Legalization of Recreational Marijuana in Canada: Implications from Provinces' Price Difference

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Abstract

Due to the positive and negative returns that may come with marijuana legalization, it is of prime importance to assess the interdependence that might be generated at the provincial level. Specifically, how can the provincial price difference affect the level of consumption and violent criminal code violations within each province and in neighboring regions. So, investigating whether there is a spatial dependence that might generate spillover effects will reveal how can a province and/or its neighbors benefits from the price difference or to which extend it can be prejudicial. I analyzed the effect of variations in price of medical and non-medical marijuana in thirteen Canadian provinces including territories from 2011 to 2016 using panel data with 65 observations. The results although sensitive to alternative specifications and models, showed a constant pattern. On one hand, an increase in the price of medical marijuana increases the demand for non-medical marijuana in neighboring areas whereas, an increase in the price of non-medical marijuana reduces its demand in neighboring provinces. Thus, the variable non-medical cannabis does not exhibit the expected bootlegging behavior. On the other hand, the variation in one element of justice namely total violent criminal code violations is very sensitive to the functional form of the variables. While the logarithmic specification did not capture any spatial dependence in the variables, the percentage change modelling showed that an increase in the price of medical marijuana in one region leads to an increase in the total transgressions in neighboring regions whereas, an increase in the price of non-medical marijuana in one area decreases the number of violent criminal code violations in neighboring areas. These results on quantity demanded of non-medical marijuana and total violent criminal code violations complement each other.

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I am grateful to my director of research Professor Nasser Ary Tanimoune for his valuable inputs specifically, in terms of econometric modelling. I am also grateful to all my friends who assisted me in any meaningful way toward the completion of my research. Last but not least, I wish to thank my family for the unconditional moral support specifically, my brothers Daniel and Cedric, my sister Denise, my husband Joseph and my daughters Callie-Paule and Jade Evry whom simple thought motivates my strong desire to succeed.

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1. Introduction

Canada is about to approve the legal consumption of marijuana for recreational purpose. After many years of ban and criminalization started in 1923 through the voice of Henri Severin Beland, federal minister of health who argued that marijuana destroys the youths. Slowly, the legal view on marijuana use has evolved. After allowing its growth and possession for medical research purposes and medical use, finally, the decision to legalize marijuana in Canada for recreational use is about to be implemented. This new law will settle into the context of a federal country where provinces experience political and economic differences such as, a difference in products prices.

According to its 2015 report, the Canadian Tobacco Alcohol and Drugs Survey (CTADS), claims that marijuana is the most habitually consumed illicit substance in Canada among those aged 15 years and older. According to the same source, the 2015 prevalence is about 12.3% translating into 3,701,206.3[1] individuals on average. The legalization of marijuana may lead to many potential economic returns (Hajizadeh 2016; Caulkin and al, 2012) such as tax revenue increase, reduction of the black market and associated crimes or better control of the product quality.

However, the current concern is still the potential negative implications of its legalization. Indeed, in line with the Centre of Addiction and Mental Health (CAMH)[2], marijuana has a mind-altering effect on users and its continuous consumption may evolve from euphoria to cognitive and mental deficiency. Teenage users experience a reduction of their IQ (Meier and al 2012), a diminution of their cognitive abilities translating into a lower educational achievement and, on a later stage to less chances of obtaining substantial future employments (Van Ours and Williams 2009). Moreover, according to a recent report from the government of Canada[3] on drug-impaired driving, it is argued that marijuana doubles by two the likelihood of having a car accident, and is after alcohol the next substance frequently found in car crash victims' in Canada. Actually, the Canadian Centre of Substance Use and Addiction evaluate to 40.0% the share of drivers mortally wounded due to marijuana against 33.3% for those due to alcohol. So, the legalization of marijuana might in term be a source of additional expenses for provincial governments. For instance, in Ontario from 2013 to 2014, cannabis is the cause of 20.2% demand for medical assistance[4]. In addition, in line with the National Institute on Drug Abuse (NIDA) in the USA, marijuana use disorder result from marijuana consumption and may lead on a later stage to an addiction problem. On the judicial level, there is also room for concerns as many studies (Niveau &

[1] The average population aged 15 years and more in Canada in 2015 is 30,091,108. Source, Statistic Canada, CANSIM table N^0 051-0001
[2] August 2016 reports
[3] https://www.canada.ca/en/services/policing/police/community-safety-policing/impaired-driving/drug-impaired-driving.html
[4] Source: Centre of Addiction and Mental Health, August 2016

dang 2003; Moore & Stuart 2005; Howard & Menkes 2007) have established a link between regular marijuana consumption and violent behavior.

The problem at hand evolves around the first law of geography of Waldo Tobler, "everything is related to everything else but near things are more related than distant things". That is, I expect the marijuana price difference across provinces to cause variations in quantity demanded of marijuana in neighboring regions and consequently, a variation in the level of transgressions depending on the degree of interdependence provinces have with one another. This effect is supposedly increased with marijuana legalization as it is assumed that it will augment the number of consumers and quantity consumed (Gieringer, 1994). The spatial dependence here refers to any interprovincial connection such as, shared borders, trade relations, a certain level of immigration flux or the number of location within a certain distance (Anselin, 2002). The origin of the problematic raised here is dual. First, the bootlegging effect whose precursors are Balgati and Li (1992) implies that if prices are higher in a specific region, people will tend to buy from neighboring regions with lower prices. Secondly, if indeed there is a bootlegging behavior in the data, I expect a spillover effect in terms of increase in the total number of criminal code violations in neighboring locations based on the potential link between marijuana use and violent behavior. The purpose of this study is therefore, to evaluate whether there is a spillover effect in quantity demanded of non-medical marijuana and in total violent criminal code violations due to price differences across provinces.

The methodology I use follows from Elhorst (2010) and consists in running an Ordinary Least Square (OLS) regression and then, test for spatial dependence in the residuals. Following the spatial autocorrelation tests and base on Elhorst (2010), I have selected the spatial Durbin model (SDM) and the spatial error model (SEM) as regression tool. I generated nine different weighting matrices for this study that I used to conduct the spatial estimations. They are: rook contiguity matrices of order 1 (rooknorm_1) and or order 2 (rooknorm1_2), the 3-neighbor matrix (kmat_3) and the 4-neighbor matrix (kmat_4), queen contiguity matrices of order 1 (queen_1) and of order 2 (queen_2). A socio-economic matrix using interprovincial migrations (matmig) as variable of interest, an economic matrix using interprovincial trade (matcom) and finally, the inverse distance matrix.

