A Case Study of the Crime Rate in Chinese Mainland and Hong Kong

Yitian Wang
The University of Sydney, Sydney, Australia
ywan5022@uni.sydney.edu.au

Abstract. A series of studies have explored the relationship between crime rates and socioeconomic factors. Few researchers, however, have made an empirical analysis of the crime rate in China over the past 30 years. In terms of the data spanning 30 years involving five probable factors: Gross Domestic Product, Consumer Price Index, employment rate, divorce rate and educational rate, I find that the change in crime rates is mainly correlated with the change in education level and unemployment rate in Chinese mainland and Hong Kong. But the growth of the gross domestic product, which is a macroeconomic indicator, may not be as important as one might think in the change in crime rate. In particular, I also look at the impact of major events on crime rates -- the return of Hong Kong and the promulgation of the Criminal Law Amendment in 1997 and found that the Criminal Law Amendment had a positive impact on the crime rate in the Chinese mainland. This paper conducts an empirical modelling analysis of panel data from 1990 to 2020 in Chines mainland and Hong Kong from different social systems, measures the impact of different factors on the crime rate, and tries to find the most effective way to reduce the crime rate for China. Through the analysis, it can be found that in the Chinese mainland and Hong Kong, the most effective way to reduce the crime rate is not to develop the economy but to improve the overall level of education.

Keywords: Crime Rate; Fixed Effect; Major Events.

1. Introduction

Crime is a topic involving law, sociology, economics and other factors. The crime endangers social stability and affects the sustainable development of the economy (Islam, 2014). As Islam said, crime is highly likely to lead to social instability and deterioration of the investment climate, which in turn may be detrimental to future economic growth. While some studies look at specific aspects of crime, such as tax payments (Baliamoune-Lutz and Garello, 2014) or how the quality of institutions influences the performance of those firms in developing countries (Aidis, 2012; LiPuma, 2013), this paper focus on making an empirical analysis in terms of the panel data from the Chinese mainland and Hong Kong, which have a different social system, to measure the effects of different factors on crime rate and intend to find the most effective way to reduce the crime rate in China.

After the founding of The People's Republic of China, there was a historic period of low crime rate in China. Still, social and economic development was prolonged and even stagnant. After the reform and opening up, the economy proliferates, and the crime rate kept increasing. Is increased crime a necessary cost of economic growth? The development history of some countries and regions confirms this is not the case. This paper aims to determine what factors affect crime, from GDP, CPI, divorce rate, education level, and employment situation in Mainland China and Hong Kong respectively from 1990 to 2020 to find the methods to decline the crime rate. I hypothesized that all five factors had an impact on crime rates and used panel data to model it.

In the research process, I find that the return of Hong Kong and the revision of criminal law in China in 1997 have potential effects on the crime rate in mainland China and Hong Kong. This leads us to a new topic: the impact of significant events on crime rates.

2. Literature Review

Matias and Diana (2010) find that when the length of schooling was reformed, from half-day to full-day schooling, the probability of teens engaging in dangerous criminal behaviour decreased.

Lance and Enrico (2004) analyze the effect of completing high school education on the crime rate, they argue that completing high school education reduces the likelihood of crime and supports increased spending on education for all to reduce crime. Numerous studies have shown a positive relationship between income inequality and homicide rates (e.g., Messner, Raffalovich and Shrock 2002; Chamlin and Cochran 2005). Pare et al. (2014) challenge this idea and suggest that income inequality is unrelated to variation in crime across countries when poverty is controlled. Bankston (1998) has observed that changes to U.S. immigration law in 1865 led to a dramatic increase in the number of immigrants arriving in the United States, which exacerbated the problem of race-based gangs and affected crime rates in the United States.

Britt (1994) claims that crime among youth is associated with both the current level of youth unemployment and the annual change in the rate of youth unemployment. Ludwig et al. (2001) discuss the relationship between poverty levels and violent crime and show that giving families the opportunity to move to lower-poverty neighbourhoods can reduce violent crime among youth. Li et al. (2017) explore the weak correlation between changes in crime rates and changes in GDP growth rates. Andrade and Cifuentes (2021) illustrate that general crime has a negative effect on real estate prices, but the magnitude of this effect varies by crime type. Their research also found that apartments can respond almost immediately to changes in crime rates, while single-family homes take longer to respond.

