Unraveling the Dynamics of Clearance Rates and Crime Incidence: An In-Depth Examination Across Canadian Provinces

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1 Executive Summary

This research endeavors to delve into the intricate relationship between the rates at which criminal cases are resolved (clearance rates) and the incidence of crimes (crime rates), providing fresh insights and challenging established criminological paradigms. Spanning from the year 2000 to 2021 across various provinces in Canada, the study draws inspiration from Becker's seminal work on crime theory[1] and responds to recent shifts in the emphasis of quantitative studies in the field, exemplified by the research conducted by Curry et al.[2]

The independent regression analyses for property and violent crime rates unveil intricate dynamics in their relationship. Significantly, a noticeable negative correlation is observed between property crime rates and the effectiveness in resolving nonviolent offenses. This correlation becomes more pronounced with the inclusion of the count of law enforcement personnel relative to the overall population. These findings imply a nuanced approach to addressing distinct categories of criminal activities, emphasizing the importance of targeted interventions and strategic resource allocation.

Unexpected findings include a positive association between government transfers per person, adjusted for specific conditions, and the rates of property crimes, shedding light on potential unintended consequences. Policymakers are urged to critically evaluate the conditional nature of these transfers to mitigate potential adverse effects on low-income individuals. Similar patterns are observed in the context of violent crimes, where the number of law enforcement personnel relative to the overall population exhibits a statistically significant and negative impact, contradicting existing research findings from Curry et al.[2]

The subsequent analysis, which incorporates historical clearance rates and utilizes advanced statistical techniques to address potential biases, enhances the robustness of the results. The instrumental variable regressions underscore a substantial negative association between clearance rates and property crimes, emphasizing the imperative for policies that enhance the efficiency of resolving such crimes. Recommendations include strategic investments in law enforcement training and technology.

This study goes beyond academic exploration, carrying immediate implications for decision-makers across diverse sectors, such as policymakers, law enforcement agencies, and our overall comprehension of crime dynamics. It fills crucial gaps in our understanding of the criminal justice system, impacting decisions related to resource allocation and adding to the conversation about public trust in law enforcement. In summary, this study navigates the potential negative correlation between the effectiveness of clearing criminal cases and the incidence of crimes, offering profound insights with far-reaching consequences for policy, resource allocation, and our broader understanding of crime.

2 Introduction

In criminology, Becker's foundational theory delineates a rational decision-making process for potential criminals, where the probability of apprehension, or the likelihood of getting caught, is a crucial component.[1] Potential criminals assess the risk of being apprehended, considering it a cost associated with engaging in illegal activities. By incorporating this probability into the analysis, researchers can empirically examine its impact on criminal behavior, aligning with the rational choice framework outlined in Becker's theory.[1]

While past empirical studies traditionally used police-reported clearance rates to assess the probability of apprehension, recent econometric investigations have shifted focus toward exploring the impact of the number of police officers on crime.[2] Despite insights garnered from research on police force size, a significant gap persists in understanding the specific relationship between clearance rates, a direct measure of the criminal justice system's efficacy, and crime rates. This statement of the problem underscores the imperative to revisit and comprehensively investigate the correlation between clearance rates and crime rates.

Our research endeavors to bridge this gap by delving into the nuanced dynamics defining the relationship, aiming to offer valuable insights for criminological theory and policy formulation. The correlation between clearance rates and crime rates has been a central theme in criminological research, with conventional wisdom asserting that higher clearance rates lead to lower crime rates. Building upon the groundwork laid by Curry et al.'s seminal work[2], this research seeks to deepen our understanding of the intricate interplay between clearance rates and crime rates. Utilizing updated data spanning from 2000 to 2021 across Canadian provinces, the study aims to contribute new perspectives to the ongoing discourse on the subject.

In undertaking this research endeavor, our approach is anchored in an attempt to replicate and extend the model presented in Curry et al.'s influential paper.[2] We collect panel data spanning Canadian provinces from 2000 to 2021, encompassing key variables such as property crime rate, violent crime rate, clearance rate, and relevant independent variables. We execute two distinct regression analyses to unravel the multifaceted relationship between crime rates and a myriad of influencing factors. The first regression centers on property crime rates, scrutinizing the intricate dynamics with a specialized emphasis on the impact of clearance rates. Leveraging Ordinary Least Squares (OLS) regression, this analysis provides insights into the interplay between property crime and the selected covariates. To address potential confounding effects, Fixed Effect (FE) estimation is applied, incorporating time (year) and district (province) indices as invariant controls. Additionally, First Difference (FD) estimation is implemented to capture changes over time, offering a more dynamic perspective.

Simultaneously, we conduct a parallel regression focusing on violent crime rates, ensuring a comprehensive exploration of the impact of clearance rates across different crime categories. In line with the approach outlined in Curry et al.'s study,[2] we incorporate the Instrumental Variable (IV) method to tackle potential endogeneity bias. Unlike their exclusive use of the IV method on clearance rates, our research takes a more inclusive approach by applying the IV method to other covariates. By extending the application of IV to all pertinent covariates, we seek to enhance the robustness of our analysis, ensuring the credibility and validity of our estimated relationships. The outlined approach allows for a robust and nuanced analysis, providing insights into the multifaceted dynamics between clearance rates and property crime while addressing methodological challenges and ensuring the reliability of our findings.

The motivation behind this research lies in the potential disruption it poses to established paradigms within criminology and law enforcement. If the findings reveal a positive and significant correlation between clearance rates and crime rates, it challenges the assumptions that guide current policies and resource allocations in crime prevention. This study is not merely an academic exercise; it has direct implications for policymakers, law enforcement agencies, and the general public. The results of this research can be intriguing and valuable for several reasons. Firstly, it addresses a critical gap in our understanding of the criminal justice system's dynamics. Secondly, it has immediate policy implications, urging a reconsideration of resource allocation strategies. Thirdly, the study contributes to the discourse on public trust and perceptions of law enforcement, crucial for fostering a sense of security and cooperation. Lastly, the findings can potentially reshape criminological theories, providing a more nuanced understanding of the factors influencing crime rates.

In summary, this research embarks on a journey to contribute to the refinement of crime prevention strategies. By navigating the correlation between clearance rates and crime rates, this study aspires to offer meaningful insights with far-reaching consequences for policy, resource allocation, and our broader understanding of crime.

The subsequent sections of this paper are structured as follows: Section 3 encompasses a brief literature review summarizing the key findings of pertinent studies. Section 4 provides a description of the data, introducing the empirical method employed in this research. In Section 5, we introduced the theoretical econometrics model we applied. In Section 6, we present the empirical results and offer interpretations. Finally, Section 7 concludes the paper with a summary of our main findings.

3 Literature Review

Gary Becker's seminal theory of crime introduced the idea that individuals engage in criminal behavior by weighing the expected benefits against the expected costs.[1] His theory posited that individuals engaging in criminal activities seek to maximize their overall satisfaction or utility. The advantages gained from unlawful acts are carefully considered in relation to potential drawbacks, encompassing legal consequences, societal disapproval, and the likelihood of being apprehended. The pivotal element in this decision-making process is the probability of detection and subsequent punishment, as increased chances of being caught are anticipated to serve as a deterrent, dissuading individuals from participating in criminal conduct. Since then, research in criminology has focused on understanding criminal behavior through the lens of rational decision-making and economic incentives. An essential area of investigation revolves around comprehending how the presence of police forces influences the rational decision-making and incentives for potential criminals to engage in illegal activities, along with assessing the effectiveness of the police in preventing and reducing crime.

In Levitt's paper, he found that changes in number of police is weakly positively correlated with changes in crime rate, while increase in per-capita income are positively correlated with violent crime but not strongly related to property crime.[5] Klick and Tabarrok evaluated the causal effect of police presence on crime in Washington, D.C.[4] Their results indicate that a 50 percent increase in police presence leads to a statistically and economically significant 15 percent decrease in crime. Nevertheless, there is ongoing debate regarding the explanatory strength of the correlation between the size of the police force and crime rates in the context of deterrence, as the precise mechanism through which the number of police officers influences crime rates remains unclear. An escalation in the number of police officers might lead to diminished crime not necessarily due to an increased likelihood of apprehension, but rather owing to heightened visibility.[2].

Curry et al. delved into the impact of clearance rates on violent and property crime rates by analyzing data from the United States and Canada.[2] Their study challenged the conventional emphasis on the number of police officers in crime deterrence, asserting that increased visibility, rather than a higher likelihood of apprehension, may contribute to reduced crime rates. Accordingly, their research aimed to redirect attention to clearance rates as a potential indicator of police force efficiency.

Their findings consistently indicated a negative and statistically significant correlation between clearance rates and both violent and property crime. Employing various models and methodologies, such as OLS, FE, Generalized Method of Moments (GMM) and Generalized Least Squares (GLS). The researchers revealed a robust negative correlation that persisted even with adjustments for per capita police officers and province-specific trends. Notably, the inclusion of these variables altered the statistical significance of clearance rates but did not negate their overall impact. Even after accounting for covariates and introducing province and year fixed effects, clearance rates remained statistically significant in the panel data spanning Canadian provinces from 1986 to 2005. The robustness of the negative correlation between clearance rates and crime rates persisted despite the incorporation of additional measures, such as arrest rates and police expenditures. Importantly, the inclusion of per capita police rates failed to show the correct sign or statistical significance, challenging previous research that focused exclusively on police numbers and potentially underestimated the comprehensive impact of law enforcement in deterring crime.

Recognizing potential issues of endogeneity and measurement errors, Curry et al. employed diverse instruments, including political party dummies for clearance rate, and conducted IV regressions.[2] The IV estimates aligned with the reduced form estimates, reinforcing the consistent negative and statistically significant relationship between clearance rates and crime rates. However, it's crucial to note that their investigation exclusively utilized IV estimation for clearance rates, acknowledging the potential endogeneity bias in coefficient estimates for other covariates.

Despite Curry et al.'s robust findings[2] regarding the negative correlation between clearance rates and crime rates, their estimation relied on historical data up to 2005 and did not capture some of the significant economic shocks to the Canadian economy in the recent two decades such as the 2008 subprime mortgage crisis and the onset of the COVID-19 pandemic in late 2019. These substantial changes in economic conditions could potentially exert a significant influence on criminal behavior. Furthermore, the legalization of cannabis in 2018 undoubtedly had implications for crime in Canada. Our study aims to augment the existing literature through two key contributions. Firstly, we extend the research horizon by utilizing updated and more recent panel data spanning from 2000 to 2021, encompassing various provinces in Canada, thereby providing a contemporary comparative analysis. Secondly, we extend the application of the IV method beyond clearance rates to include other covariates. This strategic expansion goes beyond the exclusive implementation of the IV method on clearance rates as observed in the past studies.[2] The decision to apply the IV method comprehensively to various covariates arises from our commitment to addressing potential endogeneity bias in coefficient estimates.

4 Data

Our primary data source is the Canadian Socioeconomic Information Management (CANSIM) Database administered by Statistics Canada, supplemented by information from the Government of Canada's Minimum Wage Database. Adjustments for nominal measures of income and government transfers are made using annual provincial-level consumer price indices, with a base year of 2002. The regression analyses include data from all 10 provinces spanning 2000 to 2021, excluding territories to maintain internal validity due to their unique way of life and insufficient data for robust analysis, despite concerns about crime in these regions.

4.1 Crime Rate

The focal point of our analysis is the crime rate, with a specific focus on two distinct categories: property crime and violent crime. To ensure a standardized and comparable assessment across provinces with different population sizes, we utilize property and violent crime rates per 100,000 population. It's important to highlight that the population data for a jurisdiction typically represent only its permanent residents. This exclusion of temporary populations, such as tourists, commuters, and seasonal staff, may introduce bias into the results when investigating the impact of clearance rates on the overall crime rate for the entire province. This consideration emphasizes the need for a nuanced interpretation of our findings, recognizing the potential influence of population dynamics on the relationship between clearance rates and overall crime rates.

4.2 Clearance Rate

Embracing Curry et al.'s methodology,[2] we gauge apprehension likelihood through clearance rates, aligning with Becker's crime theory.[1] While many recent econometric studies focus on police officer numbers as a policy gauge, we contend that clearance rates offer a more direct indicator of deterrence effects tied to an increased likelihood of apprehension. Unlike the number of police officers, clearance rates more accurately reflect the impact on crime rates. We calculate clearance rates by dividing cleared crimes by the total recorded crimes. Additionally, we introduce the measure that weighs incidents based on severity, complementing the original measure to account for variations in crime significance. Changes in the weighted clearance rate may indicate shifts in the effectiveness of policing against a specific subset of particularly harmful crimes.

4.3 Other Covariates

While our main emphasis in this paper revolves around the clearance rate, which serves as the principal independent variable of interest, we also account for variables emphasized by ecological theories of crime, including the size of police force, employment rate, adjusted median income of low income household, the young adult male ratio and incarcerations rate.

1. **Police Officers**

   Kelly's paper emphasized that the size of the police force serves as a crucial indicator of law enforcement presence and acts as a deterrent to criminal activities.[3] A sufficient police force plays a key role in maintaining public order and safety, reducing opportunities for criminal behavior. To assess the size of the police force, we use the number of officers per 100,000 population. Utilizing per capita rates enables a population-adjusted analysis, facilitating a more nuanced evaluation of policing effectiveness, especially when comparing provinces with varying demographic profiles.

2. **Employment Rate**

   The employment rate, indicating the percentage of persons employed aged 15 and above, captured the impact of economic conditions on crime. Formal labor market employment reduces opportunities and incentives for criminal behavior, fostering routines, supervision, and diminishing economic motivations for crime.[1] Conversely, studies show unemployment's significantly positive effects on property crime rates, potentially linked to the emotional toll of unemployment and limited avenues for legal income.[7]

3. **Poverty Level**

   The influence of poverty on property crime, emphasizing that regions with higher concentrations of economically disadvantaged individuals may experience increased property crime due to low market activity returns.[3] Poverty is gauged using the median after-tax income of households classified as low income, defined as those falling below 50% of the total population median adjusted after-tax income. Adjustments consider the economies of scale in larger families, the rise in people living alone, and the decline in family size over time.

4. **Young Adult Male Ratio**

   Piquero et al.'s criminal career paradigm underscores the importance of the young adult male ratio in the population as a key determinant of crime rates.[6] This introduces complexity to the age-crime relationship, emphasizing high recidivism rates among young adults. Defining young men as aged 15 to 24, as per Curry et al.[2], we calculate the young adult male ratio by dividing the male population aged 15 to 24 by the total population. This ratio potentially influences crime rates, providing nuance to our understanding of the age-crime dynamic.