The main finding related to the variation in the price of non-medical marijuana appears to be contradicting the theory advocated by Baltagi and Levin (1992). Using the SDM, an increase in the price of non-medical marijuana in one province decreases the demand in that province by a maximum of 0.19 percentage point. But also, does it decrease the demand for recreational marijuana in nearby provinces to up to 0.88 percentage point, the bootlegging effect is not verified. These results are obtained using the matrices queen_2, kmat_3 and matmig. The direct effect is inversed with the rooknorm_1 and queen_1 matrices, however, with these two weighting matrices also, the variables do not show a bootlegging behavior.

As for the variation in total violent criminal code violations, increasing the price of non-medical marijuana increases the number of transgressions in the particular province by about 5 percentage point on average. Whereas in neighboring locations, it leads to a decrease in the number of felonies by about 6 percentage point. This result is sustained based on the assumption of a link between recreational cannabis consumption and crime, the previous result of price of non-medical marijuana negatively correlated to its demand in nearby locations. Although the results do not validate the expected bootlegging effects and are very sensitive to model choices and weighting matrices functional forms, both equations results seem to complement each other based on the theories at hand. Indeed, if there is a decrease in quantity consumed thus we expect a decrease in crime level as there is an established link between marijuana consumption for recreational purposes and crime.

The paper is structured as follow: Section 2 reviews the literature on the spillover effects of marijuana law on an element of justice and on demand; Section 3 discusses the dataset used, the descriptive and cluster analysis; Section 4 presents the empirical design; Section 5 discusses the spatial dependence tests and model selection; Section 6 presents the estimation results from the different specifications; Section 7 compare the results from the different models; Section 8 discusses results using an alternative functional form of the variables and Section 9 recognizes the limitations and concludes.

1. Literature Review

In this study, the provincial price difference of cannabis is considered at the origin of potential spillover effects in terms of criminal violations and quantity demanded, in the latter case, it is called bootlegging effect. Even though the literature on the spillover effects due to marijuana price difference across provinces specifically is not abundant, there is still a body of research that have evaluated the impact of marijuana legalization on crime in neighboring locations when the latter still apply prohibitive laws toward marijuana use. Whereas, other researchers have analyzed the bootlegging effect in cigarettes demand.

Hao and Cowan (2017) analyze spillover effects of marijuana legalization in Colorado and Washington using a difference in difference estimation method and data from 2009 to 2014 collected from Uniform Crime Reports for Colorado and Washington. They find as main result that after marijuana legalization in Colorado and Washington, there were an increase in the number of arrests in border locations compared to non-border locations. Very close to this are Elison and Spohn (2015) who have a similar interest and find overall the same positive spillover effect of marijuana legalization on neighboring arrests and imprisonments using a different approach. They investigated whether the legalization of marijuana in Colorado increases marijuana prevalence in Nebraska and law enforcement costs after 2009 considered as the time when federal prosecutions really disappeared and the use of marijuana increased. They used data from the Nebraska Center for Justice Research covering two five-year period intervals from 2000 to 2004 inclusive and from 2009 to 2014 inclusive. They employed a multivariate ordinary least square estimation technique and found an increase in the number of arrests related to marijuana as well as the number of condemnations due to the legalization of marijuana.

Other studies found instead that, there is no spillover effects due to marijuana legalization in neighboring areas in terms of criminal activities. Indeed, Brinkman (2017) investigates the effect of marijuana legalization in Colorado using geospatial panel data for a period of 36 months going from 2013 to 2016. Specifically, he investigates the relationship between dispensary density and level of crime. They use an instrumental variable approach with miles to border and miles to major road as instruments and found that additional dispensaries generate a decrease in crime level in the neighborhood. Specifically, there is a stronger decrease in nonviolent crimes than in violent crimes in the neighborhood. However, no spillover effect in the crime level of neighboring regions due the increase in the number of dispensaries following marijuana legalization. In the same way, Kreit (2017) argues that there are very negligible effects of marijuana legalization from one state to other states border with prohibitive laws. Indeed, marijuana is easily available in states with restrictive laws and its price is low thus, consumers will just continue to buy from their usual black markets. Moreover, he sustains that the so-called traffic of marijuana from Colorado to nearby states implementing prohibition has no evidence that is because the law on legalization is strong on enforcement and deterrence making it very uneasy to turn illicit exportation into a lucrative operation.

The studies that have assessed the bootlegging effects of marijuana price within a country experiencing price differences are very scarce. However, there are many evidences of spatial assessments on cigarette demand, (Baltagi and Li 2004; Elhorst 2005; Helhorst 2013; Debarsy et al. 2012; Kelejian and Piras, 2014; Vega and Elhorst, 2015). For instance, Vega and Elhorst (2015) evaluate the demand for cigarettes in 46 states in the US from 1963 to 1992 using panel data. They include time and state fixed effect and use a binary contiguity matrix at first with different spatial models and find that an increase in the price of cigarettes in a particular region decreases demand within the region and in nearby locations which contradicts the expected bootlegging behavior. Later, using the parametrized inverse distance matrix and spatial lag of X model (SLX model), they found evidence of bootlegging behavior stating that people will buy from cheaper neighbors in case of a price increase in their own location. Their contribution was the use of the SLX model as point of departure. Debarsy, Ertur and Lesage (2012) addressed the same problematic but with 45 states and using a dynamic panel data model that will capture the effect estimates in both space and time. They ran a log-log model where demand for cigarettes is explained by its average retail price and real per capita disposable income. They found evidences of a positive bootlegging effects in the short run and long run when estimating a dynamic spatial Durbin model using binary contiguity matrix and border length. Kelejian and Piras (2014) step aside from the exogenous weighting matrix usually employed in spatial econometrics and estimate the demand for cigarette over the same period of time and using 46 U.S. states using an endogenous weighting matrix and found evidence of bootlegging effects.

2. Dataset

Below, I present the main source of the data used and discuss the choice of the variables employed in the regressions. Then, I evaluate the descriptive and cluster analysis.

2.1 Source and Variables Discussion

All quantitative results obtained throughout this study are derived from the Canadian socioeconomic database of Statistic Canada[5]. It provided me with the Cannabis Stats Hub 13-610-X that gives frequently updated socio-economic cannabis-related time-series variables. Usually, statistic Canada uses one of the following two data collection methods. Either self-enumeration where individuals or organization answer to a questionnaire without an assessor assistance. Or, interviewer-assisted including both personal interviews when the respondent is assisted in person and telephone interviews when the assistance happens over the phone. Each of these methods are either paper-based or computer-based.

However, since marijuana is not yet legalized in Canada, Statistic Canada uses crowdsourcing method[6] to fill the information gap on cannabis related variables such as the prices, quantity consumed, frequency of consumption level of production and so on. 17,139 responses gathered from January 25 to February 28, 2018 helped to build the database. Either way, the confidentiality of all respondents is preserved at all times.