Sampson (1987) identified three reasons why family breakdown may affect delinquency and juvenile delinquency. Ouimet (2000) study the social disorganization and criminal opportunities in 495 census tracts and 84 neighborhoods in Montreal in 1991 and find that the percentage of single-parent families had positive effects on the juvenile offender rate and the juvenile violent crime rate. However, Knoester and Haynie (2005) reported that the neighborhood-level percentage of single parents increased the probability of youth violence, which means that in neighborhoods that are considered higher-risk environments, family integration is often less effective in deterring youth violence than it is in lower risk environments.

3. Data and Data Issues

The dataset is collected mainly from the National Bureau of Statistics and Hong Kong's Census and Statistics Department. On the one hand, for the Chinese Mainland, I find the data related to the crime rate, GDP, CPI, urban unemployment rate, education rate and divorce rate in China Statistical Yearbook. It should be noted that the crime rate is computed according to the total number of cases accepted by police per 10000 population since I have not found data on the crime rate in China. In addition, the yearbook shows the data of the population aged 6 and above which is divided into different groups according to education level based on random sampling and I take the ratio of the population with college degrees or above to the population aged 6 and above as the education rate. The divorce rate is computed as the number of divorces in every one thousand persons. On the other hand, I compute Hong Kong's crime rate in terms of overall crime per 100000 population based on the data in the Police in Figures from the Hong Kong Police Force. And other data are collected from Hong Kong in Figures, Key Statistics of the Population Census and Marriage and Divorce Trends in Hong Kong.

I first download all the tables and figures which contain the data between 1990 and 2020 and summarized them in Excel. Then, I set zero as the ID code of China and 1 as the ID code of Hong Kong. Thus, I get a crude long panel data set (n=2 and T=31) with a few missing values. After that, I imported the dataset into Stata. In Stata, I transform all the data to be numeric and cope with some of the missing values by interpolation method. Remaining missing values, for example, education rate in China from 1990 to 1994, since it is hard to predict the trend, I decided to do nothing with them. The summary statistics are presented in the appendix.

4. Empirical Models and Estimation Methods

4.1 The First Model

Except for the education rate and unemployment rate which are usually considered important factors, I also take income level, price level and family factors into account to research the change in crime rate. Because of the lack of effective data about the level of resident income in both China mainland and Hong Kong, I choose GDP to capture the change in income level. In addition, CPI represents the inflation rate which influences the price level. Besides, a series of research shows that the increase in the divorce rate has a significant effect on juvenile delinquency because parents' divorce usually leads to a lack of parental care. Divorce to a large extent is a consequence of family conflicts which may lead to crime between families as well. Therefore, I believe the divorce rate is a potential factor that affect the crime rate. In the first model, I do not take the effect of the amendment to the criminal law and the effect of Hong Kong's return in 1997 into consideration.

$$Crimr_{it} = \beta_0 + \beta_1 Educa_{it} + \beta_2 Unemp_{it} + \beta_3 iGDP_{it} + \beta_4 iCPI_{it} + \beta_5 Divor_{it} + \alpha_i + e_{it}$$

$$iCPI_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}$$

Based on the results of POLS regression, I replace the value of the gross domestic product with its growth rate since the magnitude of the total GDP is large compared with the crime rate. Similarly, because the consumer price index (CPI) between 1990 and 2020 is computed in terms of different based years, I replace it with its growth rate as well. The results show that these changes make the variables more statistically significant and R^2 increases.