5. **Incarceration Rate**

   Becker's economic theory suggested that higher incarceration rates deter crime stems from rational decision-making.[1] Elevated incarceration rates heighten detection and imprisonment chances, amplifying the perceived costs of criminal conduct and creating a deterrence effect. This influences rational choices to avoid legal consequences. "Incarceration per 100,000 population" is used to measure law enforcement's deterrent impact, factoring in actual-in counts and population estimates from Statistics Canada. It encompasses federal and provincial offenders in federal facilities and those temporarily detained.

4.4 Summary Statistics

Table 1: Summary Statistics for weighted crime rates per 100,000 population, clearance rate and other explanatory variables

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
Property Crimes Per100k	1	240.00	4651.34	1713.76	4325.44	4517.57	1588.18	1554.18	9152.79	7598.61	0.63	-0.32	110.62
Nonviolent Weighted Clearance Rate	2	240.00	29.17	5.41	29.47	29.13	5.20	17.37	43.87	26.50	0.16	0.09	0.35
Violent Crimes Per100k	3	240.00	25664.06	41713.19	1715.66	15380.85	878.41	876.48	156880.00	156003.52	1.78	1.93	2692.57
Violent Weighted Clearance Rate	4	240.00	59.84	7.32	60.67	60.15	6.77	41.89	77.77	35.88	-0.34	-0.02	0.47
Employment Rate	5	240.00	91.73	3.03	92.00	92.06	3.12	82.36	96.44	14.09	-0.86	0.31	0.20
Median Income Adjusted	6	220.00	12044.40	1363.45	12007.31	12003.08	1363.59	8895.90	15551.58	6655.68	0.22	-0.19	91.92
Real Transfer per Person	7	240.00	6123.63	2657.49	5573.58	5711.66	2033.82	2121.45	15275.57	13154.12	1.44	2.02	171.54
Total Population	8	240.00	3385809.25	3999084.79	1159201.50	2576712.78	1219146.43	135804.00	14809257.00	14673453.00	1.45	1.00	258139.81
Young Men Rate	9	240.00	13.45	1.03	13.51	13.43	0.92	11.07	15.92	4.84	0.07	-0.11	0.07
Immigrants Per100k	10	240.00	646.00	409.62	633.01	618.92	502.14	60.83	2085.48	2024.65	0.48	-0.32	26.44
Minimum Wage	11	230.00	9.19	2.39	9.45	9.06	2.74	5.40	15.20	9.80	0.35	-0.62	0.16
Officers Per100k	12	230.00	180.85	17.69	181.85	181.59	18.68	136.00	218.90	82.90	-0.30	-0.60	1.17
Incarcerations Per100k	13	237.00	94.97	49.74	75.53	86.33	19.50	34.72	251.69	216.97	1.53	1.32	3.23

Table (1) is the descriptive statistics for each variable employed in our investigation. The dataset under scrutiny exhibits distinct characteristics. It is evident that the total population's standard deviation is exceptionally high, indicating significant variations in population sizes across provinces and throughout the observed period. Additionally, there is a noteworthy discrepancy, with violent crimes displaying a considerably higher incidence compared to property crimes.

5 Econometrics Model

5.1 Parsimonious Regression Model

We test the effect of clearance rates on two different types of crime using an adaptation of the parsimonious reduced form specification put forth by Curry et al:[2]

$$lnY_{it} = \beta_0 + \beta_1 lnX_{it} + \beta_2 ln\Psi_{it} + \beta_3 ln\theta_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{1}$$

A key advantage of a parsimonious model lies in facilitating a more manageable analysis of the results, enabling us to compare our findings with the original work and assess the model's validity. Some of our measure captured by the variables in the presentation of this equation differ from Curry et al.'s[2] in several aspects. A number of the measures used in the original work were gathered from statistical programs that have long been terminated. Appropriate substitutions were made not only out of necessity but also as a means of making original contributions to this model specification.

The dependant variable, $\ln Y_{it}$, is the natural logarithm of the annual crime rate per 100,000 of population of province i at time t. On the right hand side of equation (1), X_{it} is our measure of the probability of apprehension, which is represented by the weighted clearance rate. The coefficient estimate of β_1 is of central importance to our empirical analysis. Given the log-log specification, β_1 assumes the significance of being the elasticity of crime concerning apprehension. This means that β_1 quantifies the percentage change in the crime rate associated with a one percent change in the clearance rate.

Other covariates include a vector of government policies represented by Ψ_{it}, time-varying demographic and province specific factors represented by θ_{it}, as well as province and year fixed effects represented by α_i and γ_i, respectively. The vector of government policies denoted by Ψ_{it} is used to capture province specific policies such as hourly minimum wages and average government transfers to the poorest quantile of the population. An increase in the minimum wage or average government transfer size is expected to have a positive income effect, assuming other factors remain constant.[2] The lack of access to fundamental resources and legal income opportunities can lead individuals to illicit means to fulfill basic needs. A change in the financial resources available to the less affluent is likely to influence incentives for engaging in financially motivated crimes.

The time-varying demographic and province specific factors represented by θ_{it} include the employment rate of individuals 15 years and older, the number of officers per 100,000 population, the number of males aged 15 to 24 as a proportion of the total population, and the median after-tax income of households considered low income.

To capture potential enduring effects of clearance rates on crime rates, our model includes lagged measures of clearance rates. Additionally, we test our regression model by introducing the number of incarcerations per 100,000 population as a supplementary control. This inclusion provides insights into the dynamics of the criminal justice system, examining the impact of strict law enforcement, sentencing practices, and societal attitudes on crime rates for a comprehensive understanding of the system's influence.

5.2 First Difference Regression

Much like in the original work, we also evaluate the sensitivity of our model by running a first differences regression in which all the variables are transformed by subtracting a lagged value of the variable from its current value. The regression model is as follows:

$$lnY_{it} - lnY_{i,t-1} = \alpha_0 + \alpha_1(lnX_{it} - lnX_{i,t-1}) + \alpha_2(ln\Psi_{it} - ln\Psi_{i,t-1}) + \alpha_3(ln\theta_{it} - ln\theta_{i,t-1}) + \gamma_t + \epsilon_{it} \quad (2)$$

This first differences specification deviates slightly from conventional models by incorporating overlapping time and entity fixed effects, a methodology adopted from Curry et al.[2] This approach involves subtracting lagged values of regressors, addressing endogeneity concerns and accounting for individual heterogeneity through fixed effects.

5.3 Instrumental Variables Regression

We consider two instrumental variable models where we relax exogeneity assumption about key explanatory variables that is implicit in the model. We implement the IV regression following the general two-stage least squares (2SLS) procedure. Our structural equation can be represented by

$$lnY_{it} = \beta_0 + \beta_1 ln\hat{X}_{it} + \beta_2 ln\Psi_{it} + \beta_3 ln\theta_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{3}$$

where ζ_{it} is the instrumental variable for the potentially endogenous variable X_{it}. In the first stage, we obtain the predicted values $\hat{X}_{it}$ from

$$\hat{X}_{it} = \delta_0 + \delta_1\zeta_{it} + \mu_{it} \tag{4}$$

by regressing the potentially endogenous variable X_{it} on the instrumental variable ζ_{it}.

In our instrumental variable approach, we employ two distinct instruments to address potential endogeneity in our regression model. First, we use the average number of criminal code incidents per officer as an instrument for clearance rates. This variable serves as a proxy for the workload of law enforcement personnel, implying that a higher workload may impact officers' efficiency in solving crimes. The utilization of this variable indicates law enforcement personnel's workload, determined by external factors not included in the regression model, ensuring its exogeneity.

Our assumption that criminal code incidents per officer influences case resolution efficiency without directly affecting crime rates aligns with the exclusion restriction. This variable, representing officers' workload, is not expected to directly determine crime occurrence, making it a valid instrument for estimating the causal relationship between clearance rates and crime rates. This approach not only captures the average burden borne by peace officers in the fight against crime but also acknowledges that the effect of this variable on crime rates primarily comes through its impact on clearance rates. For a crime to be cleared, it must first be codified as a criminal code infraction, and any deterrence effects associated with it materialize only after the incident is resolved.

The second instrumental variable involves using authorized police officer strength per 100,000 population as an instrument for the number of officers per 100,000 population. A higher authorized strength suggests a greater intended law enforcement presence, making it directly relevant to the number of officers per 100,000 population. This authorized strength primarily influences the number of officers available for duty, with its impact on crime rates mediated through this variable, satisfying the exclusion restriction.

While one could argue that authorized police officer strength is determined by various policy decisions or budget allocations, potentially encompassing unobservable factors affecting crime rates, we contend that these determinants are indirect and secondary to the primary pathway through which authorized strength affects crime rates via law enforcement presence. Therefore, we maintain that this variable satisfies the exogeneity condition.

6 Empirical Results

6.1 Primary Model Specification

Our analysis, presented in Tables (2) and (3), delves into the primary model results for property and violent crimes. In the context of property crime rates, our regression findings closely mirror Curry et al.'s conclusions,[2] unveiling a discernible negative correlation between property crime incidence per 100,000 population and clearance rates for nonviolent offenses. Specifically, a 1% increase in the clearance rate is associated with a substantial decrease in property crimes per 100,000, approximately 0.65%. This outcome strengthens the argument that a heightened likelihood of apprehension acts as a deterrent for potential offenders. The same relationship holds for violent crimes, where a 1% increase in clearance rates corresponds to a reduction in violent crimes per 100,000 by approximately 0.45%.

Within our foundational model, we make a noteworthy discovery regarding the inverse correlation between crime rates and the median income of low-income households. A 1% rise in the median income among low-income households results in a significant reduction of 0.58% in the count of property crimes per 100,000 population. Furthermore, although statistically insignificant, the persistence of the negative sign on this coefficient in the model examining violent crime rates is worth highlighting. Upon introducing the number of officers per 100,000 population into both regressions, the coefficient estimates for clearance rates experience a slight increase, yet the overall impact remains negligible.

Another substantial finding in our base model is the negative correlation between the number of immigrants per 100,000 population and violent crime rates. In the model incorporating the number of officers per 100,000 population, a 1% increase in the number of immigrants per 100,000 population is linked to a decrease in the number of violent crimes per 100,000 population by approximately 0.05%. While statistically significant, the overall effect is relatively modest. Importantly, our findings diverge from Curry et al.[2] in two key aspects. Firstly, we observe larger coefficient estimates for the impact of clearance rates on both property and violent crimes. Secondly, all our coefficient estimates for clearance rates achieve statistical significance at the 1% level.

The results of the research provide valuable perspectives on crime prevention and law enforcement dynamics. Government is encouraged to explore the implementation of policies focused on enhancing the efficiency of crime resolution. This could entail strategic investments in law enforcement training and technology to streamline the resolution process. The proposed recommendations seek to bolster the effectiveness of crime prevention strategies and improve the overall efficiency of law enforcement endeavors.

6.2 Models Including Lags and Incarcerations

Tables (4) and (5) present regression outcomes for property and violent crimes, respectively, incorporating controls for lagged clearance rates. Our base model findings remain robust with consistent sign and slightly decreased magnitude of the effect for contemporaneous clearance rates in both crime types. An interesting finding is the statistical significance of the one-year lagged clearance rate measure, especially in the regression involving violent crime. This is potential evidence for a persistent effect of clearances rates. Another notable finding is that the coefficient estimate for the effect of the number of officers per 100,000 population remains negative in the violent crime regression.

The findings of our base model also hold when the number of incarcerations per 100,000 population is included in the regression. In fact, the coefficient estimates on clearance rates in this model are nearly identical to that of the base model involving property crimes and only slightly smaller than when considering violent crimes. One interesting result of the inclusion of this new variable in our model is that the coefficient estimate is found to be positive and statistically significant for both types of crimes. A potential explanation for this is that crime rates and incarceration rates may trend in the same direction. For instance, if we assume effective policing, as crime rates increase so too will incarceration rates as criminals face the consequences of their actions.

6.3 First Differences and Instrumental Variable Regressions

The first differences regression in Table (8) supports our findings on both property crimes and violent crimes. Clearance rates negatively and significantly impact both types of crimes, albeit to a lesser extent than in our base model.

Tables (9) and (10) present results from instrumental variable regressions. Using criminal code reports per officer as an instrument for clearance rates, the coefficient estimate shows a significant, large negative impact on both types of crime. The instrument's validity is supported by both the F-test and Wu-Hausman test. However, caution is advised due to questionable coefficient estimates for other variables such as the minimum wage and the employment rate. Our second instrumental variable regression, in which authorized police strength per 100,000 is used as an instrument for the number of officers per 100,000, we get results consistent with all previous findings. Moreover, the coefficient estimates are nearly as large as in our base model and equally statistically significant. One final thing to note is the failure to reject the null hypothesis of the Wu-Hausman test in the regression involving violent crimes. Although this isn't cause for concern per se, it might suggest that the use of this instrument was unnecessary as the coefficient estimates that would have been obtained without instrumenting would not have been much different.

7 Conclusion

In conclusion, our research set out to conduct a comprehensive investigation into the intricate relationship between clearance rates and crime rates, inspired by Becker's foundational theory[1] and in response to recent econometric studies that underscored the significance of police officer numbers. By leveraging data spanning from 2000 to 2021 across Canadian provinces, our regression analyses on property and violent crime rates uncovered nuanced dynamics.

Aligned with Curry et al.'s seminal work,[1] our findings unveiled a substantial negative correlation between property crime rates and clearance rates, underscoring the impact of policing programs on property crimes. The incorporation of the number of officers per 100,000 population accentuated these effects, emphasizing the nuanced treatment of different crime types by clearance rate measures. Policymakers should consider targeted interventions and community policing programs, recognizing the potential for heightened police visibility to more effectively deter violent crimes.

Furthermore, our research brought to light an inverse correlation between crime rates and the median income of low-income households, shedding light on the financial motives underlying specific property crimes. Unexpectedly, our results revealed a positive association between real government transfers per person and property crimes, emphasizing the conditional nature of these transfers. Policymakers are urged to evaluate and potentially adjust these transfers to mitigate unintended consequences, particularly in exacerbating deprivation among low-income individuals.