My population of interest is individuals aged 15 to 64 years of age living in one of the thirteen Canadian provinces including territories. I have transformed the original dataset into a panel dataset covering the period going from 2011 to 2016. The lower bound of my age range is 15 years of age because, it is the lower bound from which the data were available. However, I chose to restrict my upper

[5] However, I used a matrix of interprovincial commercial flux from the "Institut de la statistique du Québec" to build my economic-based matrix for spatial analysis.
[6] http://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=5263#a2

bound sample to 64 years of age although the data go beyond. That is because, according to a health report from Michelle Rottermann and Ryan Macdonald published by Statistic Canada in February 2018, before 2012, there was a very small number of data available for seniors aged 65 and more. Even though there is an increase nowadays, they represent only 1.6% of the 2014 cannabis use prevalence[7].

Many variables from my dataset where not available straight from the Statistic Canada database. Specifically, when I was lacking provincial data, I had to generate them in a linear fashion determining first the proportion of each province in the total population aged 15 to 64 and deduce the corresponding variable per province by simple multiplication of the proportion obtained by the value of the Canadian population targeted in each year of interest. Then, the variables are converted into percentage changes[8].

According to Lacambra, Gomez & Marin (2013), if there is some sort of cooperation among individuals dispersed over a geographical area that is divided in locations then, there is a spatial dependence and the spatial weight matrix (W) is aimed to capture the spatial link between the geographical entities. The elements of each matrix represent the weights for each pair of locations and capture the extent of the spatial link among provinces. The choice and construction method follow from Lacambra, Gomez & Marin (2013). They argue that W must be standardized in the row (row-normalization), for data with geographical identities, W is a square matrix whose elements are positive with diagonal elements equal to zero. The method of construction is exogenous and can take multiple forms. Lacambra & al (2013) argue that georeferenced data enable the modeler to build W based on geographical considerations. Thus, following Anselin (1988) and Cliff & Ord (1981) I have constructed a matrix function of the distance between the provinces centroids that uses the inverse distance formulation[9] and two k- nearest neighbors' matrices limiting the number of neighbors to 3 and 4 respectively. Then, I have constructed binary contiguity matrices of order 1 as suggested by Stakhovych and Bijmolt (2009) who believes that they perform better. A queen contiguity of order 1 referring to provinces that share either a border or a vertex (queen_1), a rook contiguity of order 1 considering as neighbor provinces sharing at least a border[10] rooknorm_1). I have created two additional contiguity matrices that gives the value of 1 to the neighbor of their neighbor. These two contiguity matrices of order 2 are named queen_2 and rooknorm1_2. Following Corrado and Fingleton (2012), I constructed

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[7] The estimates referred to here are not representative of the whole population targeted in my study because on one hand, in the age group 18 to 64 women are not as willing as men to declare that they are users. Thus, estimates for women in that age range were not published due to too much imprecision. On the second hand, people living in territories, institutionalized or homeless as well as those unable to converse in English or French or not possessing a phone were excluded from the sample.

[8] Percentage change = $\frac{x_t - x_{t-1}}{x_{t-1}} \times 100$

[9] Other formulations such as the negative exponential model or the threshold distance could have been used.

[10] There is a third type of contiguity namely, Bishop contiguity where the neighbors share only a vertex.

a matrix called matcom whose elements are constituted of interprovincial trade volume. Indeed, they advocate the concept of economic distance arguing that large cities can actually be close in terms of economic relations. To obtained the volume of trade of each province with another, I added total exports from province *i* to province *j* to total import from province *j* to province *i*. That is because I am mostly interested in the intensity of the exchanges. Cliff and Ord (1981) sustain that products of the network economics such as migration can help to build W. In that regard, I have constructed a matrix (matmig) whose elements represent the total flux of people from one province to the other and vice versa. I added province *i* outmigration to province *j* and province *j* outmigration to province *i* to build each spatial weight in order to capture the intensity of the migrations.

I run two regressions in this study therefore, I will have two dependent variables. First, quantity consumed of non-medical cannabis per provinces in percentage change. This variable was not directly available from the Cannabis Stats Hub CANSIM database[11]. Therefore, I had to derived it using the share of each province proportion in the total Canadian population. The second dependent variable is the total violent criminal code violations including among others, homicide, violations causing death, sexual assault, assault against peace officer, abduction[12]. The main explanatory variables used in my regressions are the price indexes for both medical and non-medical marijuana since the goal of this study is to evaluate how non-medical cannabis price change in one region affects its demand and the level of violent crimes within the province and in nearest locations. Thus, instead of current prices that simply represent the market value of goods, I use price indexes that evaluate the relative change in prices and therefore enable the comparison between geographical areas. These variables will enter both equations of interest based on the law of demand establishing an inverse relationship between the quantity demanded of a product and its price holding other factors unchanged[13]. I also include as independent variable, the household disposable income[14] calculated as a percentage change for each province over the period of study. This variable will enter the regression explaining the quantity consumed of cannabis based on the notion of income effect that highlights the positive correlation between income and demand[15]. I use the percentage change of police officer strength[16] as explanatory variable for the variation quantity consumed of marijuana. Indeed, in line with a September 1994 report from the US Department of Justice, Office of Justice Programs, Bureau of Justice Statistics, drug users a more likely than non-users to commit a felony and in accordance to Becker (1968), government expenditures on law enforcement affect the probability that a violation is uncover, then the number of police officers might affect the quantity consumed of cannabis. This variable will therefore also help to explain the variation

[11] Source Statistic Canada, http://www.statcan.gc.ca/pub/13-610-x/cannabis-eng.htm
[12] CANSIM, table 252-0051
[13] Except for luxury and giffen goods whose demand increases with an increase in price
[14] Source: CANSIM, table 378-0153
[15] The demand for inferior goods contradicts this prediction.
[16] Source: CANSIM, table 254-002

in total violent criminal code violations. Finally, the last explanatory variable use in the empirical approach is the number of cannabis consumers[17] per provinces. This variable will enter the equation explaining the variation in total violent felonies based on the assumption that marijuana users are more likely to commit a felony, I may expect a positive correlation between number of consumers and total violent criminal code violations.