To choose the best estimator, I make hypotheses to test the existence of unobserved heterogeneity. In fixed effect models, the test is a standard F test with 1 liner restrictions and the null hypothesis is H0: $\alpha 1=\alpha 2$. Since the P value is smaller than 0.05, I reject the null hypothesis. There are individual-specific effects in the model so the unobserved heterogeneity exists. In random effect models, I use the Breusch-Pagan test to test whether the variance of α_i is zero. I fail to reject the null hypothesis according to the result. Accordingly, in the RE models, there are no personal effects. Then, I use the WU-Hausman specification test to test the appropriateness of RE model. I fail to reject the null hypothesis so RE and FE are all consistent. Since n and T of the dataset are all small, it is better for the model to just allow for heterogeneity in intercepts. Although the result of the WU-Hausman test shows that the RE estimator is efficient and consistent, the individual effects do not exist in the RE model in terms of the Breusch-Pagan test. Therefore, I consider α_i as a fixed effect. Because my panel data is more than 2 periods, the FD estimator is usually not efficient. Moreover, the periods of the dataset are small. The degree of freedom for FD is only half of that for pooled OLS so I need to pay a high price to obtain a consistent FD estimator. Therefore, despite I find that the idiosyncratic error term is heteroskedastic using the Breusch-Pagan test, I finally choose the FE estimator to analyse the dataset.

For the FE model, I have the following hypothesis:

Assumption 1: Linearity.

This assumption states that the population regression model is linear.

$$y = x'\beta + u$$

Assumption 2: Random sample.

$$y_i = x'\beta + u_i$$

Where cross sectional units are independent.

Assumption 3: No prefect collinearity.

Assumption 4: Exogeneity.

$$E(u_i|x_i) = 0$$

This is the strict exogeneity in terms of $e_i\ as\ x_i$ contains all observations for i over T periods. Along with these conditions, the FE estimator (for the slope coefficient) is unbiased $E(\hat{\beta}_{FE}|x) = \beta$ and consistent $plim(\hat{\beta}_{FE}) = \beta$.

As can be seen from the previous description, the first three assumptions are established. For Assumption 4, the error term may not be exogenous, because the error term may contain terms related to independent variables, such as parents' education level may affect both the child's crime rate and the child's education level. So Assumption 4 is hard to achieve.

It is easy to see that $\hat{\beta}_{FE}$ will follow some normal distribution as n goes to infinity.

And the assumptions required for efficiency are as usual: u_{it} is homoscedastic and serially uncorrelated across t. For fixed effect, I allow arbitrary correlation between unobserved effect and observed explanatory variable. These assumptions make the FE estimator $\widehat{\beta_{FE}}$ consistent with β.

Table 1. Summary of regression results for different models.

	(1)	(2)	(3)	(4)
VARIABLES	POLS1	POLS2	FE	RE
Educa	-0.0476***	-0.0499***	-0.0666***	-0.0499***
	(0.00817)	(0.00774)	(0.00916)	(0.00774)
Unemp	-0.0870	-0.116**	-0.136***	-0.116**
	(0.0521)	(0.0500)	(0.0464)	(0.0500)
iGDP	-0.0135	-0.0119	0.00476	-0.0119
	(0.0126)	(0.0122)	(0.0126)	(0.0122)
CPI1	-0.00219			
	(0.00867)			
Divor	0.0258	0.0243	0.0300	0.0243
	(0.0307)	(0.0286)	(0.0263)	(0.0286)
iCPI		0.00606	0.0117	0.00606
		(0.0144)	(0.0133)	(0.0144)
Constant	2.350**	2.272***	2.475***	2.272***
	(0.910)	(0.275)	(0.262)	(0.275)
Observations	46	44	44	44
R-squared	0.584	0.650	0.625	
rmse	0.380	0.354	0.325	0.354
Number of ID			2	2

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1 shows the regression results using different models. According to the regression result using the fixed effect estimator, I find that the education rate, unemployment rate and constant are statistically significant. One percent increase in the education rate is associated with approximately 0.07 percent decrease in the crime rate, which is a significant effect when multiplied by the population. The regression result of the slope of the unemployment rate seems counter-intuitive since it implies an increase in the unemployment rate leads to a decrease in the crime rate. This may because the bias of the slope is so large that its sign change from positive to negative. According to Cameron and Trivedi (2005), I have controlled for 5 factors in the model, so I take the crime rate in the previous year into consideration. However, the slope is still significant and negative. Thus, I believe the reason for the issue may not be bias. I choose the urban unemployment rate in the China Yearbook as the unemployment rate. During the period 1990 to 2000, the urbanization process in China continued to accelerate, so a large number of the potential labor force in rural areas came to urban to find jobs during this period. While the urban unemployment rate increased because of the urbanization process, the crime rate dropped with the development of economy. Therefore, contrary to my expectation, the increase in the urban unemployment rate is related to the improvement of social well-being in that time. In addition, the regression results imply that the rise in the divorce rate and inflation rate contribute to increasing in the crime rate though their P value is relatively high. The effect of the growth rate of GDP on the crime rate is statistically insignificant and its P value is close to 1, possibly because of the endogeneity problem. Besides, the increase of total GDP may not be a good indicator of the income level.