Similar patterns were observed for violent crimes, where weighted measures exhibited larger coefficients. Although the effects of clearance rates on violent crimes were smaller, they remained significant. The negative correlation between the median income of low-income households and violent crimes persisted, and notably, the number of officers per 100,000 population demonstrated a negative and significant impact on violent crimes, contrary to Curry et al.'s findings.[2]

Further analysis, incorporating lagged clearance rates and instrumental variable regressions, bolstered the robustness of our results. Instrumental variable regressions, utilizing the number of criminal code reports per officer, underscored a substantial negative association between clearance rates and property crimes. The noteworthy impact of clearance rates on property crimes underscores the necessity for policies that enhance the efficiency of clearing such crimes, potentially involving investments in law enforcement training and technology to streamline the resolution process.

This research challenges existing assumptions and provides valuable insights for policymakers, law enforcement agencies, and our broader understanding of crime dynamics. By navigating the potential negative correlation between clearance rates and crime rates, this study contributes to the refinement of crime prevention strategies, offering meaningful insights with far-reaching consequences for policy, resource allocation, and our broader understanding of crime dynamics. Policymakers are encouraged to consider these findings within the context of their specific regions, fostering collaboration with law enforcement agencies and community stakeholders to ensure evidence-based policies that address the unique dynamics of crime in their jurisdictions.

References

[1] Gary S Becker. Crime and punishment: An economic approach. *Journal of political economy*, 76(2):169–217, 1968.

[2] Philip A Curry, Anindya Sen, and George Orlov. Crime, apprehension and clearance rates: Panel data evidence from canadian provinces. *Canadian Journal of Economics/Revue canadienne d'économique*, 49(2):481–514, 2016.

[3] Morgan Kelly. Inequality and crime. *Review of economics and Statistics*, 82(4):530–539, 2000.

[4] Jonathan Klick and Alexander Tabarrok. Using terror alert levels to estimate the effect of police on crime. *The Journal of Law and Economics*, 48(1):267–279, 2005.

[5] Steven D Levitt. The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. *The quarterly journal of economics*, 111(2):319–351, 1996.

[6] Alex R Piquero, David P Farrington, and Alfred Blumstein. The criminal career paradigm. *Crime and justice*, 30:359–506, 2003.

[7] Steven Raphael and Rudolf Winter-Ebmer. Identifying the effect of unemployment on crime. *The journal of law and economics*, 44(1):259–283, 2001.

8 Appendix

Table 2: Property Crimes Regressions

Dependent Variable:	Property Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Nonviolent Weighted Clearance Rate	-0.6475***	-0.6693***
	(0.1075)	(0.1050)
Total Population	-0.0769	-0.1312
	(0.2763)	(0.2870)
Males aged 15 to 24 (% of Population)	-0.0529	0.1672
	(0.4244)	(0.4380)
Employment Rate	-0.0363	0.3233
	(3.354)	(3.637)
Median Income of Low Income Households	-0.5811*	-0.5000
	(0.2994)	(0.3142)
Real Government Transfers per Person	0.1062	0.1269
	(0.0986)	(0.0975)
Immigrants per 100,000 Population	0.0102	0.0137
	(0.0212)	(0.0217)
Minimum Wage	4.951	4.511
	(6.701)	(7.734)
Employment Rate × Minimum Wage	-1.018	-0.9074
	(1.486)	(1.710)
Officers per 100,000 Population		0.2945
		(0.2531)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	220	210
Size of the 'effective' sample	22	21
R^2	0.96175	0.96484
Adjusted R^2	0.95347	0.95677
Within R^2	0.56461	0.58729
Within Adjusted R^2	0.54284	0.56302

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the result from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 3: Violent Crimes Regressions

Dependent Variable:	Violent Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Violent Weighted Clearance Rate	-0.4528***	-0.4539***
	(0.0867)	(0.0955)
Total Population	0.4488	0.4431
	(0.3051)	(0.3146)
Males aged 15 to 24 (% of Population)	0.1870	0.1487
	(0.2978)	(0.3415)
Employment Rate	2.386	2.413
	(2.602)	(2.898)
Median Income of Low Income Households	-0.1621	-0.3249
	(0.2811)	(0.3118)
Real Government Transfers per Person	-0.1514	-0.1483
	(0.0975)	(0.1090)
Immigrants per 100,000 Population	-0.0385	-0.0448*
	(0.0230)	(0.0236)
Minimum Wage	0.5664	0.3679
	(5.137)	(6.000)
Employment Rate × Minimum Wage	-0.0883	-0.0454
	(1.137)	(1.326)
Officers per 100,000 Population		-0.2150
		(0.2459)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	220	210
Size of the 'effective' sample	22	21
R^2	0.99851	0.99852
Adjusted R^2	0.99819	0.99817
Within R^2	0.32152	0.32229
Within Adjusted R^2	0.28760	0.28243

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the result from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 4: Property Crimes Regressions with Lagged Weighted Clearance Rates

Dependent Variable:	Property Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Nonviolent Weighted Clearance Rate	-0.5771***	-0.6336***
	(0.1243)	(0.1179)
Nonviolent Weighted Clearance Rate (One-year Lag)	-0.2382*	-0.1490
	(0.1159)	(0.1230)
Nonviolent Weighted Clearance Rate (Two-year Lag)	0.0770	0.0681
	(0.1048)	(0.1022)
Total Population	0.1064	0.0919
	(0.3036)	(0.3211)
Males aged 15 to 24 (% of Population)	-0.0444	0.1136
	(0.4158)	(0.4456)
Employment Rate	0.1248	0.9475
	(3.633)	(4.043)
Median Income of Low Income Households	-0.4445	-0.4010
	(0.3073)	(0.3222)
Real Government Transfers per Person	0.0495	0.0918
	(0.1020)	(0.1021)
Immigrants per 100,000 Population	-0.0044	6.59×10^{-5}
	(0.0228)	(0.0235)
Minimum Wage	5.698	6.496
	(7.328)	(8.565)
Employment Rate × Minimum Wage	-1.208	-1.371
	(1.625)	(1.894)
Officers per 100,000 Population		0.1698
		(0.2688)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	200	190
Size of the 'effective' sample	20	19
R^2	0.96382	0.96574
Adjusted R^2	0.95500	0.95683
Within R^2	0.55360	0.56259
Within Adjusted R^2	0.52291	0.52760

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the results from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 5: Violent Crimes Regressions with Lagged Weighted Clearance Rates

Dependent Variable:	Violent Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Violent Weighted Clearance Rate	-0.2801***	-0.2777***
	(0.0865)	(0.0931)
Violent Weighted Clearance Rate (One-year Lag)	-0.2646***	-0.2497**
	(0.0885)	(0.0968)
Violent Weighted Clearance Rate (Two-year Lag)	-0.0148	-0.0330
	(0.0969)	(0.1033)
Total Population	0.5672	0.5617
	(0.3510)	(0.3397)
Males aged 15 to 24 (% of Population)	0.1541	0.0368
	(0.3403)	(0.3980)
Employment Rate	2.917	2.900
	(3.047)	(3.392)
Median Income of Low Income Households	-0.1432	-0.3338
	(0.3074)	(0.3425)
Real Government Transfers per Person	-0.1298	-0.1151
	(0.0925)	(0.1046)
Immigrants per 100,000 Population	-0.0388	-0.0477*
	(0.0250)	(0.0258)
Minimum Wage	1.594	1.371
	(5.908)	(6.876)
Employment Rate × Minimum Wage	-0.3142	-0.2671
	(1.308)	(1.518)
Officers per 100,000 Population		-0.2857
		(0.2640)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	200	190
Size of the 'effective' sample	20	19
R^2	0.99859	0.99860
Adjusted R^2	0.99825	0.99824
Within R^2	0.36875	0.37386
Within Adjusted R^2	0.32536	0.32377

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the results from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 6: Property Crimes Regressions controlling for Incarcerations per 100,000 Population

Dependent Variable:	Property Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Nonviolent Weighted Clearance Rate	-0.6619***	-0.6865***
	(0.1019)	(0.0998)
Total Population	0.1556	0.1433
	(0.2937)	(0.3042)
Males aged 15 to 24 (% of Population)	0.0598	0.2930
	(0.4859)	(0.4669)
Employment Rate	2.757	3.827
	(4.158)	(4.214)
Median Income of Low Income Households	-0.2814	-0.2052
	(0.3165)	(0.3197)
Real Government Transfers per Person	0.1743	0.2283*
	(0.1087)	(0.1118)
Immigrants per 100,000 Population	0.0031	0.0026
	(0.0211)	(0.0222)
Minimum Wage	9.569	10.07
	(7.863)	(8.620)
Incarceration Rate per 100,000 Population	0.1812*	0.2201**
	(0.0881)	(0.0817)
Employment Rate × Minimum Wage	-2.032	-2.130
	(1.738)	(1.905)
Officers per 100,000 Population		0.2527
		(0.2534)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	217	207
Size of the 'effective' sample	22	21
R^2	0.96410	0.96771
Adjusted R^2	0.95594	0.95993
Within R^2	0.58692	0.61640
Within Adjusted R^2	0.56345	0.59098

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the results from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 7: Violent Crimes Regressions controlling for Incarcerations per 100,000 Population

Dependent Variable:	Violent Crimes per 100,000 Population	
Model:	(1)	(2)
Variables		
Violent Weighted Clearance Rate	-0.4090***	-0.4041***
	(0.0881)	(0.0931)
Total Population	0.6376*	0.7161**
	(0.3097)	(0.3200)
Males aged 15 to 24 (% of Population)	0.2884	0.2740
	(0.3236)	(0.3617)
Employment Rate	4.543	5.671*
	(2.848)	(3.221)
Median Income of Low Income Households	0.0411	-0.0813
	(0.2892)	(0.3140)
Real Government Transfers per Person	-0.0678	-0.0158
	(0.1003)	(0.1083)
Immigrants per 100,000 Population	-0.0457*	-0.0574**
	(0.0256)	(0.0255)
Minimum Wage	4.002	5.574
	(5.537)	(6.602)
Incarceration Rate per 100,000 Population	0.1348	0.1948**
	(0.0842)	(0.0881)
Employment Rate × Minimum Wage	-0.8437	-1.190
	(1.225)	(1.459)
Officers per 100,000 Population		-0.2995
		(0.2413)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	217	207
Size of the 'effective' sample	22	21
R^2	0.99858	0.99863
Adjusted R^2	0.99826	0.99830
Within R^2	0.34277	0.36297
Within Adjusted R^2	0.30543	0.32076

Newey-West (L=2) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1) and (2) reflect the result from regressions excluding and including the number of officers per 100,000 population as an additional regressor respectively.

Table 8: First Differences Regression with Fixed Effects

Dependent Variables:	d(property_crimes_per100k,1)	d(violent_crimes_per100k,1)
Model:	(1)	(2)
Variables		
d(nonviolent_weighted_clearance_rate,1)	-0.4135***	
	(0.0717)	
d(total_population,1)	0.1622	0.8159
	(0.7470)	(0.7123)
d(young_men_rate,1)	0.3254	1.058*
	(0.5437)	(0.5386)
d(employment_rate,1)	-0.6476	0.6261
	(0.6895)	(0.5347)
d(median_income_adjusted,1)	-0.1661	0.1809
	(0.1781)	(0.1659)
d(Real_transfer_per_person,1)	-0.0944	0.0128
	(0.0735)	(0.0603)
d(immigrants_per100k,1)	0.0051	-0.0374*
	(0.0206)	(0.0190)
d(minimum_wage,1)	0.1903*	0.1274
	(0.0921)	(0.1004)
d(employment_rate,1) × d(minimum_wage,1)	-1.705	3.556
	(8.042)	(9.511)
d(violent_weighted_clearance_rate,1)		-0.1733***
		(0.0589)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	210	210
Size of the 'effective' sample	21	21
R^2	0.58076	0.57931
Adjusted R^2	0.48759	0.48582

Newey-West (L=2) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Instrumental Variable Regression using Criminal Code Reports per Officer to instrument Weighted Clearance Rate

Dependent Variables:	Property Crimes per 100,000 Population	Violent Crimes per 100,000 Population
Model:	(1)	(2)
Variables		
Nonviolent Weighted Clearance Rate	-2.683***	
	(0.6196)	
Officers per 100,000 Population	0.9441**	0.0621
	(0.4231)	(0.3551)
Total Population	-1.456*	0.2161
	(0.7212)	(0.3976)
Males aged 15 to 24 (% of Population)	1.154	-0.0522
	(0.7125)	(0.5328)
Employment Rate	-17.71**	-4.585
	(8.066)	(4.898)
Median Income of Low Income Households	0.6376	0.5949
	(0.5691)	(0.4518)
Real Government Transfers per Person	-0.4168	-0.4062**
	(0.2657)	(0.1595)
Immigrants per 100,000 Population	-0.0394	0.0242
	(0.0595)	(0.0430)
Minimum Wage	-32.89*	-11.14
	(17.01)	(9.777)
Employment Rate × Minimum Wage	7.351*	2.528
	(3.754)	(2.164)
Violent Weighted Clearance Rate		-1.603***
		(0.3967)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Adjusted R^2	0.82001	0.99605
F-test (1st stage), Nonviolent Weighted Clearance Rate	47.245	
F-test (1st stage), Violent Weighted Clearance Rate		41.162
F-test (1st stage), p-value, Nonviolent Weighted Clearance Rate	7.88×10^{-11}	
F-test (1st stage), p-value, Violent Weighted Clearance Rate		1×10^{-9}
Wu-Hausman	509.97	53.606
Wu-Hausman, p-value	6.51×10^{-53}	9.52×10^{-12}

Newey-West (L=2) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Instrumental Variable Regression using Authorized Police Officer Strength per 100,000 Population to instrument Officers per 100,000 Population

Dependent Variables:	Property Crimes per 100,000 Population	Violent Crimes per 100,000 Population
Model:	(1)	(2)
Variables		
Officers per 100,000 Population	-0.2727	-0.5263
	(0.4444)	(0.3725)
Nonviolent Weighted Clearance Rate	-0.6260***	
	(0.1074)	
Total Population	-0.0658	0.4668
	(0.3056)	(0.3050)
Males aged 15 to 24 (% of Population)	-0.0402	0.0481
	(0.4270)	(0.3418)
Employment Rate	0.9360	2.637
	(4.380)	(3.170)
Median Income of Low Income Households	-0.6986*	-0.4347
	(0.3564)	(0.3369)
Real Government Transfers per Person	0.1262	-0.1515
	(0.1023)	(0.1107)
Immigrants per 100,000 Population	0.0016	-0.0532*
	(0.0246)	(0.0256)
Minimum Wage	6.301	1.079
	(9.221)	(6.586)
Employment Rate × Minimum Wage	-1.298	-0.2004
	(2.035)	(1.455)
Violent Weighted Clearance Rate		-0.4377***
		(0.1014)
Fixed-effects		
Province	Yes	Yes
Year	Yes	Yes
Fit statistics		
Adjusted R^2	0.95421	0.99814
F-test (1st stage), Officers per 100,000 Population	86.953	88.990
F-test (1st stage), p-value, Officers per 100,000 Population	2.19×10^{-17}	1.07×10^{-17}
Wu-Hausman	4.5004	1.4116
Wu-Hausman, p-value	0.03535	0.23646

Newey-West (L=2) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

***Note:** In line with the work of Curry et al.[2], the standard errors of coefficient estimates in all regressions are White and Newey-West corrected for second-order autocorrelation. The purpose of this adjustment is to address both serially correlated and heteroskedastic error terms that would obscure the relationships we were attempting to capture given the time horizon we cover and the presence of outliers.