3.2 Descriptive Analysis

Table 1 shows the descriptive statistics for all the nine spatial weight matrices created for this study. It appears that the matrix of contiguity of order 1 named rooknorm_1 establishes a total of forty neighbors across the provinces. Specifically, Northwest Territories and Nunavut exhibit five neighbors that is the highest number of neighbors against only two neighbors each for Newfoundland and Labrador, Prince Edward Island, Nova Scotia and Yukon. The matrix of contiguity queen of order 1 named queen_1 shows a total of forty-four neighbors across the study area with a maximum of six neighbors each for Northwest Territories and Nunavut and only two neighbors each for Newfoundland and Labrador, Prince Edward Island, Nova Scotia and Yukon. The contiguity matrix of order 2 called queen_2 produces a total of forty-six neighbors in which Newfoundland and Labrador, Quebec, Manitoba and Saskatchewan have five neighbors each representing the maximum number of neighbors generated with this matrix. while, Prince Edward Island and Nova Scotia only have one neighbor each which is the lowest number of neighbors calculated with this matrix.

From the two matrices based on socio-economic and economic variables migration and interprovincial trade respectively, it appears that migrations happen in every location. Thus, each province happens to have twelve neighbors which translates to a total of 156 neighbors. However, from the matrix of interprovincial trade it results a total of 152 neighbors because Prince Edward Island do not trade with Nunavut and Yukon[18]. For the inverse distance matrix, each province has twelve neighbors corresponding to the remaining regions. And for the k nearest neighbor matrices, I have set the number of neighbors to 3 and 4 per provinces thus, it gives a total of 39 and 52 links respectively.

Table 2 summarizes the means and standard deviations of my variables of interest. I have included the maximum and minimum values of the variables in order to have an idea of how wide the discrepancies are between lower and upper values. It appears that there is on average a 4.72 percentage point increase in the quantity consumed of cannabis over the sample period across all regions. This

[17] Source: Statistic Canada, http://www.statcan.gc.ca/pub/13-610-x/cannabis-eng.htm
[18] Interprovincial trade of goods for 2013; updated in December 2016

result comforts the findings of Statistics Canada[19] attesting that the quantity consumed of cannabis increases over time in Canada. Figure 2 shows that Nunavut, Saskatchewan and Alberta are the provinces with the highest consumption level with quantile values ranging between 5.366 and 6.205 whereas, newfoundland and Labrador, Nova Scotia, New Brunswick and Prince Edward Island exhibit the lowest consumption level with quantile values ranging between 3.401 and 4.234.

On average, there is a decrease by about 3.036 percentage points in the level of violent criminal code violations. The highest decrease is experienced by Prince Edward Island with a drop by about 19.29 percentage point between 2012 and 2013 while Northwest Territories witnessed a pick between 2014 and 2015 of 10.91 percentage point on average. Indeed, figure 3 shows that Prince Edward Island experience one of the lowest average total violent criminal code violations within the sample period with a quantile value ranging between -6.952 and -4.392. Whereas Northwest Territories is at the other extreme with one of the highest average total violent criminal code violations with a quantile value raging between -1.732 and 0.132.

The mean price index for medical marijuana is slightly higher than of non-medical marijuana. It ranges at 100.79 against 97.78. Figure 4 and figure 5 show the repartition of price of medical and non-medical marijuana respectively across provinces including territories. It appears that Yukon, New Brunswick and Nova Scotia have the highest prices of medical marijuana whilst Nunavut, Newfoundland and Labrador, Alberta and Prince Edward Island have the lowest prices. The main difference between the medical and non-medical marijuana prices is that medical marijuana appears to be a little more expensive that non-medical cannabis.

The police officer strength declines by 0.87 percentage point on average from one year to the next across the regions. However, in Yukon, there is an increase by about 10.15 percentage point between 2012 and 2013. The provincial household disposable income increases by 2.5 percentage point on average from one year to the other between 2011 and 2016. However, Alberta has experienced a decrease by about 10 percentage point between 2015 and 2016[20].

Lastly, the number of consumers augments overall by 3.76 percentage point however, the highest percentage increase comes from Alberta with 6.27 percentage point between 2012 and 2013. Whilst, Newfoundland and Labrador has the lowest percentage increase raging at 2.2 percentage point from 2015 to 2016.

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[19] http://www.statcan.gc.ca/pub/11-626-x/11-626-x2017077-eng.htm

[20] According to statistic Canada, in 2016, the decrease in household disposable income evaluated in nominal terms in Alberta is 7.4%. http://www.statcan.gc.ca/pub/11-626-x/11-626-x2017077-eng.htm

3.3 Cluster analysis

The Global Moran's I test assesses spatial autocorrelation across areal locations and investigates whether the sample is clustered or not. Table 3 gives the values of the Moran's I test on the base ordinary least squares (OLS) regressions with different matrices.

From equation (1) OLS residuals, it appears that all contiguity matrices but the rook contiguity of order 2 show a significant[21] but moderate autocorrelation in the area of study. Same goes for the inverse distance matrix, the 3-nearest neighbor's matrix and the matrix based on interprovincial migrations. As from equation (2) OLS residuals, only the rook and queen contiguity matrices of order 1, as well as the inverse distance matrix show a moderate autocorrelation in the study region. These results confirm the intuition that there is clustering in the area of my analysis.

The Moran's I scatter plot gives a clearer idea of how the clustering might happened. Figures 6 to 9 represent Moran's I scatter plots for queen and rook contiguity matrices of order 1 as they both showed a significant potential spatial dependence in the residuals from both OLS equations. It appears from this graphical illustration that the potential spatial dependence in the dependent variables across the area of the analysis seem not to be very strong. Moreover, there are many outliers and there is much spread in the quantity consumed of cannabis over the sample period as well as in the total violent crimes[22].

3. Empirical Framework

Following is a description of the statistical strategy I may develop in order to capture the effect of a variation in the price of cannabis on its quantity demanded and total violent transgressions within and across Canadian provinces. I first present the basic OLS model which appears to be limited when it comes to evaluating the spatial implications of provincial price difference. I therefore extend the model to more appropriate spatial specifications in a fashion advocated by Elhorst (2010).

4.1 Base Modelling

My empirical work assesses the impact of provincial prices on an element of economy namely quantity consumed of cannabis and on an element of justice namely, total violent criminal code violations. The goal being to evaluate whether there is a spillover effect due to the price variation across

[21] 5% level of significance for rooknorm_1 and queen_1 and 10% significance level for queen_2
[22] quantity consumed of marijuana and total violent criminal code violations have been averaged over the sample period due to computations constraint. Indeed, the sketch of the Moran's I necessitates that the number of observations be equal to the order of the matrix used. As this study uses panel data, I had to calculate the mean of each variables to account for the whole period of study.

provinces. Even though the cluster analysis has shed some light into a potential spatial dependence in my area of study, I shall make use of an additional test, Lagrange Multiplier (LM) tests on residuals from OLS estimation evaluate any presence of a spatial autocorrelation. The two base regressions that will later be adapted to spatial regression look like follow:

$$QCCP_{it} = \alpha PIM_{it} + \beta PIN_{it} + \gamma HDI_{it} + \delta POLP_{it} + u_{it} \quad (1)$$
$$TVCCV_{it} = \sigma PIM_{it} + \varphi PIN_{it} + \theta POLP_{it} + \psi QCCP_{it} + \xi NCP_{it} + u_{it} \quad (2)$$
$$for\ i = 1,2,\dots,13\ and\ t = 1,\dots,5$$

Where *QCCP* is the percentage change in the quantity consumed of non-medical cannabis in the province *i* during the time interval *t* going from 2011 to 2016. *PIM* and *PIN* represent percentage changes in price of medical and non-medical marijuana respectively. *HDI* is the percentage change in household disposable income, *POLP* is the police strength[23], *TVCCV* is the total violent criminal code violations and lastly, *NCP* is the percentage change in the number of consumers.

