistent with the theory that property crime can have a short-run negative effect on GDP through decreased property rights, trade and accumulation. However, in the long run as GDP increases so do the expected benefits of property crime resulting in an increased number of property crimes.

GDP is found to share a long-run equilibrium with vandalism. While both respond to maintain this equilibrium in the long-run, in the short-run GDP Granger causes vandalism but not vice versa. These results are consistent regardless of what methodology is used. Both the estimates of the long-run relationship and the short-run imply that the effect is positive. These results are in accordance with the theory that as GDP increases so do investments. This further decreases the opportunity costs of vandalism (e.g. time cost of finding the object to vandalise) and hence vandalism increases.

GDP and drug crime also share a long-run equilibrium relationship which suggests that GDP Granger causes drug crime in the long run. However, no short-run Granger causality was found, neither by applying traditional methods nor the Toda-Yamamoto method. The results imply the theory that as GDP increases people become richer which leads to increased drug production and use, but the effects only appear in the long run. However, as drug crime is believed to be the most common crime while it is also the least reported crime, the data may not give very reliable results (Brå, n.d.b).<sup>17</sup> Krüger (2011) found that GDP and drug crime in Sweden move pro-cyclically which is consistent with our results and further strengthens the evidence of the results found.

It is a bit surprising that while some crimes were found to have an equilibrium relationship with GDP, such a relationship was not detected between total crime and GDP. However, Granger causality was found running from total crime to GDP, so most likely the data was simply not discriminating enough to detect the relationship when adding all crimes together. However, whether the Granger causality is positive or negative remains unknown. The relationship is unquestionably complicated and may differ between time periods and in the crime categories mostly responsible for the variation within total crime. As more information is necessary to make any meaningful deductions we will simply conclude that fluctuations in total crime lead to fluctuations in GDP.

No cointegration nor Granger causality was found between GDP and violent and sexual crime. Hence, there does not seem to be any systematic relationship between GDP and violent and sexual crime. This is not a surprising result as the motivation for these types of crimes is more likely to be mental or emotional than financial or logical (see e.g. Lawteacher, n.d. for an overview of literature discussing the reasons for violent crime). Although it seems reasonable that declining economic activity results in increased stress and hence increased violence, this kind of indirect causation may not be detectable in the empirical data.

While no cointegration is established between GDP and fraud the Granger causality tests indicate bidirectional causality in the short run. Although, the sign of the effect remains undetected, it appears reasonable that GDP positively affects fraud and fraud negatively affects GDP.<sup>18</sup> If so, it indicates that as GDP grows, the expected benefits from committing fraud increase relative to the expected costs and individuals are more inclined to commit fraudulent

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<sup>17</sup> The unreliable data makes it more likely that the cointegration relationship found is spurious.

<sup>18</sup> A simple VAR analysis reinforces this belief.

acts such as tax evasion and accounting crimes (which are the most common frauds reported to Brå (n.d.c)). However, performing such acts negatively affects GDP, which may be channelled through decreased property rights, declining trust etc.

In general the results point to GDP affecting crime rather than crime affecting GDP. Thus, although the relationship between GDP and crime is complex, the analysis implies that GDP is one of the determinants of crime rather than that crime systematically affects GDP. However, when looking at the results of this analysis it is important to remember that the crime data used includes only reported crime. If the actual crime rate were used instead the results could be very different, depending on the evolution of the report rate over time. It is further important to note that there is always a possibility of the results being spurious, thus indicating a relationship when there is none. Nevertheless, the results are interesting and should be considered by policy makers.

## 7. Conclusions

This thesis has introduced new evidence on the relationship between GDP and crime in Sweden. It does this by investigating the existence of long-run equilibriums between GDP and various crime categories using annual data for the period of 1950-2012. For those relationships that show signs of cointegration, VECMs are estimated making it possible to distinguish between short-run and long-run effects. Granger causality tests further show if there exists short-run causality and in what directions it goes.

It is important to keep in mind that the results found in this thesis are based on reported crime rate but not the true crime rate. Hence, the results are only valid to the extent that the fluctuations in the reported crime rate reflect the fluctuations in the true crime rate.

The results show that GDP has a long-run equilibrium relationship with property crime, vandalism and drug crime. Property crime is found to Granger cause GDP both in the short run and in the long run. GDP also Granger causes property crime in the short run. There is a long-run bidirectional Granger causality between GDP and vandalism. In the short-run Granger causality is found to run only from GDP to vandalism. In the long-run drug crime Granger causes GDP but no short-run causality is found, which makes the results somewhat ambiguous.

The findings suggest that the long-run relationships are all of positive nature. This further means that if GDP continues to increase over time it is not possible to expect that property crime, vandalism and drug crime decrease, *ceteris paribus*. However, some exogenous change, for example in the form of increased law-enforcement, may be able to break up the relationship. Whether this exogenous change needs to be drastic or more modest remains unknown.

No long-run relationships are found between GDP and total crime, violent and sexual crime and fraud. However, bidirectional short-run Granger causality is found between GDP and fraud and total crime is found to Granger cause GDP. No causality is found between GDP and violent and sexual crime. Hence, no kind of relationship is found between GDP and violent and sexual crimes.