ECO1400 Final Project Code

Shun Wing Wong & Zachary Tolliver

2023-12-07

```
library(fixest)
library(tidyverse)
library(purrr)
library(lubridate)
library(plm)
library(recipes)
library(tibble)
library(tidyr)
library(dplyr)
library(readxl)
library(profvis)
library(MASS)
library(lmtest)
library(ggplot2)
library(AER)
library(dynlm)
library(sandwich)
library(stargazer)
library(xtable)
library(pastecs)
library(psych)
library(descr)

#Loading Data
Pop <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Populationnoterritories.csv")
labour <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/labour_data.csv")
low_inc <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Low_incomenoterritories.csv")
min_wage <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Minimumwagenoterritories.csv")
crime <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/crimenoterritories.csv")
Police <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Police_numbersnoterritories.csv")
Immigrants <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Immigrant_numbersnoterritories.csv")
net_transfers <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Net_gov_transfer_withpeoplenoterritories.csv")
Prison <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Prisonnoterritories.csv")
```

```
police2 <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/police2.csv")
pop_men <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Pop_men.csv")
violent_crime <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/violent_crime.csv")
dependency <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/dependency.csv")
alcohol <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/Alcohol.csv")
outdoors <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/outdoortime.csv")
transport <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/buses_registered.csv")
education <-read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/education.csv")
crimegraphics <- read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/crimechange.csv")
viocrime <-read.csv("C:/Users/ztoll/OneDrive/Desktop/Econometrics
project/viocrime.csv")

#Creating a vector of province names
prov_names <-
c("Newfoundland.and.Labrador","Prince.Edward.Island","Nova.Scotia","New.Bruns
wick","Quebec","Ontario","Manitoba","Saskatchewan","Alberta","British.Columbi
a")

#Creating a list to assign province specific data frames.
crime_list <- list()

#Filling data frames created with province specific property crime data.
  for (i in seq_along(prov_names)) {
    crime_list[[i]] <- crime %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Clearance_rate= 100*(.[, 4] / .[, 2]),Province = prov_names[i])
%>%
      dplyr::select(1,Province,everything())
  }

#Creating a vector to name the columns of the data frames created.
crime_column_names <-
c("Year","Province","total_property_crimes","property_crimes_per100k","total_
property_crimes_cleared","fraud", "b&e",
"possession_stolen_goods","theft_under_5k", "motor_vehicle_theft",
"theft_over_5k", "nonviolent_clearance_rate")

#Assigning these names to the columns of each data frame.
crime_list <- lapply(crime_list, function(df) setNames(df,
crime_column_names))
```

```r
#Creating a list to assign province specific data frames.
viocrime_list <- list()

#Filling data frames created with province specific violent crime data.
  for (i in seq_along(prov_names)) {
    viocrime_list[[i]] <- viocrime %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Province = prov_names[i]) %>%
      dplyr::select(1,Province,everything())
  }

#Creating a vector to name the columns of the data frames created.
viocrime_column_names <-
c("Year","Province","total_violent_crimes","violent_crimes_per100k","total_vi
olent_crimes_cleared")

#Assigning these names to the columns of each data frame.
viocrime_list <- lapply(viocrime_list, function(df) setNames(df,
viocrime_column_names))

#Creating a list to assign province specific data frames.
crime_graphics <- list()

#Filling data frames created with province specific crime data.
  for (i in seq_along(prov_names)) {
    crime_graphics[[i]] <- crimegraphics %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Province = prov_names[i])%>%
      dplyr::select(1, Province, everything())
  }
#Creating a vector to name the columns of the data frames created.
crime_graphics_column_names <-
c("Year","Province","Percentage_change_Property_Crime","Percentage_change_Vio
lent_Crime")

#Assigning these names to the columns of each data frame.
crime_graphics <- lapply(crime_graphics, function(df) setNames(df,
crime_graphics_column_names))

#Creating a list to assign province specific data frames.
bus_list <- list()

#Filling data frames created with province specific bus registration data.
  for (i in seq_along(prov_names)) {
    bus_list[[i]] <- transport %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Province = prov_names[i])%>%
      dplyr::select(1, Province, everything())
  }
#Creating a vector to name the columns of the data frames created.
```

```r
bus_column_names <- c("Year","Province","bus_registrations")

#Assigning these names to the columns of each data frame.
bus_list <- lapply(bus_list, function(df) setNames(df, bus_column_names))

#Creating a list to assign province specific data frames.
educ_list <- list()

#Filling data frames created with province specific education data.
  for (i in seq_along(prov_names)) {
    educ_list[[i]] <- education %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Province = prov_names[i])%>%
      dplyr::select(1, Province, everything())
  }
#Creating a vector to name the columns of the data frames created.
educ_column_names <- c("Year","Province","secondary_school_graduates")

#Assigning these names to the columns of each data frame.
educ_list <- lapply(educ_list, function(df) setNames(df, educ_column_names))

#Creating a list to assign province specific data frames.
alc_list <- list()

#Filling data frames created with province specific alcohol consumption data.
  for (i in seq_along(prov_names)){
    alc_list[[i]] <- alcohol %>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())
  }
#Creating a vector to name the columns of the data frames created.
alc_column_names <-c("Year","Province","alc_vol_percapita")

#Assigning these names to the columns of each data frame.
alc_list<- lapply(alc_list, function(df) setNames(df,
alc_column_names))

#Creating a list to assign province specific data frames.
outdoors_list <- list()

#Filling data frames created with province specific outdoors data.
  for (i in seq_along(prov_names)){
    outdoors_list[[i]] <- outdoors %>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())
  }
#Creating a vector to name the columns of the data frames created.
outdoors_column_names <-c("Year","Province","percent_time_outdoors")
```

```r
#Assigning these names to the columns of each data frame.
outdoors_list<- lapply(outdoors_list, function(df) setNames(df,
outdoors_column_names))

#Creating a list to assign province specific data frames.
labour_list <- list()

#Filling data frames created with province specific employment data.
  for (i in seq_along(prov_names)){
    labour_list[[i]] <- labour %>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())%>%
      mutate(employment_rate = 100*((.[,4])/(.[,3])))
  }

#Creating a vector to name the columns of the data frames created.
labour_column_names <-
c("Year","Province","labour_force","employment","unemployment_rate","employme
nt_rate")

#Assigning these names to the columns of each data frame.
labour_list<- lapply(labour_list, function(df) setNames(df,
labour_column_names))

#Creating a list to assign province specific data frames.
pop_list <- list()

#Merging two dataframes with population information.
Pop <- merge(Pop, pop_men)

#Filling data frames created with province specific demographic data.
for (i in seq_along(prov_names)) {
  pop_list[[i]] <- Pop %>%
    dplyr::select(1, contains(prov_names[i])) %>%
    dplyr::mutate(
      Province = prov_names[i],
      young_men = rowSums(dplyr::select(.,
contains(c("15.to.24","25.to.29","30.to.34")))),
      young_men_rate = 100*(young_men / dplyr::select(., contains("Both"))[,
1])) %>%
    dplyr::select(1, Province, contains("Both"), young_men, young_men_rate)
}
#Creating a vector to name the columns of the data frames created.
pop_column_names<-
c("Year","Province","total_population","young_men","young_men_rate")

#Assigning these names to the columns of each data frame.
pop_list<- lapply(pop_list, function(df) setNames(df, pop_column_names))
```

```r
#Creating a list to assign province specific data frames.
poor_list <- list()

#Filling data frames created with province specific income data.
  for (i in seq_along(prov_names)){
    poor_list[[i]] <- low_inc%>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())
  }

#Creating a vector to name the columns of the data frames created.
poor_column_names<-
c("Year","Province","percentage_low_income","percentage_males18.64_low_income
","median_income","CPI_2002_base","median_income_adjusted","total_people_low_
income","low_income_gap_ratio")

#Assigning these names to the columns of each data frame.
poor_list<- lapply(poor_list, function(df) setNames(df,
poor_column_names))

#Creating a list to assign province specific data frames.
transfer_list <- list()

#Creating a data frame with a single variable that will be used later.
add_transfer_per_person <- function(df) {
  df$Real_transfer_per_person <-
df$Total_Net_Gov_Transfers_Current_Year_Dollars / df$Persons
  return(df)
}

#Filling the data frames with provincial government transfer data.
transfer_list <- lapply(prov_names, function(prov) {
  df <- net_transfers %>% filter(Province == prov) %>%
    mutate_at(vars(starts_with("Total_")), list(~ . * -1))
  return(if (nrow(df) > 0) add_transfer_per_person(df) else NULL)
})

dependency_list <- lapply(seq_along(dependency)[-1], function(i)
cbind(dependency[, 1, drop = FALSE], dependency[, i, drop = FALSE]))

process_df <- function(df) {
  # Extract the name of the second column
  col_name <- colnames(df)[2]

  # Add a new column with the name of the original second column
  df$Province <- col_name

  # Rename the original second column to something else
  new_col_name <- paste0("dependency_ratio")
```

```r
  colnames(df)[2] <- new_col_name
  return(df)
}
dependency_list <- lapply(dependency_list, process_df)%>%
  lapply(function(df) dplyr::select(df, 1, 3, 2))


join_function <- function(df1, df2) {
  left_join(df1, df2, by = c("Year", "Province"))
}
transfer_list <- Map(join_function, transfer_list, dependency_list)

#Changing the order of columns in the min_wage data frame.
wage_min <- min_wage%>%
  dplyr::select("Jurisdiction","Effective.Date","Minimum.Wage")

#Changing the "Effective.Date" column to a time variable.
wage_min$Effective.Date <-year(dmy(wage_min$Effective.Date))

#Changing the order of the columns again.
wage_min <- wage_min %>%
  dplyr::select(2,1,3)

#Creating a vector of names for the data frame.
wage_min_names<- c("Year","Province","minimum_wage")

#Assigning the name vector to the columns of the data frame.
colnames(wage_min)<- wage_min_names

#Reordering the data frame again.
wage_min <- wage_min %>%
  arrange(Year, Province, desc(minimum_wage)) %>%
  distinct(Year, Province, .keep_all = TRUE)%>%
  arrange(Province)

#Splitting the larger dataframe into a list of provincial dataframes.
minwage_list <- split(wage_min, wage_min$Province)

#Applying a change to each data frame in the list which involves filling in
any missing years with an NA value, filling those NA values with the last
known measure of minimum wage, and then reordign the columns again.
minwage_list <- lapply(minwage_list, function(df_i) {
  df_i %>%
    arrange(Province, Year) %>%
    group_by(Province) %>%
    complete(Year = seq(1998, 2021), fill = list(minimum_wage = NA), explicit
= FALSE) %>%
    fill(minimum_wage, .direction = "down") %>%
    filter(Year >= 1998 & Year <= 2021)%>%
```

```
    dplyr::select(2,1,3)
})

#Assigning the corresponding province names to each data frame in the list of
data frames.
minwage_list <- minwage_list[prov_names]

#Creating a list to assign province specific data frames.
police_list <- list()

#Merging the two different data sets containing information on the police
force.
Police <-merge(Police, police2, all.x = T, all.y = T)

#Filling data frames created with province specific police data.
  for (i in seq_along(prov_names)){
    police_list[[i]] <- Police %>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())
  }

#Creating a vector to name the columns of the data frames created.
police_column_names <-
c("Year","Province","officers_per100k","criminal_codes_per_officer",
"violent_weighted_clearance_rate","nonviolent_weighted_clearance_rate",
"potential_officers_per100k")

#Assigning these names to the columns of each data frame.
police_list<- lapply(police_list, function(df) setNames(df,
police_column_names))

#Creating a list to assign province specific data frames.
immigrant_list <- list()

#Filling data frames created with province specific immigration data.
  for (i in seq_along(prov_names)){
    immigrant_list[[i]] <- Immigrants %>%
      dplyr::select(1, contains(prov_names[i]))%>%
      mutate(Province=prov_names[i])%>%
      dplyr::select(1,Province,everything())
  }
immigrant_column_names <- c("Year","Province","immigrants")
immigrant_list<- lapply(immigrant_list, function(df) setNames(df,
immigrant_column_names))


#Appending some of the columns from the population data frames to the
immigration data frames to calculate the number of immigrants per 100,000
people, then dropping the extra columns that show up.
```

```r
for (i in seq_along(immigrant_list)) {
  immigrant_list[[i]] <- left_join(immigrant_list[[i]], pop_list[[i]], by =
c("Year", "Province")) %>%
    dplyr::select(-young_men, -young_men_rate) %>%
    mutate(immigrants_per100k = (immigrants / total_population) * 100000) %>%
    as.data.frame()
}
#Creating a vector to name the columns of the data frames created.
immigrant_column_names <-
c("Year","Province","total_immigrants","total_population","immigrants_per100k
")
#Assigning names to the columns of each data frame.
immigrant_list<- lapply(immigrant_list, function(df) setNames(df,
immigrant_column_names))

#Creating a list to assign province specific data frames.
prison_list <- list()

#Filling data frames created with province specific incarceration data.
  for (i in seq_along(prov_names)) {
    prison_list[[i]] <- Prison %>%
      dplyr::select(1, contains(prov_names[i])) %>%
      mutate(Province = prov_names[i])

    col_index <- grep("Incarceration", colnames(prison_list[[i]]))
    col_name <- colnames(prison_list[[i]])[col_index]
    colnames(prison_list[[i]])[col_index] <- "incarcerations_per100k"
  }

#Reordering the columns in the data frame.
  for (i in seq_along(prov_names)) {
    prison_list[[i]] <- prison_list[[i]] %>%
      dplyr::select(Year, Province, incarcerations_per100k, everything())
  }

#Creating a list to which all the data frames can be merged to.
combined_list <- list()

#Combining all the data frames created through the steps above as entries in
a list.
for (i in seq_along(crime_list)) {
  combined_list[[i]] <- left_join(crime_list[[i]], labour_list[[i]], by =
c("Year", "Province")) %>%
    left_join(poor_list[[i]], by = c("Year", "Province")) %>%
    left_join(pop_list[[i]], by = c("Year", "Province")) %>%
    left_join(minwage_list[[i]],by = c("Year","Province"))%>%
    left_join(police_list[[i]],by = c("Year","Province"))%>%
    left_join(immigrant_list[[i]],by =
c("Year","Province","total_population"))%>%
    left_join(transfer_list[[i]],by = c("Year","Province"))%>%
```

```
    left_join(prison_list[[i]],by = c("Year","Province"))%>%
    left_join(viocrime_list[[i]], by = c("Year","Province"))%>%
    left_join(alc_list[[i]], by = c("Year", "Province"))%>%
    left_join(outdoors_list[[i]], by = c("Year","Province"))%>%
    left_join(bus_list[[i]], by = c("Year","Province"))%>%
  left_join(educ_list[[i]], by = c("Year","Province"))%>%
  left_join(crime_graphics[[i]], by = c("Year","Province"))
}

#Stacking all the data frames in the list of data frames into one large data
frame containing all the data.
stacked_data <- bind_rows(combined_list)

summary(stacked_data$violent_weighted_clearance_rate)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   41.89   55.53   60.67   59.84   63.93   77.77

#creating a vector of column names that I will use to exclude them from the
next operation.
exclude_columns <- c("Year", "Province")

#Creating a transformation function that I can apply to a data frame.
transformation_function <- function(x) {
 log(x)
}

#Applying that transformation to the data frame where I have excluded some of
the columns.
log_data <- stacked_data %>%
  mutate_at(vars(-one_of(exclude_columns)), transformation_function)%>%
  mutate(Province_trend = ave(Year, Province, FUN = seq_along))

## Warning: There were 2 warnings in `mutate()`.
## The first warning was:
## ℹ In argument: `Percentage_change_Property_Crime = (function (x) ...`.
## Caused by warning in `log()`:
## ! NaNs produced
## ℹ Run
]8;;ide:run:dplyr::last_dplyr_warnings()dplyr::last_dplyr_warnings()]8;; to
see the 1 remaining warning.

lagged_log_data <- log_data%>%
  mutate(property_crimes_per100k_1 =
dplyr::lag(property_crimes_per100k,1),property_crimes_per100k_2 =
dplyr::lag(property_crimes_per100k,2),nonviolent_clearance_rate_1 =
dplyr::lag(nonviolent_clearance_rate,1),nonviolent_clearance_rate_2 =
dplyr::lag(nonviolent_clearance_rate,2), incarcerations_per100k_1 =
dplyr::lag(incarcerations_per100k,1), nonviolent_weighted_clearance_rate_1 =
dplyr::lag(nonviolent_weighted_clearance_rate,1),nonviolent_weighted_clearanc
e_rate_2 =
```

```
dplyr::lag(nonviolent_weighted_clearance_rate,2),violent_weighted_clearance_r
ate_1 =
dplyr::lag(violent_weighted_clearance_rate,1),violent_weighted_clearance_rate
_2 = dplyr::lag(violent_weighted_clearance_rate,2))

lagged_log_data <- lagged_log_data[lagged_log_data$Year %in% seq(from=2000,
to=2021, by=1),,drop=FALSE]

#NOTE ERROR FROM PERCENTAGE CHANGES IN CRIME RATES IS IRRELEVANT SINCE WE
DON'T USE THAT DATA IN REGRESSION.

#Creating dictionary of names to rename variables in regression tables.
dict = c(property_crimes_per100k = "Property Crimes per 100,000 Population",
nonviolent_clearance_rate = "Nonviolent Clearance Rate",
nonviolent_weighted_clearance_rate = "Nonviolent Weighted Clearance
Rate",officers_per100k = "Officers per 100,000 Population",
violent_crimes_per100k = "Violent Crimes per 100,000 Population",
violent_clearance_rate = "Violent Clearance Rate",
violent_weighted_clearance_rate = "Violent Weighted Clearance Rate",
'l(nonviolent_weighted_clearance_rate,1)'= "Nonviolent Weighted Clearance
Rate (One-year Lag)",'l(nonviolent_weighted_clearance_rate,2)'= "Nonviolent
Weighted Clearance Rate (Two-year
Lag)",'l(violent_weighted_clearance_rate,1)'= "Violent Weighted Clearance
Rate (One-year Lag)",'l(violent_weighted_clearance_rate,2)'= "Violent
Weighted Clearance Rate (Two-year Lag)",
incarcerations_per100k = "Incarceration Rate per 100,000 Population",
employment_rate = "Employment Rate", Real_transfer_per_person = "Real
Government Transfers per Person", minimum_wage = "Minimum Wage",
young_men_rate = "Males aged 15 to 24 (% of Population)", total_population =
"Total Population", median_income_adjusted = "Median Income of Low Income
Households", immigrants_per100k = "Immigrants per 100,000 Population")

#Fixed effects regression of property crimes per 100k on weighted clearance
rates, officers per 100k, along with other covariates.
fepropweighted <- feols(property_crimes_per100k ~
csw(nonviolent_weighted_clearance_rate,officers_per100k) + total_population +
young_men_rate +  employment_rate + median_income_adjusted +
Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate | Province + Year, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")

#Creating latex output of regression table.
etable(fepropweighted, fitstat = c("n","g","r2", "ar2","wr2","awr2"), dict =
dict, tex = T)

## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variable: & \multicolumn{2}{c}{Property Crimes per 100,000
```

```
Population}\\
##    Model:                                 & (1)            & (2)\\
##    \midrule
##    \emph{Variables}\\
##    Nonviolent Weighted Clearance Rate      & -0.6475$^{***}$ & -
0.6693$^{***}$\\
##                                          & (0.1075)        & (0.1050)\\
##    Total Population                       & -0.0769         & -0.1312\\
##                                          & (0.2763)        & (0.2870)\\
##    Males aged 15 to 24 (\% of Population) & -0.0529         & 0.1672\\
##                                          & (0.4244)        & (0.4380)\\
##    Employment Rate                        & -0.0363         & 0.3233\\
##                                          & (3.354)         & (3.637)\\
##    Median Income of Low Income Households & -0.5811$^{*}$   & -0.5000\\
##                                          & (0.2994)        & (0.3142)\\
##    Real Government Transfers per Person   & 0.1062          & 0.1269\\
##                                          & (0.0986)        & (0.0975)\\
##    Immigrants per 100,000 Population      & 0.0102          & 0.0137\\
##                                          & (0.0212)        & (0.0217)\\
##    Minimum Wage                           & 4.951           & 4.511\\
##                                          & (6.701)         & (7.734)\\
##    Employment Rate $\times$ Minimum Wage  & -1.018          & -0.9074\\
##                                          & (1.486)         & (1.710)\\
##    Officers per 100,000 Population        &                 & 0.2945\\
##                                          &                 & (0.2531)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                               & Yes             & Yes\\
##    Year                                   & Yes             & Yes\\
##    \midrule
##    \emph{Fit statistics}\\
##    Observations                           & 220             & 210\\
##    Size of the 'effective' sample         & 22              & 21\\
##    R$^2$                                  & 0.96175         & 0.96484\\
##    Adjusted R$^2$                         & 0.95347         & 0.95677\\
##    Within R$^2$                           & 0.56461         & 0.58729\\
##    Within Adjusted R$^2$                  & 0.54284         & 0.56302\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup

#Fixed effects regression of violent crimes per 100k on weighted clearance
rates, officers per 100k, along with other covariates.
feviolentweighted <- feols(violent_crimes_per100k ~
csw(violent_weighted_clearance_rate, officers_per100k) + total_population +
young_men_rate +  employment_rate + median_income_adjusted +
Real_transfer_per_person + immigrants_per100k + minimum_wage +
```

```
minimum_wage*employment_rate | Province + Year, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")


#Creating latex output of regression table.
etable(feviolentweighted, fitstat = c("n","g","r2", "ar2","wr2","awr2"),
title = "", dict = dict, tex = T)
```

```
## \begin{table}[htbp]
##    \caption{}
##    \centering
##    \begin{tabular}{lcc}
##       \tabularnewline \midrule \midrule
##       Dependent Variable: & \multicolumn{2}{c}{Violent Crimes per 100,000
Population}\\
##       Model:                                 & (1)              & (2)\\
##       \midrule
##       \emph{Variables}\\
##       Violent Weighted Clearance Rate        & -0.4528$^{***}$ & -
0.4539$^{***}$\\
##                                              & (0.0867)        &
(0.0955)\\
##       Total Population                       & 0.4488          & 0.4431\\
##                                              & (0.3051)        &
(0.3146)\\
##       Males aged 15 to 24 (\% of Population) & 0.1870          & 0.1487\\
##                                              & (0.2978)        &
(0.3415)\\
##       Employment Rate                        & 2.386           & 2.413\\
##                                              & (2.602)         &
(2.898)\\
##       Median Income of Low Income Households & -0.1621         & -
0.3249\\
##                                              & (0.2811)        &
(0.3118)\\
##       Real Government Transfers per Person   & -0.1514         & -
0.1483\\
##                                              & (0.0975)        &
(0.1090)\\
##       Immigrants per 100,000 Population      & -0.0385         & -
0.0448$^{*}$\\
##                                              & (0.0230)        &
(0.0236)\\
##       Minimum Wage                           & 0.5664          & 0.3679\\
##                                              & (5.137)         &
(6.000)\\
##       Employment Rate $\times$ Minimum Wage  & -0.0883         & -
0.0454\\
##                                              & (1.137)         &
(1.326)\\
```

```
##       Officers per 100,000 Population        &                 & -
0.2150\\
##                                              &                 &
(0.2459)\\
##       \midrule
##       \emph{Fixed-effects}\\
##       Province                               & Yes             & Yes\\
##       Year                                   & Yes             & Yes\\
##       \midrule
##       \emph{Fit statistics}\\
##       Observations                           & 220             & 210\\
##       Size of the 'effective' sample         & 22              & 21\\
##       R$^2$                                  & 0.99851         &
0.99852\\
##       Adjusted R$^2$                         & 0.99819         &
0.99817\\
##       Within R$^2$                           & 0.32152         &
0.32229\\
##       Within Adjusted R$^2$                  & 0.28760         &
0.28243\\
##       \midrule \midrule
##       \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##       \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *:
0.1}}\\
##    \end{tabular}
## \end{table}

#Fixed effects regression of violent crimes per 100k on weighted clearance
rates, officers per 100k, along with other covariates.
feprop_inst <- feols(property_crimes_per100k ~ officers_per100k +
total_population + young_men_rate +  employment_rate + median_income_adjusted
+ Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate | Province +
Year|nonviolent_weighted_clearance_rate ~ criminal_codes_per_officer, data =
lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")

## NOTE: 10 observations removed because of NA values (RHS: 10, IV: 0/10).

feprop_inst2 <- feols(property_crimes_per100k ~
nonviolent_weighted_clearance_rate + total_population + young_men_rate +
employment_rate + median_income_adjusted + Real_transfer_per_person +
immigrants_per100k + minimum_wage + minimum_wage*employment_rate | Province +
Year|officers_per100k ~ potential_officers_per100k, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")

## NOTE: 10 observations removed because of NA values (IV: 10/10).

feviolent_inst <- feols(violent_crimes_per100k ~ officers_per100k +
total_population + young_men_rate +  employment_rate + median_income_adjusted
+ Real_transfer_per_person + immigrants_per100k + minimum_wage +
```

```r
minimum_wage*employment_rate | Province + Year |
violent_weighted_clearance_rate ~ criminal_codes_per_officer, data =
lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 10 observations removed because of NA values (RHS: 10, IV: 0/10).
```

```r
feviolent_inst2 <- feols(violent_crimes_per100k ~
violent_weighted_clearance_rate +  total_population + young_men_rate +
employment_rate + median_income_adjusted + Real_transfer_per_person +
immigrants_per100k + minimum_wage + minimum_wage*employment_rate | Province +
Year |officers_per100k ~ potential_officers_per100k, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 10 observations removed because of NA values (IV: 10/10).
```

```r
etable(feprop_inst, feviolent_inst,fitstat
=c("ar2","ivf","ivf.p","wh","wh.p"), dict = dict, tex = T)
```

```
## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variables:                                              &
Property Crimes per 100,000 Population & Violent Crimes per 100,000
Population\\
##    Model:                                                            & (1)
& (2)\\
##    \midrule
##    \emph{Variables}\\
##    Nonviolent Weighted Clearance Rate                                & -
2.683$^{***}$                            &   \\
##                                                                      &
(0.6196)                                  &   \\
##    Officers per 100,000 Population                                   &
0.9441$^{**}$                             & 0.0621\\
##                                                                      &
(0.4231)                                  & (0.3551)\\
##    Total Population                                                  & -
1.456$^{*}$                              & 0.2161\\
##                                                                      &
(0.7212)                                  & (0.3976)\\
##    Males aged 15 to 24 (\% of Population)                            & 1.154
& -0.0522\\
##                                                                      &
(0.7125)                                  & (0.5328)\\
##    Employment Rate                                                   & -
17.71$^{**}$                             & -4.585\\
##                                                                      &
(8.066)                                   & (4.898)\\
##    Median Income of Low Income Households                            &
0.6376                                    & 0.5949\\
```

```
##                                                                      &
(0.5691)                              & (0.4518)\\