Starting with equation (1), the law of demand predicts a negative relationship between price and quantity consumed if dealing with a normal good. The type of good marijuana is, will determine the direction of the correlation between disposable income and quantity consumed. However, the economic theory advocates that for a normal good, any increase in revenue leads to an increase in demand for that good. In accordance with Becker (1968), I expect that ultimately, an increase in police strength increases the likelihood of a felony to be uncover which may in turn reduce the pick of consumption as people may choose to stay in possession of their cognitive faculties and avoid arrests.

In equation (2), I expect the total violent criminal code violations due to cannabis consumption to be negatively correlated with price of non-medical marijuana. This is because, if marijuana is a normal good then, an increase in its price leads to a reduction in quantity consumed and thus a reduction of related felonies assuming that the higher the consumption of cannabis, the higher the chances to commit a felony. This logic follows from More and Steward (2005) who argued that cannabis consumption alters the ability to temper owns behavior in situation of conflict and accentuates a sensation of panic, rage and loss of temper likely to lead into violence. These arguments are sustained later by Howard and Menkes (2007) who attest that cannabis consumption reduces one's ability to make thoughtful decisions, control one's behavior suggesting a mental process that links a violent attitude to the lack of self-containment due to marijuana consumption. Thus, logically I may expect based on these very arguments a positive correlation between total violent criminal code violations, quantity consumed of marijuana

[23] Police officers per 100,000 population not including civilian and other personnel

and number of consumers. Indeed, an increase in the number of consumers translates into an increase in demand. Again, a negative correlation is expected between police officer's strength and total violent criminal code violation based on Becker's (1968) arguments. After confirming on the base of the LM tests that there is a spatial dependence in my variables I may use spatial econometric as estimation tool.

4.2 Spatial Conceptualization

The principal motivation toward considering a spatial influence is due to the bootlegging effect as rational consumers are expected to purchase from cheaper provinces close by. Elhorst (2010) argue that after running the LM-tests (error and lag), if the OLS regression is rejected in favor of either the spatial error model (SEM), the spatial lag model (SAR) or ideally both models, then the spatial Durbin model can be used.

From figure 1 it appears that, the spatial Durbin model is a generalization of the other three models depending on the restrictions imposed on its coefficients. Elhorst (2010) claims that starting the empirical analysis using the spatial Durbin model is the most appropriate method. Indeed, due to the dramatic effects on the relevance of the results such as biased and inconsistent coefficient estimates, it is better to neglect the spatial autocorrelation in the residuals rather than in either the dependent variable or the independent variable or in both. Moreover, because spatial error model, spatial lag model and spatial Durbin model are nested models, taking the spatial Durbin model as starting point eliminate the possibility of omitted variables bias even if the true data generating process is either of the two others.

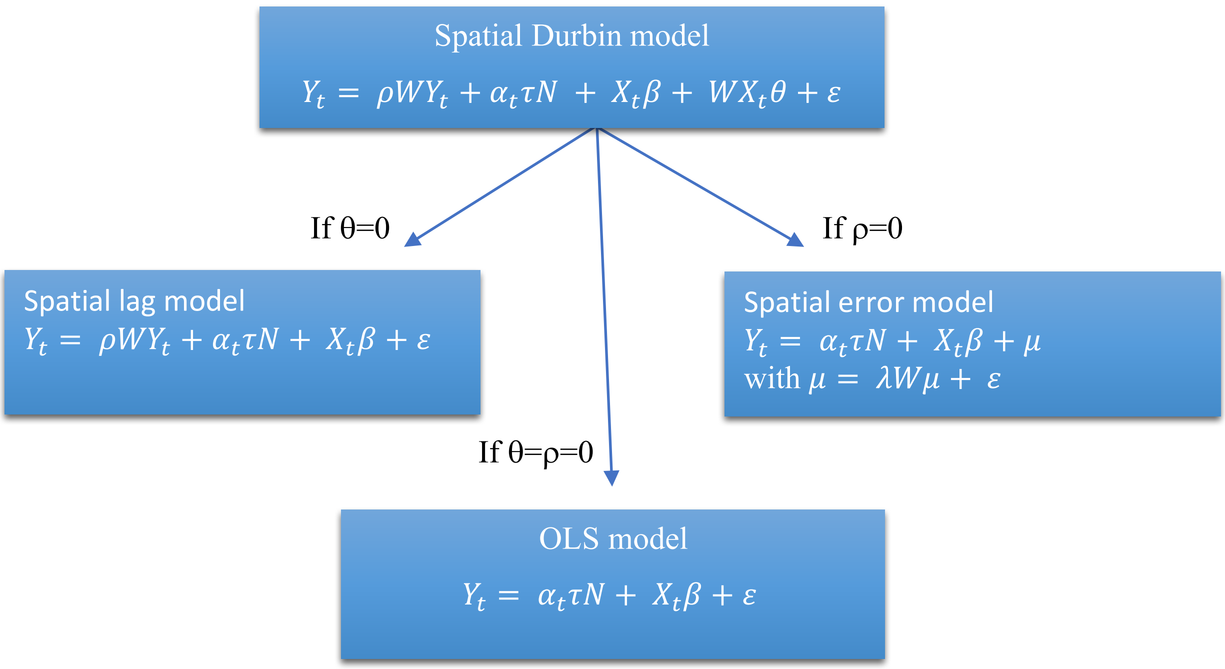

Figure1: Link between OLS, SDM and SEM
Source: Elhorst (2010)

Where, μ is the vector of spatial fixed effect and $\propto_t$ is the time period fixed effects. Fixed effects help to differentiate correlation from causality (Elhorst, 2012). Fixed effects are preferred to random effect in this study because the area of study covers all regions in the country[24]. Two parameters assess the indirect or spillover effect that is, ρ that captures the global effect and θ the local effect and β captures the direct effect. The direct effect refers to the outcome on the dependent variable in a province from a change in the explanatory variable in that province while the indirect effect is the result on the dependent variable in a province due to a change in the explanatory variable from a neighboring province. W is the weight matrix, Y_t is the dependent variable and X_t the vector of explanatory variables.