Although, the results of the analysis cannot exclude the possibility of crime systematically decreasing GDP, they do not particularly imply it either. The Granger causality tests indicate that GDP affects crime more often than crime affects GDP. Hence, these results suggest that GDP is one of the determinants of crime. This further implies that when estimating the total cost associated with criminal activity it is not necessary to factor in the possible indirect cost caused by a decrease in GDP, making estimations of the costs simpler.

Because of the various possible theoretical relationships between GDP and crime the external validity of the results is compromised. That is, the relationship between GDP and crime may differ between various countries for numerous reasons. However, since Sweden is one of the Nordic countries which are often grouped together in terms of government involvement as well as in terms of crime rates and crime management it is probable that these results can be generalized over all of the Nordic countries.

While the current study provides new and valuable information for policy-makers, there still remains uncertainty regarding the relationship between crime and GDP. The field requires increased research. It is especially recommended to look at different indicators of crime rates than the reported crime rates. For example, victimization surveys provide an interesting option for researchers. It would further be of great interest to inspect the relationship between various components of GDP and crime.

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## Appendix 1

The results of the Perron tests are shown in table A.1. According to the test results it is not possible to reject the null of a unit root in the levels of the data when the model contains a structural break in the intercept. The same applies when the model contains a structural break in both the intercept and the trend. The exception is in the case of drug crime where the null can be rejected, implying a possible trend-stationary series. After taking the first difference the null hypothesis of a unit root can be rejected for all variables irrespective of whether the model includes an intercept or an intercept and a trend.<sup>19</sup>

**Table A.1:** Results of Perron unit root test for data with a structural break.

	Perron for structural <sup>1</sup>	
	Intercept	Intercept + trend
$\ln(Y_t)$	-3.262	-3.712
$\ln(TC_t)$	-3.702	-3.828
$\ln(P_t)$	-0.747	-2.361
$\ln(VS_t)$	-3.945	-3.744
$\ln(D_t)$	-3.480	-6.163
$\ln(F_t)$	-4.145	-3.291
$\ln(Va_t)$	-2.054	-3.639
$\Delta \ln(Y_t)$	-6.413	-6.529
$\Delta \ln(TC_t)$	-8.022	-8.021
$\Delta \ln(P_t)$	-7.179	-7.192
$\Delta \ln(VS_t)$	-8.381	-8.347
$\Delta \ln(D_t)$	-11.525	-11.817
$\Delta \ln(F_t)$	-9.448	-9.437
$\Delta \ln(Va_t)$	-5.531	-5.529

<sup>1</sup> Critical values for the Perron's test are (i) with intercept; 1% -5,92, 5% -5,23, 10% -4,92; (ii) with intercept and trend; 1% -6,32, 5% -5,59, 10% -5,29.

<sup>19</sup> However, it should be noted that in the case of vandalism when the model has an intercept and a trend the test-statistic is 5.53 while the 5% critical value is 5.59. However, the difference is small enough to be disregarded.

## Appendix 2

Table A.2 shows the details of the bounds-tests results. It shows the calculated  $F$ -statistic of each model, the number of lags in the model, the SBC and AIC of the model and the results of the Breusch-Godfrey test for first, second and third order autocorrelation.

**Table A.2:** Detailed results of the bounds-testing approach to cointegration.

<i>F</i> -statistic	ARDL	SBC	AIC	LM 1	LM 2	LM 3
$F(Y_t TC_t) = 3.126$	(1,1)	-4.723	-4.930	0.363	0.491	0.707
$F(TC_t Y_t) = 4.113$	(1,3)	-3.083	-3.364	0.046	0.567	0.670
$F(Y_t VS_t) = 2.445$	(1,1)	-4.606	-4.813	0.629	1.826	2.086
$F(VS_t Y_t) = 2.151$	(1,2)	-2.961	-3.205	0.003	0.004	0.050
$F(Y_t P_t) = 3.777$	(1,1)	-4.672	-4.880	0.275	0.652	0.652
$F(P_t Y_t) = 6.708$	(2,1)	-2.743	-2.987	2.236	3.596	4.797
$F(Y_t Va_t) = 2.478$	(1,1)	-4.608	-4.816	0.454	1.728	1.771
$F(Va_t Y_t) = 6.444$	(1,1)	-2.331	-2.539	0.623	1.276	1.738
$F(Y_t Fr_t) = 2.196$	(1,1)	-4.683	-4.890	0.451	1.519	2.222
$F(Fr_t Y_t) = 1.300$	(1,2)	-0.397	-0.641	0.111	0.739	3.187
$F(Y_t D_t) = 0.571$	(1,1)	-4.553	-4.760	1.421	3.193	4.847
$F(D_t Y_t) = 7.287$	(6,1)	1.338	0.940	0.337	0.592	1.938

$F(Y_t|TC_t)$  gives the F-value when  $Y_t$  is modelled as the dependent variable and  $TC_t$  as the independent variable.

LM 1, LM 2 and LM 3 show the results of the first, second and third order autocorrelation tests respectively.