##    Real Government Transfers per Person                              & -
0.4168                               & -0.4062$^{**}$\\
##                                                                      &
(0.2657)                              & (0.1595)\\
##    Immigrants per 100,000 Population                                 & -
0.0394                               & 0.0242\\
##                                                                      &
(0.0595)                              & (0.0430)\\
##    Minimum Wage                                                      & -
32.89$^{*}$                          & -11.14\\
##                                                                      &
(17.01)                               & (9.777)\\
##    Employment Rate $\times$ Minimum Wage                             &
7.351$^{*}$                           & 2.528\\
##                                                                      &
(3.754)                               & (2.164)\\
##    Violent Weighted Clearance Rate                                   &
& -1.603$^{***}$\\
##                                                                      &
& (0.3967)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                                                          & Yes
& Yes\\
##    Year                                                              & Yes
& Yes\\
##    \midrule
##    \emph{Fit statistics}\\
##    Adjusted R$^2$                                                    &
0.82001                               & 0.99605\\
##    F-test (1st stage), Nonviolent Weighted Clearance Rate            &
47.245                                & \\
##    F-test (1st stage), Violent Weighted Clearance Rate               &
& 41.162\\
##    F-test (1st stage), p-value, Nonviolent Weighted Clearance Rate &
$7.88\times 10^{-11}$                 & \\
##    F-test (1st stage), p-value, Violent Weighted Clearance Rate    &
& $1\times 10^{-9}$\\
##    Wu-Hausman                                                        &
509.97                                & 53.606\\
##    Wu-Hausman, p-value                                               &
$6.51\times 10^{-53}$                 & $9.52\times 10^{-12}$\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup
```

```r
etable(feprop_inst2, feviolent_inst2,fitstat
=c("ar2","ivf","ivf.p","wh","wh.p"), dict = dict, tex = T)
```

```
## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variables:                                              & Property
Crimes per 100,000 Population & Violent Crimes per 100,000 Population\\
##    Model:                                                            & (1)
& (2)\\
##    \midrule
##    \emph{Variables}\\
##    Officers per 100,000 Population                                   & -0.2727
& -0.5263\\
##                                                                      & (0.4444)
& (0.3725)\\
##    Nonviolent Weighted Clearance Rate                                & -
0.6260$^{***}$                        &   \\
##                                                                      & (0.1074)
&   \\
##    Total Population                                                  & -0.0658
& 0.4668\\
##                                                                      & (0.3056)
& (0.3050)\\
##    Males aged 15 to 24 (\% of Population)                            & -0.0402
& 0.0481\\
##                                                                      & (0.4270)
& (0.3418)\\
##    Employment Rate                                                   & 0.9360
& 2.637\\
##                                                                      & (4.380)
& (3.170)\\
##    Median Income of Low Income Households                            & -
0.6986$^{*}$                          & -0.4347\\
##                                                                      & (0.3564)
& (0.3369)\\
##    Real Government Transfers per Person                              & 0.1262
& -0.1515\\
##                                                                      & (0.1023)
& (0.1107)\\
##    Immigrants per 100,000 Population                                 & 0.0016
& -0.0532$^{*}$\\
##                                                                      & (0.0246)
& (0.0256)\\
##    Minimum Wage                                                      & 6.301
& 1.079\\
##                                                                      & (9.221)
& (6.586)\\
##    Employment Rate $\times$ Minimum Wage                             & -1.298
```

```
& -0.2004\\
##                                                                  & (2.035)
& (1.455)\\
##    Violent Weighted Clearance Rate                               &
& -0.4377$^{***}$\\
##                                                                  &
& (0.1014)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                                                      & Yes
& Yes\\
##    Year                                                          & Yes
& Yes\\
##    \midrule
##    \emph{Fit statistics}\\
##    Adjusted R$^2$                                                & 0.95421
& 0.99814\\
##    F-test (1st stage), Officers per 100,000 Population           & 86.953
& 88.990\\
##    F-test (1st stage), p-value, Officers per 100,000 Population &
$2.19\times 10^{-17}$                  & $1.07\times 10^{-17}$\\
##    Wu-Hausman                                                    & 4.5004
& 1.4116\\
##    Wu-Hausman, p-value                                           & 0.03535
& 0.23646\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup
```

```
#Fixed effects regression of property crimes per 100k on clearance rates and
lagged clearance rates, officers per 100k, along with other covariates.
feproplag <- feols(property_crimes_per100k ~
csw(nonviolent_weighted_clearance_rate +
(l(nonviolent_weighted_clearance_rate,1) +
l(nonviolent_weighted_clearance_rate,2)),officers_per100k) + total_population
+ young_men_rate +  employment_rate + median_income_adjusted +
Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate | Province + Year, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 20 observations removed because of NA values (RHS: 20).
##       |-> this msg only concerns the variables common to all estimations
```

```
#Creating latex output of regression table.
etable(feproplag, dict =dict, fitstat = c("n","g","r2", "ar2","wr2","awr2"),
title = "", tex = T)
```

```
## \begin{table}[htbp]
##    \caption{}
##    \centering
##    \begin{tabular}{lcc}
##       \tabularnewline \midrule \midrule
##       Dependent Variable: & \multicolumn{2}{c}{Property Crimes per 100,000
Population}\\
##       Model:                                            & (1)
& (2)\\
##       \midrule
##       \emph{Variables}\\
##       Nonviolent Weighted Clearance Rate                & -0.5771$^{***}$
& -0.6336$^{***}$\\
##                                                         & (0.1243)
& (0.1179)\\
##       Nonviolent Weighted Clearance Rate (One-year Lag) & -0.2382$^{*}$
& -0.1490\\
##                                                         & (0.1159)
& (0.1230)\\
##       Nonviolent Weighted Clearance Rate (Two-year Lag) & 0.0770
& 0.0681\\
##                                                         & (0.1048)
& (0.1022)\\
##       Total Population                                  & 0.1064
& 0.0919\\
##                                                         & (0.3036)
& (0.3211)\\
##       Males aged 15 to 24 (\% of Population)            & -0.0444
& 0.1136\\
##                                                         & (0.4158)
& (0.4456)\\
##       Employment Rate                                   & 0.1248
& 0.9475\\
##                                                         & (3.633)
& (4.043)\\
##       Median Income of Low Income Households            & -0.4445
& -0.4010\\
##                                                         & (0.3073)
& (0.3222)\\
##       Real Government Transfers per Person              & 0.0495
& 0.0918\\
##                                                         & (0.1020)
& (0.1021)\\
##       Immigrants per 100,000 Population                 & -0.0044
& $6.59\times 10^{-5}$\\
##                                                         & (0.0228)
& (0.0235)\\
##       Minimum Wage                                      & 5.698
& 6.496\\
##                                                         & (7.328)
```

```
& (8.565)\\
##        Employment Rate $\times$ Minimum Wage              & -1.208
& -1.371\\
##                                                           & (1.625)
& (1.894)\\
##        Officers per 100,000 Population                    &
& 0.1698\\
##                                                           &
& (0.2688)\\
##        \midrule
##        \emph{Fixed-effects}\\
##        Province                                           & Yes
& Yes\\
##        Year                                               & Yes
& Yes\\
##        \midrule
##        \emph{Fit statistics}\\
##        Observations                                       & 200
& 190\\
##        Size of the 'effective' sample                     & 20
& 19\\
##        R$^2$                                              & 0.96382
& 0.96574\\
##        Adjusted R$^2$                                     & 0.95500
& 0.95683\\
##        Within R$^2$                                       & 0.55360
& 0.56259\\
##        Within Adjusted R$^2$                              & 0.52291
& 0.52760\\
##        \midrule \midrule
##        \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##        \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *:
0.1}}\\
##     \end{tabular}
## \end{table}
```

```
#Fixed effects regression of violent crimes per 100k on clearance rates and
lagged clearance rates, officers per 100k, along with other covariates.
feviolentlag <- feols(violent_crimes_per100k ~
csw(violent_weighted_clearance_rate + (l(violent_weighted_clearance_rate, 1)
+ l(violent_weighted_clearance_rate, 2)), officers_per100k) +
total_population + young_men_rate +  employment_rate + median_income_adjusted
+ Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate | Province + Year, data = lagged_log_data,
panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 20 observations removed because of NA values (RHS: 20).
##       |-> this msg only concerns the variables common to all estimations
```

```r
#Creating latex output of regression table.
etable(feviolentlag, fitstat = c("n","g","r2", "ar2","wr2","awr2"), dict =
dict, tex = T)
```

```
## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variable: & \multicolumn{2}{c}{Violent Crimes per 100,000
Population}\\
##    Model:                                         & (1)             &
(2)\\
##    \midrule
##    \emph{Variables}\\
##    Violent Weighted Clearance Rate                & -0.2801$^{***}$ & -
0.2777$^{***}$\\
##                                                   & (0.0865)        &
(0.0931)\\
##    Violent Weighted Clearance Rate (One-year Lag) & -0.2646$^{***}$ & -
0.2497$^{**}$\\
##                                                   & (0.0885)        &
(0.0968)\\
##    Violent Weighted Clearance Rate (Two-year Lag) & -0.0148         & -
0.0330\\
##                                                   & (0.0969)        &
(0.1033)\\
##    Total Population                               & 0.5672          &
0.5617\\
##                                                   & (0.3510)        &
(0.3397)\\
##    Males aged 15 to 24 (\% of Population)         & 0.1541          &
0.0368\\
##                                                   & (0.3403)        &
(0.3980)\\
##    Employment Rate                                & 2.917           &
2.900\\
##                                                   & (3.047)         &
(3.392)\\
##    Median Income of Low Income Households         & -0.1432         & -
0.3338\\
##                                                   & (0.3074)        &
(0.3425)\\
##    Real Government Transfers per Person           & -0.1298         & -
0.1151\\
##                                                   & (0.0925)        &
(0.1046)\\
##    Immigrants per 100,000 Population              & -0.0388         & -
0.0477$^{*}$\\
##                                                   & (0.0250)        &
(0.0258)\\
```

```
##    Minimum Wage                                      & 1.594           &
1.371\\
##                                                      & (5.908)         &
(6.876)\\
##    Employment Rate $\times$ Minimum Wage             & -0.3142         & -
0.2671\\
##                                                      & (1.308)         &
(1.518)\\
##    Officers per 100,000 Population                   &                 & -
0.2857\\
##                                                      &                 &
(0.2640)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                                          & Yes             &
Yes\\
##    Year                                              & Yes             &
Yes\\
##    \midrule
##    \emph{Fit statistics}\\
##    Observations                                      & 200             &
190\\
##    Size of the 'effective' sample                    & 20              & 19\\
##    R$^2$                                             & 0.99859         &
0.99860\\
##    Adjusted R$^2$                                    & 0.99825         &
0.99824\\
##    Within R$^2$                                      & 0.36875         &
0.37386\\
##    Within Adjusted R$^2$                             & 0.32536         &
0.32377\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup
```

```
#Fixed effects regression of property crimes per 100k on clearance rates,
officers per 100k, incarcerations per 100k, along with other covariates.
fepropincar <- feols(property_crimes_per100k ~
csw(nonviolent_weighted_clearance_rate,officers_per100k) + total_population +
young_men_rate +  employment_rate + median_income_adjusted +
Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate + incarcerations_per100k | Province + Year, data
= lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 3 observations removed because of NA values (RHS: 3).
##       |-> this msg only concerns the variables common to all estimations
```

```r
#Creating latex output of regression table.
etable(fepropincar, dict = dict,  fitstat = c("n","g","r2",
"ar2","wr2","awr2"), tex = T)
```

```
## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variable: & \multicolumn{2}{c}{Property Crimes per 100,000
Population}\\
##    Model:                                    & (1)              & (2)\\
##    \midrule
##    \emph{Variables}\\
##    Nonviolent Weighted Clearance Rate        & -0.6619$^{***}$ & -
0.6865$^{***}$\\
##                                              & (0.1019)         &
(0.0998)\\
##    Total Population                          & 0.1556           & 0.1433\\
##                                              & (0.2937)         &
(0.3042)\\
##    Males aged 15 to 24 (\% of Population)    & 0.0598           & 0.2930\\
##                                              & (0.4859)         &
(0.4669)\\
##    Employment Rate                           & 2.757            & 3.827\\
##                                              & (4.158)          & (4.214)\\
##    Median Income of Low Income Households    & -0.2814          & -0.2052\\
##                                              & (0.3165)         &
(0.3197)\\
##    Real Government Transfers per Person      & 0.1743           &
0.2283$^{*}$\\
##                                              & (0.1087)         &
(0.1118)\\
##    Immigrants per 100,000 Population         & 0.0031           & 0.0026\\
##                                              & (0.0211)         &
(0.0222)\\
##    Minimum Wage                              & 9.569            & 10.07\\
##                                              & (7.863)          & (8.620)\\
##    Incarceration Rate per 100,000 Population & 0.1812$^{*}$     &
0.2201$^{**}$\\
##                                              & (0.0881)         &
(0.0817)\\
##    Employment Rate $\times$ Minimum Wage     & -2.032           & -2.130\\
##                                              & (1.738)          & (1.905)\\
##    Officers per 100,000 Population           &                  & 0.2527\\
##                                              &                  &
(0.2534)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                                  & Yes              & Yes\\
##    Year                                      & Yes              & Yes\\
```

```
##    \midrule
##    \emph{Fit statistics}\\
##    Observations                                & 217             & 207\\
##    Size of the 'effective' sample              & 22              & 21\\
##    R$^2$                                       & 0.96410         & 0.96771\\
##    Adjusted R$^2$                              & 0.95594         & 0.95993\\
##    Within R$^2$                                & 0.58692         & 0.61640\\
##    Within Adjusted R$^2$                       & 0.56345         & 0.59098\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup
```

```
#Fixed effects regression of violent crimes per 100k on clearance rates,
officers per 100k, incarcerations per 100k, along with other covariates.
feviolentincar <- feols(violent_crimes_per100k ~
csw(violent_weighted_clearance_rate, officers_per100k) + total_population +
young_men_rate +  employment_rate + median_income_adjusted +
Real_transfer_per_person + immigrants_per100k + minimum_wage +
minimum_wage*employment_rate + incarcerations_per100k| Province + Year, data
= lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 3 observations removed because of NA values (RHS: 3).
##       |-> this msg only concerns the variables common to all estimations
```

```
#Creating latex output of regression table.
etable(feviolentincar, dict = dict, fitstat = c("n","g","r2",
"ar2","wr2","awr2"),tex = T)
```

```
## \begingroup
## \centering
## \begin{tabular}{lcc}
##    \tabularnewline \midrule \midrule
##    Dependent Variable: & \multicolumn{2}{c}{Violent Crimes per 100,000
Population}\\
##    Model:                                      & (1)             & (2)\\
##    \midrule
##    \emph{Variables}\\
##    Violent Weighted Clearance Rate             & -0.4090$^{***}$ & -
0.4041$^{***}$\\
##                                                & (0.0881)        &
(0.0931)\\
##    Total Population                            & 0.6376$^{*}$    &
0.7161$^{**}$\\
##                                                & (0.3097)        &
(0.3200)\\
##    Males aged 15 to 24 (\% of Population)      & 0.2884          & 0.2740\\
##                                                & (0.3236)        &
(0.3617)\\
```

```
##    Employment Rate                            & 4.543           &
5.671$^{*}$\\
##                                               & (2.848)         & (3.221)\\
##    Median Income of Low Income Households     & 0.0411          & -0.0813\\
##                                               & (0.2892)        &
(0.3140)\\
##    Real Government Transfers per Person       & -0.0678         & -0.0158\\
##                                               & (0.1003)        &
(0.1083)\\
##    Immigrants per 100,000 Population          & -0.0457$^{*}$   & -
0.0574$^{**}$\\
##                                               & (0.0256)        &
(0.0255)\\
##    Minimum Wage                               & 4.002           & 5.574\\
##                                               & (5.537)         & (6.602)\\
##    Incarceration Rate per 100,000 Population & 0.1348          &
0.1948$^{**}$\\
##                                               & (0.0842)        &
(0.0881)\\
##    Employment Rate $\times$ Minimum Wage      & -0.8437         & -1.190\\
##                                               & (1.225)         & (1.459)\\
##    Officers per 100,000 Population            &                 & -0.2995\\
##                                               &                 &
(0.2413)\\
##    \midrule
##    \emph{Fixed-effects}\\
##    Province                                   & Yes             & Yes\\
##    Year                                       & Yes             & Yes\\
##    \midrule
##    \emph{Fit statistics}\\
##    Observations                               & 217             & 207\\
##    Size of the 'effective' sample             & 22              & 21\\
##    R$^2$                                      & 0.99858         & 0.99863\\
##    Adjusted R$^2$                             & 0.99826         & 0.99830\\
##    Within R$^2$                               & 0.34277         & 0.36297\\
##    Within Adjusted R$^2$                      & 0.30543         & 0.32076\\
##    \midrule \midrule
##    \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##    \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *: 0.1}}\\
## \end{tabular}
## \par\endgroup
```

```
#First differences regressions.
fdprop <- feols(d(property_crimes_per100k) ~
d(nonviolent_weighted_clearance_rate) + d(total_population) +
d(young_men_rate) +  d(employment_rate) + d(median_income_adjusted) +
d(Real_transfer_per_person) + d(immigrants_per100k) + d(minimum_wage) +
d(employment_rate)*d(minimum_wage) |  Province + Year, data =
lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")
```

```
## NOTE: 10 observations removed because of NA values (LHS: 10, RHS: 10).

fdviolent <- feols(d(violent_crimes_per100k) ~
d(violent_weighted_clearance_rate) + d(total_population) + d(young_men_rate)
+  d(employment_rate) + d(median_income_adjusted) +
d(Real_transfer_per_person) + d(immigrants_per100k) + d(minimum_wage) +
d(employment_rate)*d(minimum_wage) |  Province + Year, data =
lagged_log_data, panel.id = c("Province", "Year"), vcov= "NW")

## NOTE: 10 observations removed because of NA values (LHS: 10, RHS: 10).

#Creating latex output of regression tables.
etable(fdprop, fdviolent, fitstat = c("n","g","r2", "ar2"), dict = dict,
title = "First Differences Regression with Fixed Effects", tex = T)

## \begin{table}[htbp]
##    \caption{First Differences Regression with Fixed Effects}
##    \centering
##    \begin{tabular}{lcc}
##       \tabularnewline \midrule \midrule
##       Dependent Variables:                                & 
d(property\_crimes\_per100k,1)   & d(violent\_crimes\_per100k,1)\\
##       Model:                                              & (1)
& (2)\\
##       \midrule
##       \emph{Variables}\\
##       d(nonviolent\_weighted\_clearance\_rate,1)          & -
0.4135$^{***}$                  &   \\
##                                                           & (0.0717)
&   \\
##       d(total\_population,1)                              & 0.1622
& 0.8159\\
##                                                           & (0.7470)
& (0.7123)\\
##       d(young\_men\_rate,1)                               & 0.3254
& 1.058$^{*}$\\
##                                                           & (0.5437)
& (0.5386)\\
##       d(employment\_rate,1)                               & -0.6476
& 0.6261\\
##                                                           & (0.6895)
& (0.5347)\\
##       d(median\_income\_adjusted,1)                       & -0.1661
& 0.1809\\
##                                                           & (0.1781)
& (0.1659)\\
##       d(Real\_transfer\_per\_person,1)                    & -0.0944
& 0.0128\\
##                                                           & (0.0735)
& (0.0603)\\
##       d(immigrants\_per100k,1)                            & 0.0051
```

```
& -0.0374$^{*}$\\
##                                                                      & (0.0206)
& (0.0190)\\
##         d(minimum\_wage,1)                                           & 0.1903$^{*}$
& 0.1274\\
##                                                                      & (0.0921)
& (0.1004)\\
##         d(employment\_rate,1) $\times$ d(minimum\_wage,1)    & -1.705
& 3.556\\
##                                                                      & (8.042)
& (9.511)\\
##         d(violent\_weighted\_clearance\_rate,1)              &
& -0.1733$^{***}$\\
##                                                                      &
& (0.0589)\\
##         \midrule
##         \emph{Fixed-effects}\\
##         Province                                                     & Yes
& Yes\\
##         Year                                                         & Yes
& Yes\\
##         \midrule
##         \emph{Fit statistics}\\
##         Observations                                                 & 210
& 210\\
##         Size of the 'effective' sample                               & 21
& 21\\
##         R$^2$                                                        & 0.58076
& 0.57931\\
##         Adjusted R$^2$                                               & 0.48759
& 0.48582\\
##         \midrule \midrule
##         \multicolumn{3}{l}{\emph{Newey-West (L=2) standard-errors in
parentheses}}\\
##         \multicolumn{3}{l}{\emph{Signif. Codes: ***: 0.01, **: 0.05, *:
0.1}}\\
##      \end{tabular}
## \end{table}

columns_of_interest <-
c("property_crimes_per100k","nonviolent_weighted_clearance_rate","violent_cri
mes_per100k","violent_weighted_clearance_rate","employment_rate","median_inco
me_adjusted","Real_transfer_per_person","total_population","young_men_rate","
immigrants_per100k","minimum_wage","officers_per100k","incarcerations_per100k
")

selected_data <- stacked_data[, columns_of_interest]
if (!requireNamespace("tools", quietly = TRUE)) {
  install.packages("tools")
}
```

```r
library(tools)

# Replace underscores with spaces and capitalize each word
colnames(selected_data) <- toTitleCase(gsub("_", " ",
colnames(selected_data)))
summary(selected_data)
```

```
##  Property Crimes Per100k Nonviolent Weighted Clearance Rate
##  Min.   :1554            Min.   :17.37
##  1st Qu.:3375            1st Qu.:25.72
##  Median :4325            Median :29.47
##  Mean   :4651            Mean   :29.17
##  3rd Qu.:5703            3rd Qu.:32.70
##  Max.   :9153            Max.   :43.87
##
##  Violent Crimes Per100k Violent Weighted Clearance Rate Employment Rate
##  Min.   :   876.5       Min.   :41.89                   Min.   :82.36
##  1st Qu.:  1390.6       1st Qu.:55.53                   1st Qu.:90.14
##  Median :  1715.7       Median :60.67                   Median :92.00
##  Mean   : 25664.1       Mean   :59.84                   Mean   :91.73
##  3rd Qu.: 25946.2       3rd Qu.:63.93                   3rd Qu.:94.28
##  Max.   :156880.0       Max.   :77.77                   Max.   :96.44
##
##  Median Income Adjusted Real Transfer per Person Total Population
##  Min.   : 8896          Min.   : 2121            Min.   :  135804
##  1st Qu.:11064          1st Qu.: 4257            1st Qu.:  752433
##  Median :12007          Median : 5574            Median : 1159202
##  Mean   :12044          Mean   : 6124            Mean   : 3385809
##  3rd Qu.:12861          3rd Qu.: 6991            3rd Qu.: 4449311
##  Max.   :15552          Max.   :15276            Max.   :14809257
##  NA's   :20
##  Young Men Rate  Immigrants Per100k  Minimum Wage    Officers Per100k
##  Min.   :11.07   Min.   :  60.83    Min.   : 5.400   Min.   :136.0
##  1st Qu.:12.64   1st Qu.: 260.32    1st Qu.: 7.150   1st Qu.:169.7
##  Median :13.51   Median : 633.01    Median : 9.450   Median :181.8
##  Mean   :13.45   Mean   : 646.00    Mean   : 9.192   Mean   :180.8
##  3rd Qu.:14.01   3rd Qu.: 923.53    3rd Qu.:10.850   3rd Qu.:195.0
##  Max.   :15.92   Max.   :2085.48    Max.   :15.200   Max.   :218.9
##                                     NA's   :10       NA's   :10
##  Incarcerations Per100k
##  Min.   : 34.72
##  1st Qu.: 65.52
##  Median : 75.53
##  Mean   : 94.97
##  3rd Qu.:100.98
##  Max.   :251.69
##  NA's   :3
```

```r
# Create summary statistics or convert your data frame to LaTeX table
summary_stats <- describe(selected_data)
```

```r
# Print the summary statistics
print(summary_stats)
```

```
##                                     vars   n       mean         sd
median
## Property Crimes Per100k                1 240    4651.34    1713.76
4325.44
## Nonviolent Weighted Clearance Rate     2 240      29.17       5.41
29.47
## Violent Crimes Per100k                 3 240   25664.06   41713.19
1715.66
## Violent Weighted Clearance Rate        4 240      59.84       7.32
60.67
## Employment Rate                        5 240      91.73       3.03
92.00
## Median Income Adjusted                 6 220   12044.40    1363.45
12007.31
## Real Transfer per Person               7 240    6123.63    2657.49
5573.58
## Total Population                       8 240 3385809.25 3999084.79
1159201.50
## Young Men Rate                         9 240      13.45       1.03
13.51
## Immigrants Per100k                    10 240     646.00     409.62
633.01
## Minimum Wage                          11 230       9.19       2.39
9.45
## Officers Per100k                      12 230     180.85      17.69
181.85
## Incarcerations Per100k                13 237      94.97      49.74
75.53
##                                       trimmed        mad       min
max
## Property Crimes Per100k                4517.57    1588.18   1554.18
9152.79
## Nonviolent Weighted Clearance Rate       29.13       5.20     17.37
43.87
## Violent Crimes Per100k                15380.85     878.41    876.48
156880.00
## Violent Weighted Clearance Rate          60.15       6.77     41.89
77.77
## Employment Rate                          92.06       3.12     82.36
96.44
## Median Income Adjusted                12003.08    1363.59   8895.90
15551.58
## Real Transfer per Person               5711.66    2033.82   2121.45
15275.57
## Total Population                    2576712.78 1219146.43 135804.00
14809257.00
```