4.2 The Second Model

Figure 1. 1990-2020 Chinese mainland and Hong Kong crime rate

Figure 1 shows the crime rates in the Chinese mainland and Hong Kong from 1990 to 2020. As shown in figure 1, I find the crime rate in the Chinese mainland dropped significantly because of the amendment to the criminal law in 1997. Coincidentally, Hong Kong returned to China at the same year, which impose profound effects on Hong Kong society and economy. Therefore, In the second model, I include the effect of the amendment to the criminal law and the effect of Hong Kong's return in 1997 into the model.

$$Crimr_{it} = \beta_0 + \beta_1 Educa_{it} + \beta_2 Unemp_{it} + \beta_3 iGDP_{it} + \beta_4 iCPI_{it} + \beta_5 Divor_{it} + \beta_6 d_{it} + \alpha_i + e_{it}$$

$$d_{it} = \begin{matrix} 1 & if\ year > 1997 \\ 0 & if\ year \leq 1997 \end{matrix}$$

I include a new dummy variable d. Because my dataset has small T and n, I just allow heterogeneity in the intercept and assume the two effects in 1997 are close at first. I test for unobserved heterogeneity in FE and RE models. The F statistic performed on the FE estimator indicates that there isn't unobserved heterogeneity in intercept since the P value is bigger than 0.05. Similarly, although the dummy variable is statistically significant, the result of Breusch and Pagan shows that the heterogeneity in intercept is insignificant. Therefore, because the individual-specific effects are insignificant, pooled OLS estimator is better than FE or RE estimators.

For pooled linear regression, I pool the observations for all individuals together. This model can be estimated simply by OLS, which is called the POLS.

And I assume:

$var(u_{it}|x_{it}) = \sigma_u^2;$

$cov(u_{it}, u_{js}|x_{it}, x_{js}) = 0, \forall\ i \neq j\ or\ t \neq s.$

Which means no serial correlation in u_{it}. Then the POLS is an efficient estimator.

Along with the aforementioned Assumption 1 - Assumption 3 and u_{it} being uncorrelated to x_{it}, when the unobserved heterogeneity α_i does not exist (that is $\alpha_1 = \cdots = \alpha_n$, or when α_i is a random effect (that is $E(\alpha_i|xx_{it}) = 0$), $\widehat{\beta_{POLS}}$ is a consistent estimator for β.

In particular, the exogeneity assumption here implies two situations:

(1) There is no unobserved heterogeneity and u_{it} is not related to regressor, or

(2) There is unobserved heterogeneity but both α_i and u_{it} have regressors irrelevant, that is, α_i is random effect.

Table 2. Summary of regression results for different models with a dummy variable

	(1)	(2)	(3)	(4)
VARIABLES	FE	RE	POLS1	POLS2
Educa	-0.0625***	-0.0443***	-0.0443***	-0.0621***
	(0.0125)	(0.00784)	(0.00784)	(0.0114)
Unemp	-0.117*	-0.0612	-0.0612	-0.129**
	(0.0608)	(0.0541)	(0.0541)	(0.0615)
Lawe				-0.408**
				(0.185)
Rete				0.0844
				(0.305)
d	-0.119	-0.417**	-0.417**	
	(0.249)	(0.193)	(0.193)	
Constant	2.458***	2.317***	2.317***	2.577***
	(0.267)	(0.264)	(0.264)	(0.282)
Observations	44	44	44	44
R-squared	0.627		0.690	0.722
Number of ID	2	2		
rmse	0.328	0.339	0.339	0.324