4. Spatial Dependence Test and Model Selection

Table 4.1 and table 4.2 show the results of the spatial dependence tests for equation (1) and equation (2) respectively. The regressions include spatial fixed effects. Among the nine matrices that I have constructed, only those that showed a spatial autocorrelation are recorded in the tables.

It appears that from equation (1), The LM function value (error) and the robust measure are mainly highly significant using the rook contiguity matrix of order 1, both queen contiguity matrices of order 1 and 2 and the matrix based on migration flux. For instance, with the contiguity matrix rooknorm_1, the LM measure 9.443 has a p-value less than 0.01 and the queen contiguity matrix of order 1 originates a value for the LM error equals to 8.598 with a p-value less than 0.01. However, the lag LM is insignificant at all times.

The second equation gives similar results. However, there is presence of spatial autocorrelation in the residuals using only three matrices namely, the rook contiguity matrix of order 1, the queen contiguity matrix of order 1 and the inverse distance matrix. Moreover, the spatial autocorrelation of the residuals is mainly moderately significant. As instance, with the inverse distance matrix, the LM (error) of measure 3.146 has a p-value of 0.076. And the LM (lag) is insignificant at all times.

These results indicate that the Spatial Error model seems the most appropriate. However, I shall run both spatial error model (SEM) and spatial Durbin model (SDM) for two reasons. First, as previously stated, following Elhorst (2010) if at least one of the two LM-test is significant, I may run a Spatial Durbin model. Moreover, Liu and al (2014) suggested that if spatially autocorrelated residuals that came from omitted variables are correlated with the vector of explanatory variables, the spatial Error model shall produce inefficient estimates in such a case, the spatial Durbin model is a better fit. Since in this

[24] Elhorst (2012). He argues that random effects are appropriate for study covering a bundle of regions extracted from a larger area.

case, I ignore the source of the spatial autocorrelation in the error term, I shall use both models. Secondly, as argued by Vega and Elhorst (2013), spatial error models do not give information about spillover effects which I precisely want to investigate.

5. Estimation Results

I present my regression results by starting with the spatial Durbin model. The results from equation (1) are presented first then the results from equation (2) come thereafter. I then turn to the results of the spatial error model in the same fashion. Because the spatial dependence tests have shown that spatial models would outperform the OLS regressions, the corresponding results are recorded on the table showing the model comparison results but are not discussed.

5.1 Spatial Durbin Model

Tables 5.1 and 5.2 show the spatial regression results for equation (1) and (2) respectively using a total of five different matrices. As proposed by Elhorst (2010), I selected the matrices based on the value of the log-likelihood function. The higher its value, the better the matrix[25]. Therefore, the results from columns (3) and (4) corresponding to the estimates using the contiguity matrix queen_2 and the k-nearest neighbor matrix kmat_3 will not be interpreted for equation (1).

Table 5.1 reveals the regression results explaining the variation in non-medical cannabis consumption from a static spatial Durbin model including fixed effects. In all three specifications (columns (1), (2) and (5)), the spatial coefficient rho (ρ) is highly significant and positive. This suggests that, a variation in the neighbors' quantity consumed of recreational marijuana is positively correlated with own consumption. The magnitude of the correlation is quite stable across all three specifications and translates into the following interpretation: holding all other factors unchanged, a 1 percentage point increase in neighbors' quantity consumed of recreational cannabis generates a 0.9 percentage point increase in own-province consumption on average.

Column (1) uses the contiguity matrix of order 1, rooknorm_1 that considers as neighbor provinces sharing a border. It appears that all the explanatory variables display a direct effect estimate statistically insignificant except for the percentage change in household disposable income that is

[25] Arbitrarily, I want to keep three matrices simply because I wish to have the same number of matrices for the second equation. Indeed, from the spatial dependence tests, the second regression exhibited spatial autocorrelation of the residuals with only three matrices. However, it will not necessarily be the same matrices in both equations.

significant at 5% level. However, most of the coefficients estimates have the expected signs. Indeed, police strength happens to be negatively correlated with cannabis consumption. This result sustains the idea developed by Becker (1968) and stating that a higher rate of police officers increases the chance of a violation to be uncover and due to the link established by researchers between drugs use and crimes, it leads to a lesser cannabis consumption in order to stay away from arrests. Thus, this result suggests that holding other things constant, an increase by about one percentage point in the strength of police officers per 100,000 inhabitants leads to a decrease in cannabis consumption by about 0.004 percentage point on average. An increase in disposable income increases the demand for recreational cannabis suggesting that cannabis is a normal good. Specifically, if household disposable income goes up by 1 percentage point, it leads to a rise in cannabis consumption of 0.143 percentage point on average. A variation in the price of medical marijuana is negatively correlated with demand for recreational marijuana. This result suggests diverse interpretations. First, because this value is statistically equal to zero, it might be that the change in quantity consumed of marijuana simply has no effect of medical cannabis consumption. Or, it might be that both medical and non-medical marijuana users might consider them as complementary goods. Indeed, the theory states that when it comes to complementary goods, the increase in the price of one good leads to a decrease in the demand for the other good. In fact, less of each good are demanded. However, the regression at hand does not permits to evaluate whether the quantity demanded of medical marijuana remains unchanged. Moreover, If the quantity consumed of medical marijuana remains unchanged even in the event of an increase in its price while there is reduction in recreational marijuana consumption, it suggests that users see medical marijuana as more valuable and rather reduce the consumption of non-medical marijuana[26]. However, the magnitude of the reduction is quite low which indicates that the variation in the price of medical marijuana has little effects on the quantity consumed of recreational marijuana. The price of non-medical marijuana, is positively correlated with the quantity of cannabis used for recreational purposes. This result is not in accordance with the expectations based on the law of demand.

The results from column (2) with the queen contiguity matrix of order 1, queen_1 that treats as neighbor every province sharing either a border or just a vertex shows similar results. The difference being that the direct effect estimate of the percentage change in household disposable income is now strongly significant[27] and the variation in police strength is now positively correlated with non-medical cannabis consumption. Furthermore, the magnitudes of the estimates are more or less the same as with the previous matrix.

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[26] Medical and non-medical marijuana do not have the same effects on users. In this instance, it might suggest that people value their health more than the pleasure from recreational marijuana use.