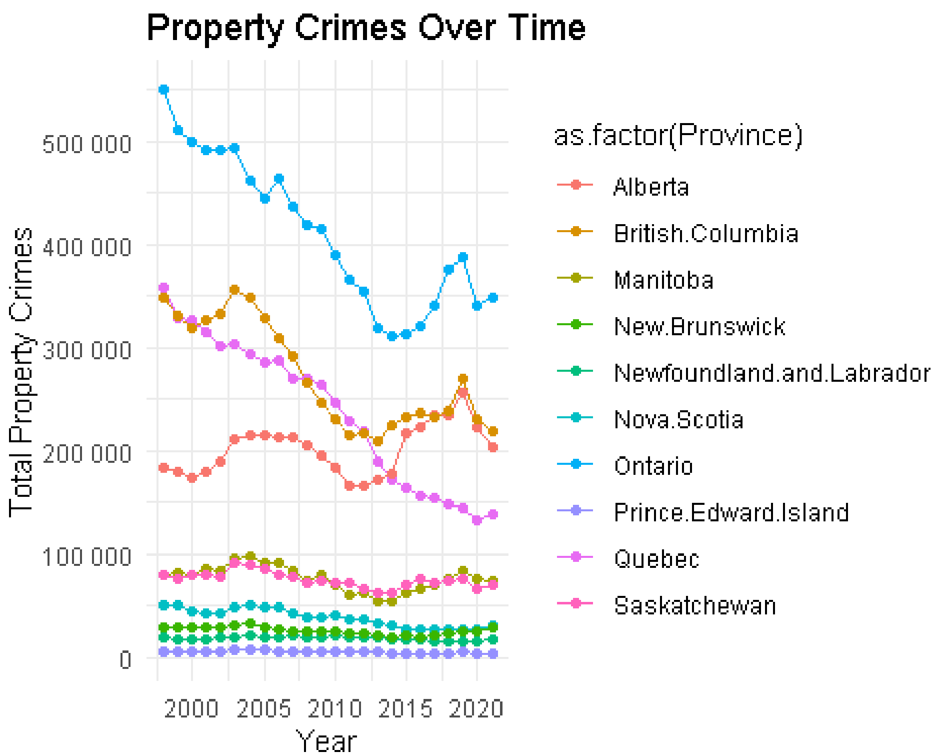
```
## Young Men Rate                               13.43       0.92     11.07
15.92
## Immigrants Per100k                          618.92     502.14     60.83
2085.48
## Minimum Wage                                  9.06       2.74      5.40
15.20
## Officers Per100k                            181.59      18.68    136.00
218.90
## Incarcerations Per100k                       86.33      19.50     34.72
251.69
##                                            range  skew kurtosis        se
## Property Crimes Per100k                  7598.61  0.63     -0.32    110.62
## Nonviolent Weighted Clearance Rate         26.50  0.16      0.09      0.35
## Violent Crimes Per100k                 156003.52  1.78      1.93   2692.57
## Violent Weighted Clearance Rate            35.88 -0.34     -0.02      0.47
## Employment Rate                            14.09 -0.86      0.31      0.20
## Median Income Adjusted                   6655.68  0.22     -0.19     91.92
## Real Transfer per Person                13154.12  1.44      2.02    171.54
## Total Population                     14673453.00  1.45      1.00 258139.81
## Young Men Rate                              4.84  0.07     -0.11      0.07
## Immigrants Per100k                       2024.65  0.48     -0.32     26.44
## Minimum Wage                                9.80  0.35     -0.62      0.16
## Officers Per100k                           82.90 -0.30     -0.60      1.17
## Incarcerations Per100k                    216.97  1.53      1.32      3.23
```

```r
xtable(summary_stats)
```