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 shows the regression results of different models after adding a dummy variable. The regression results are consistent with my expectation. The major events that took place in 1997 affected the crime rate significantly. The estimator implies that, with the time move from 1997 to 1998, the crime rate dropped approximately 0.42 percent. Related research (Jianjun Bai, 2010) points out that the amendment to the criminal law in 1997 made the punishment become moderately mild, so after 1997 the crime rate in China dropped significantly. However, according to figure 1, the effect of return in Hong Kong is inapparent compared with the effect of the amendment to criminal law in the Chinese mainland. Therefore, my assumption that the major event effects in 1997 on the Chinese mainland and Hong Kong are close is highly likely to be invalid. To measure the law effect and return effect separately, I make adjustments on the independent variables in the model.

$$Crimr_{it} = \beta_0 + \beta_1 Educa_{it} + \beta_2 Unemp_{it} + \beta_3 iGDP_{it} + \beta_4 iCPI_{it} + \beta_5 Divor_{it} + \beta_6 Lawe_{it} + \beta_7 Rete_{it} + \alpha_i + e_{it}$$

$$c_{it} = \begin{matrix} 1 & if\ ID = 0 \\ 0 & if\ ID = 1 \end{matrix} \qquad Lawe = c_{it} * d_{it}$$

$$h_{it} = \begin{matrix} 0 & if\ ID = 0 \\ 1 & if\ ID = 1 \end{matrix} \qquad Rete = h_{it} * d_{it}$$

The dummy variables c and h are used to identify the Chinese mainland and Hong Kong separately. I multiply them by a dummy variable for the year after 1997 to get the new variable's law effect and return effect. Thus, I can estimate the different major events effect by β6 and β7. Because of the lack of unobserved heterogeneity in intercept, I still choose the pooled OLS estimator.

The results indicate that the law effect is significant. With the promulgation of an amendment to the criminal law in 1997, the crime rate dropped by approximately 0.41 percent in the Chinese mainland. On the contrary, the return effect is insignificant, which is consistent with the trend in the figure.

According to the results above, I can draw a conclusion that the main factors associated with the crime rate in Chinese mainland and Hong Kong is the education rate and unemployment rate. The sign of the slope of the unemployment rate is counter-intuitive, probably because of the positive correlation between the urban unemployment rate and social well-being in the urbanization process. The growth of GDP, which is a macroeconomic indicator, may not be as important as one might think in the change in crime rate. As for the major events in 1997, an amendment to the criminal law significantly affect the crime rate in the Chinese mainland, while there is no evidence that the return of Hong Kong imposed any effects on its crime rate.

5. Conclusion

Overall, the change in crime rate is mainly associated with education and the unemployment rate. In terms of my model, the impact of the increase in GDP on crime is insignificant. As for the major events that happened in 1997, I can find that the amendment to the criminal law has a beneficial influence on crime rates in China, but the return of Hong Kong has had no apparent effect on the crime rate in Hong Kong. I initially inferred that higher unemployment would lead to social chaos and thus raise crime rates. However, it can be seen from the statistics that the coefficient of the unemployment rate is negative. One possible reason is that although there is a great improvement in social well-being in this period, the urban unemployment rate still rise because the urbanization process prompts a large number of farmers to move into cities. Thus, instead of developing the economy, in the Chinese mainland and Hong Kong, the most effective way to reduce the crime rate is improving the overall education level.

There are several limitations in my model, and I have proposed possible extensions for them in future research. First of all, Hong Kong is much smaller than the Chinese mainland and it is hard for us to recognize and control for heterogeneity in the Chines mainland. I can divide China into several districts and Macao, or Taiwan can also be added for comparison in future analysis. Furthermore, my models do not allow heterogeneity in the slopes since the dataset's periods and individuals are all small. By raising the number of individuals and periods, I can take RC or MG estimators into account. In addition, I haven't addressed the possible endogeneity problem in GDP growth rates. To cope with the issue, I can replace the GDP growth rate with the growth rate of GDP per capita or use household disposable income as an instrumental variable. Finally, the slope of the unemployment rate is negative, and the urban unemployment rate can be replaced by the natural unemployment rate in future studies.

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