[27] $p<0.01$

Finally, column (5) seems to exhibit the best results so far. Indeed, the socio-economic matrix using interprovincial migration as socio-economic variable is absolutely in phase with the expected results in terms of the directions. Still, only the household disposable income value is statistically significant (5% level of significance). The law of demand is verified here as an increase in the price of non-medical marijuana leads to a decrease in the quantity of marijuana used for non-medical purposes. An increase in the price of medical marijuana leads to a decrease in the quantity consume of non-medical marijuana showing that people value their health more than their pleasure. However, the magnitude of this effect is very low almost equal to zero and statistically insignificant. This suggests that the variation in the price of medical marijuana has no impact if not very little negative influence on the quantity consumed of non-medical marijuana. Similarly, the direct effect of police officer strength on quantity consumed of non-medical cannabis is negative, but very low and statistically insignificant. This suggests that the presence of a higher number of police officers has a little or no dissuasive effect on recreational cannabis users in terms of quantity consumed.

The spatial spillover effects are given by the indirect effects estimates[28]. It turns out that column (1) and (2) corresponding respectively to the rook and queen contiguity matrices of order 1 exhibit mostly strongly significant indirect effects estimates. However, the effect estimates associated with police strength is still statistically insignificant. With the socio-economic matrix, all estimates are significantly equal to zero except for the indirect effect estimate of the percentage change in household disposable income which is significant at 10% level. It appears that own province price increase of medical marijuana will encourage people to increase their consumption of non-medical marijuana from neighboring provinces in lesser proportion than the increase in price. Specifically, a 1 percentage point increase in the price of medical marijuana leads to a 0.7 percentage point increase in cannabis consumption for recreational purposes in neighboring provinces. Whereas, the bootlegging effect is not verified here. Indeed, an increase in the price of non-medical marijuana will lead to a reduction in quantity consumed of recreational marijuana in neighboring provinces. That is, if own province price of non-medical marijuana goes up by 1 percentage point, it generates a 0.7 percentage point decrease in the use of non-medical marijuana in neighboring provinces. Still, own province police strength increase has very little effect in cannabis consumed in neighboring provinces. With the rook contiguity and socio-economic matrices, holding other factors constant, if the rate of police strength goes up by 1 percentage point, it generates a reduction in cannabis consumption 0.01 and 0.000 percentage points respectively in the neighbors. However, with the queen contiguity matrix of order one, it produces the opposite effect. That is, if police strength increases by 1 percentage point, it leads to an increase in non-medical cannabis use of about 0.004 on average in the surrounding provinces.

[28] Since this is a static model, there are no short run effects.

Thus, from equation (1), it appears that the bootlegging effect is not verified with all matrices functional forms[29]. Any increase in the price of non-medical marijuana has the exact opposite effect with rook and queen contiguity matrices. Moreover, with the socio-economic matrix, an increase in the price of non-medical marijuana will prevent users from purchasing more within their province but also with a higher extend, in neighboring provinces. Indeed, if the price of non-medical cannabis goes up by 1 percentage point within a province, users reduce their consumption by 0.04 within the province and they reduce their purchases in neighboring provinces by 0.6 percentage point on average. This last result was obtained by Vega and Elhorst (2013) who argued that it can be a misspecification issue or the income increase may dissuade people from looking for a cheaper good elsewhere. A price increase in medical marijuana will reduce non-medical marijuana consumption within the province while increasing its consumption in neighboring provinces. A higher disposable income encourages consumption of recreational marijuana within the province and in neighboring provinces. However, using the rook and queen contiguity matrices, the increase in consumption is three times higher in neighboring provinces than in the province experiencing the income increase. Whereas, it is up to five times higher with the matrix based on interprovincial migrations.

Table 5.2 reveals the regression results explaining the variation in total violent criminal code violations from a static spatial Durbin model including fixed effects. The results are reported in column (1), (2) and (3) corresponding to a rook contiguity matrix of order 1, a queen contiguity matrix of order 1 and an inverse distance matrix respectively. The estimation results show that the spatial coefficient ρ is highly significant and positive using each of the three matrices. Thus, there is a strong positive relationship between own-province total violent criminal code violations and those from the neighboring regions. Specifically, a one percentage point increase in the neighbors' total violent criminal code violations leads to a 0.3 percentage point increase in own-province transgressions using the rook and the queen contiguity matrices of order 1 and to a 0.5 percentage point increase using the inverse distance matrix.

The direct effect estimates of both prices of medical and non-medical marijuana are strongly significant with all three matrices. It appears that a percentage point increase in the price of medical cannabis in one province decreases the rate of total violent criminal code violations within the province by about 4.9, 4.7 and 5.6 percentage points using the rook contiguity matrix or order 1, the queen contiguity matrix of order 1 and the inverse distance matrix respectively. A rise in the price of non-medical marijuana has the inverse effect. It increases the total violent criminal code violations within the province. The direct effect estimates of the rate of police strength and the quantity consumed of non-medical cannabis do not exhibit the expected signs. First, it shows that an increase in the number of

[29] Even with the queen_2 and kmat_3 matrices that I have excluded.

police officers leads to an increase in the total number of criminal code violations by about 0.5 percentage point on average with each matrix functional form. An increase in the quantity consumed of non-medical cannabis jointly decreases the rate of the transgressions within the province. Chalfin and McCrary (2017), pointed out these past researches with panel data who used to find positive correlation between police and crime. The variable number of consumers provides satisfactory results in line with the expectations. Indeed, own province increase in the number of users augments the number of violent criminal code violations within the province.

The spillover effects show that, an increase in the price of non-medical marijuana in one province decreases the number of total violent criminal code violations in neighboring provinces. The magnitude of these effects is slightly higher in the neighboring areas than within the province. Similarly, any increase in the price of medical cannabis in a particular region increases the number of total violent criminal code violations in neighboring areas by 5.6, 5.4 and 6.0 percentage points on average using the rook matrix, the queen matrix and the inverse distance matrix respectively. Any increase in the number of police officers within a location increases the number of violent criminal code violations in nearby locations. However, the increase in the number of felonies due to a rise in the number of police officers is higher within the location than in neighboring areas. An increase in the quantity consumed of non-medical cannabis in a particular location decreases the rate of the transgressions in neighboring locations. The decrease is higher within the province using both contiguity matrices however, with the inverse distance matrix, the decline is twice as high in neighboring areas. Own province increase in the number of users augments the number of violent criminal code violations within the province and in neighboring regions but in less proportion than the own province increase. However, using the inverse distance matrix, the increase is slightly higher in neighboring areas[30].

By themselves, these results are very unstable however, considering the variation in quantity of marijuana for recreational purposes and the direct and indirect effect estimates of the explanatory variables, it appears that the results complement each other.