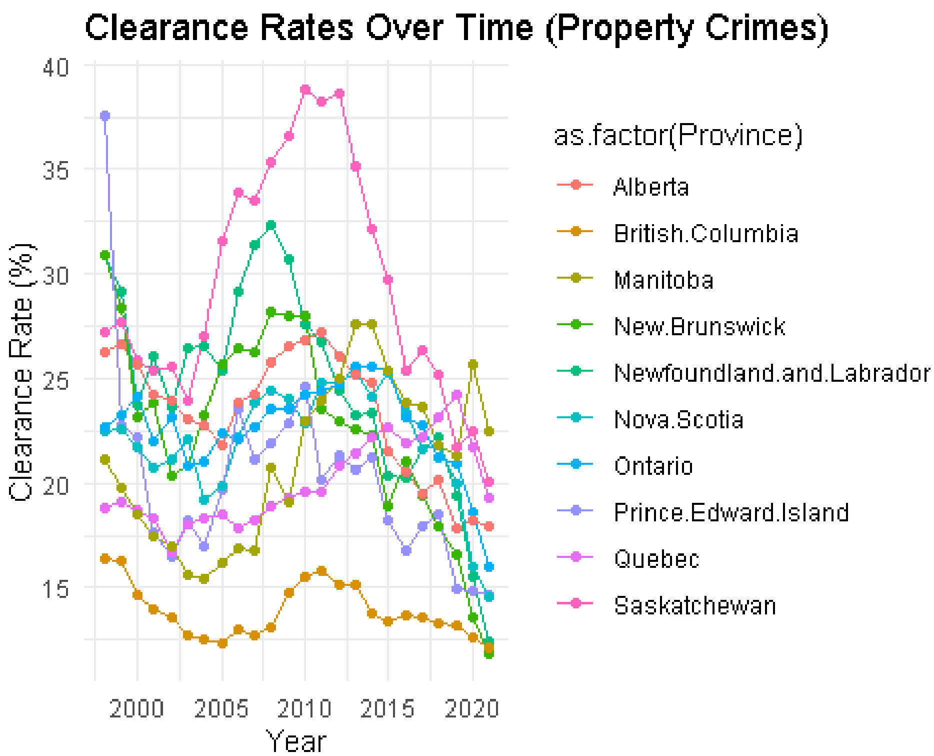
```
## % latex table generated in R 4.2.3 by xtable 1.8-4 package
## % Thu Dec  7 16:18:52 2023
## \begin{table}[ht]
## \centering
## \begin{tabular}{rrrrrrrrrrrrrr}
##   \hline
##  & vars & n & mean & sd & median & trimmed & mad & min & max & range &
skew & kurtosis & se \\
##   \hline
## Property Crimes Per100k &   1 & 240.00 & 4651.34 & 1713.76 & 4325.44 &
4517.57 & 1588.18 & 1554.18 & 9152.79 & 7598.61 & 0.63 & -0.32 & 110.62 \\
##   Nonviolent Weighted Clearance Rate &   2 & 240.00 & 29.17 & 5.41 & 29.47
& 29.13 & 5.20 & 17.37 & 43.87 & 26.50 & 0.16 & 0.09 & 0.35 \\
##   Violent Crimes Per100k &   3 & 240.00 & 25664.06 & 41713.19 & 1715.66 &
15380.85 & 878.41 & 876.48 & 156880.00 & 156003.52 & 1.78 & 1.93 & 2692.57 \\
##   Violent Weighted Clearance Rate &   4 & 240.00 & 59.84 & 7.32 & 60.67 &
60.15 & 6.77 & 41.89 & 77.77 & 35.88 & -0.34 & -0.02 & 0.47 \\
##   Employment Rate &   5 & 240.00 & 91.73 & 3.03 & 92.00 & 92.06 & 3.12 &
82.36 & 96.44 & 14.09 & -0.86 & 0.31 & 0.20 \\
##   Median Income Adjusted &   6 & 220.00 & 12044.40 & 1363.45 & 12007.31 &
12003.08 & 1363.59 & 8895.90 & 15551.58 & 6655.68 & 0.22 & -0.19 & 91.92 \\
##   Real Transfer per Person &   7 & 240.00 & 6123.63 & 2657.49 & 5573.58 &
5711.66 & 2033.82 & 2121.45 & 15275.57 & 13154.12 & 1.44 & 2.02 & 171.54 \\
```

```
##   Total Population &   8 & 240.00 & 3385809.25 & 3999084.79 & 1159201.50 &
2576712.78 & 1219146.43 & 135804.00 & 14809257.00 & 14673453.00 & 1.45 & 1.00
& 258139.81 \\
##   Young Men Rate &   9 & 240.00 & 13.45 & 1.03 & 13.51 & 13.43 & 0.92 &
11.07 & 15.92 & 4.84 & 0.07 & -0.11 & 0.07 \\
##   Immigrants Per100k &  10 & 240.00 & 646.00 & 409.62 & 633.01 & 618.92 &
502.14 & 60.83 & 2085.48 & 2024.65 & 0.48 & -0.32 & 26.44 \\
##   Minimum Wage &  11 & 230.00 & 9.19 & 2.39 & 9.45 & 9.06 & 2.74 & 5.40 &
15.20 & 9.80 & 0.35 & -0.62 & 0.16 \\
##   Officers Per100k &  12 & 230.00 & 180.85 & 17.69 & 181.85 & 181.59 &
18.68 & 136.00 & 218.90 & 82.90 & -0.30 & -0.60 & 1.17 \\
##   Incarcerations Per100k &  13 & 237.00 & 94.97 & 49.74 & 75.53 & 86.33 &
19.50 & 34.72 & 251.69 & 216.97 & 1.53 & 1.32 & 3.23 \\
##    \hline
## \end{tabular}
## \end{table}
```

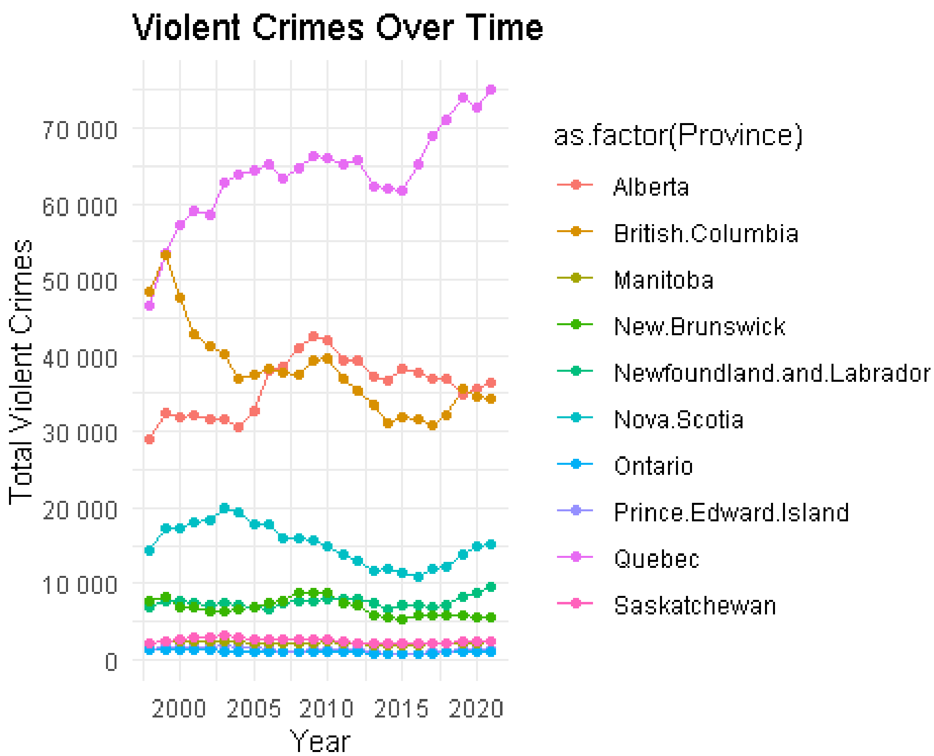
```
#Numerous graphics.
prop_crime_graph <- ggplot(stacked_data, aes(x = Year, y =
total_property_crimes, group = Province, color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Property Crimes Over Time",
       x = "Year",
       y = "Total Property Crimes") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

prop_crime_graph
```



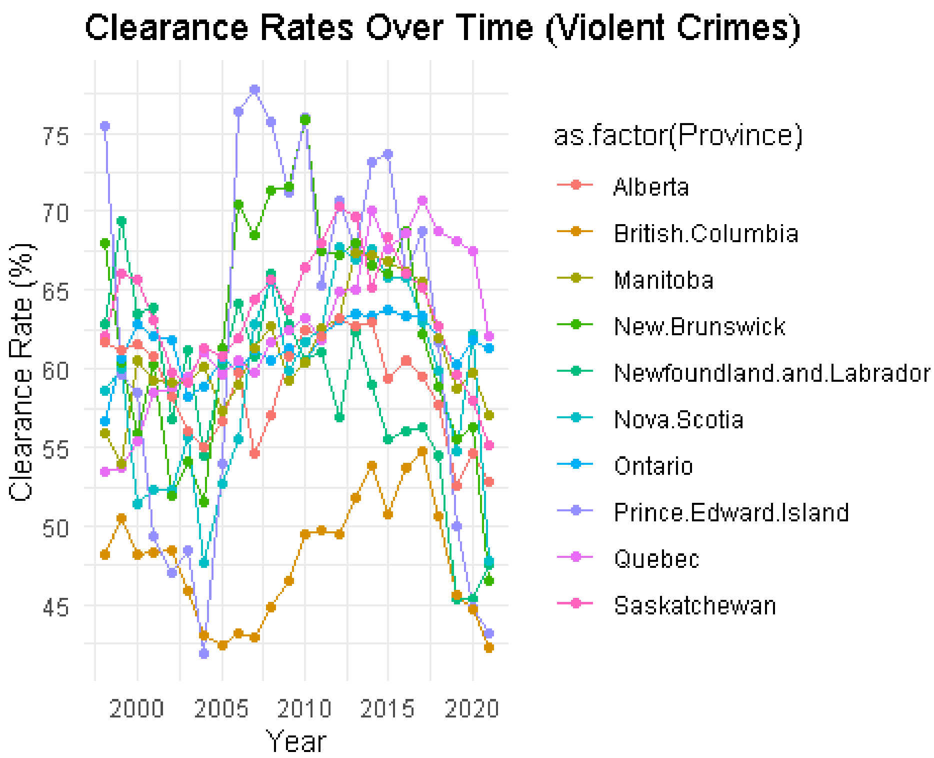

```
prop_clearance_graph <- ggplot(stacked_data, aes(x = Year, y =
nonviolent_clearance_rate, group = Province, color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Clearance Rates Over Time (Property Crimes)",
       x = "Year",
       y = "Clearance Rate (%)") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

prop_clearance_graph
```




```
violent_crime_graph <- ggplot(stacked_data, aes(x = Year, y =
total_violent_crimes, group = Province, color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Violent Crimes Over Time",
       x = "Year",
       y = "Total Violent Crimes") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

violent_crime_graph
```

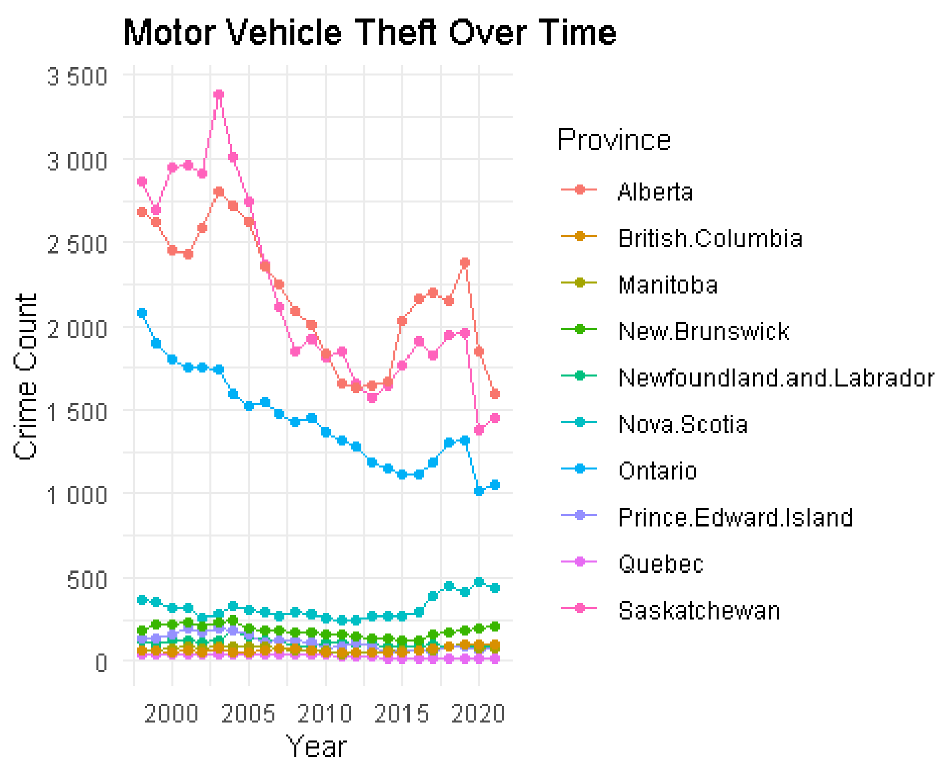



```
violent_clearance_graph <- ggplot(stacked_data, aes(x = Year, y =
violent_weighted_clearance_rate, group = Province, color =
as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Clearance Rates Over Time (Violent Crimes)",
       x = "Year",
       y = "Clearance Rate (%)") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

violent_clearance_graph
```




```r
fraud_graph <- ggplot(stacked_data, aes(x = Year, y = fraud, color =
as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Fraud Over Time",
       x = "Year",
       y = "Crime Count",
       color = "Province") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

theft_under5k_graph <- ggplot(stacked_data, aes(x = Year, y = theft_under_5k,
color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Theft under $5,000 Over Time",
       x = "Year",
       y = "Crime Count",
       color = "Province") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

theft_over5k_graph <- ggplot(stacked_data, aes(x = Year, y = theft_over_5k,
color = as.factor(Province))) +
  geom_line() +
  geom_point()+
```

```
  labs(title = "Theft over $5,000 Over Time",
       x = "Year",
       y = "Crime Count",
       color = "Province") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

motor_graph <- ggplot(stacked_data, aes(x = Year, y = motor_vehicle_theft,
color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Motor Vehicle Theft Over Time",
       x = "Year",
       y = "Crime Count",
       color = "Province") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

motor_graph
```




```
possession_graph <- ggplot(stacked_data, aes(x = Year, y =
possession_stolen_goods, color = as.factor(Province))) +
  geom_line() +
  geom_point()+
  labs(title = "Possession of Stolen Goods Charges Over Time",
       x = "Year",
       y = "Crime Count",
```

```
      color = "Province") +
  theme_minimal()+
  scale_y_continuous(n.breaks = 10, labels = scales::number_format(scale = ))

possession_graph
```