5.2 Spatial Error Model

Based on the matrix selection proposed by Elhorst (2010), I shall not interpret the results with the queen matrix of order 2 and the k nearest neighbors of order 3 because, their log-likelihood function values are lower than the three others and I wish to keep three specifications as previously just for symmetricity concern.

[30] It is worth noticing that based on the log-likelihood function value, the model using the inverse distance matrix appears to be the best.

Table 6.1 shows the regression results for equation (1) using the SEM model. The spatial error coefficient lambda (λ) is strongly statistically significant and positive. Thus, there is a positive relationship between the own-province residuals and neighbors' residuals.

The estimated coefficients associated to the rate of change in disposable income are strongly statistically significant across all specifications. Furthermore, the matrix based on interprovincial migration produced strongly statistically significant coefficients of both medical and non-medical cannabis prices'. Whereas, using the contiguity matrices rooknorm_1 and queen_1, all other estimates appear to be insignificant. Lastly, the estimates of the police strength are all statistically equal to zero using all matrices functional forms.

Specifically, a one percentage point increase in the price of medical marijuana leads to an increase in non-medical cannabis consumption in the proportions 0.2 percentage point, 0.1 percentage point and 0.5 percentage point using the rook contiguity matrix or order 1, the queen contiguity matrix of order 1 and the inverse distance matrix respectively. An increase in the price of non-medical marijuana produces quite similar magnitudes but in the opposite direction. Moreover, the Law of demand is fulfilled here and translates into a 1 percentage point increase in the price of non-medical marijuana leads to a 0.22 percentage increase point decrease in the quantity demanded. In accordance with the theory, there is a positive correlation between the variation of income and demand. Indeed, an increase by one unit in disposable income generates an increase in quantity demanded of cannabis in the proportion 0.07 percentage point when using the rook and queen matrices and 0.1 percentage point with the socio-economic matrix.

Thus, the SEM results suggest that consumers may substitute medical cannabis to non-medical cannabis since an increase in the price of medical cannabis leads to an increase in the quantity consumed of non-medical cannabis. Whereas the SEM validates the law of demand and income effect. Moreover, the SEM does not validate the hypothesis of an inverse relationship between police officer strength and quantity consumed of recreational cannabis either. Plus, even with this model, the magnitudes associated to the variable police are very small and all statistically insignificant suggesting that police strength might not have an impact on the consumption of recreational cannabis.

Table 6.2 recapitulates the estimation results of equation (2) using the SEM. The spatial coefficient λ is strongly significant attesting therefore that the errors are spatially correlated. The direct effect estimates show that every single coefficient is statistically equal to zero. Holding all other variables constant, a 1 percentage point increase in the price of medical marijuana results in an increase in total violent criminal code violations by about 0.7 percentage point using rook and queen contiguity matrices of order 1 and by 0.6 percentage point using the socio-economic matrix. A percentage increase in the price of non-medical marijuana decreases the total violent criminal violations with a magnitude of 0.7 percentage point using the rook matrix as well as the queen matrix and by 0.6 percentage point using the migrations based matrix. Quantity consumed of cannabis and number of consumers are positively correlated with the number of transgressions. Any 1 percentage point increase in the quantity consumed of cannabis augments the total violent criminal code violations by about 0.2 percentage point on average using each of the three matrices. Whereas, a one percentage point increase in the number of consumers increases the total transgressions. The magnitude of the increase reaches 2.8 percentage points with the rook contiguity matrix of order 1.

Thus, if one takes the results from both equations together, they globally complement each other. Indeed, if the price of medical marijuana is positively correlated with the quantity consumed of non-medical cannabis, then consequently, one might expect an increase in the number of felonies due to the link established by researchers between marijuana consumption and violent behavior. Which is on average what is found here. In the same way, if demand for non-medical marijuana is negatively correlated with its price as the theory predicts, then one expects an increase in the price of non-medical marijuana to leads to a reduction in the number of transgressions. Again, this is the result found here.

6. Model Comparison

Table 7.1 shows a comparison of the estimation results of equation (1) using both spatial error model and spatial Durbin model. Moreover, following Liu, griffin and Kirkpatrick (2014), I computed the Aikaike Information Criterion (AIC) to assess the fit of the models. They advocate that the higher the log likelihood function and the lower the AIC, the better the model fits the data.

Based on results reported on table 7.1, overall, the spatial Durbin model is the most appropriate model to fulfill my research objectives since as noted by Vega and Elhorst (2013) spatial error models exclude any indirect effect in advance. Moreover, the values of the log likelihood function and AIC reinforce this choice. Specifically, table 7.1 states that there is spatial autocorrelation present in my data. That is because, both spatial autoregressive parameters rho and lambda corresponding to the spatial Durbin model and spatial error model respectively are both strongly statistically significant at 1% level of significance.

Turning to the effects of my explanatory variables of interest, namely prices of medical and non-medical cannabis, it appears that the direct effect estimates of the price of medical marijuana exhibit opposite results when comparing both models across the different functional forms of the weighting matrix. Using the SEM, and increase in the price of medical cannabis increases the quantity consumed of non-medical cannabis whereas, with the SDM, the increase in the price of non-medical marijuana decreases the quantity consumed of recreational cannabis. The same variability appears in the direct effect estimates of the price of non-medical cannabis. Indeed, using both contiguity matrices, the law of demand is verified with the SEM and contradicted with the SDM. And, using the socio-economic matrix, the SDM verifies the law of demand while the SEM does not.

The spillover effects show that an increase in own-province price of non-medical marijuana decreases the demand in neighboring provinces which contradicts the bootlegging effect as one may expect people to turn to nearby regions with cheaper prices whenever prices in their own region go up (Vega and Elhosrt, 2013). These effects are strongly significant for both contiguity matrix and not significant for the socio-economic matrix. Turning to the spillover effects of medical marijuana price increase, they appear highly significant and positive when considering both contiguity matrices however, the result is still positive but not significant with the weight matrix based on interprovincial migrations. Thus, an increase in the price of medical marijuana in one region leads to an increase in the quantity demanded of non-medical marijuana in neighboring areas. Because medical and non-medical marijuana are two different goods with a certain degree of similarity[31], this result seems to tell that in the event of an increase in the price of medical marijuana, consumers will substitute away from medical marijuana in favor of cheaper non-medical marijuana. Thus, some consumers may actually treat medical and non-medical cannabis as substitute goods.

Table 7.2 compares the results on the variation in total criminal code violations using the SEM and SDM. The two spatial autocorrelation parameters are strongly statistically significant indicating the presence of spatial dependence in the data.

From the SEM, the direct effect estimates show that for all three functional forms of the weight matrix, an increase in the price of recreational cannabis decreases the number of felonies. However, these results are not statistically significant. The SDM produces opposite results that are statistically significant and bigger in magnitude. An increase in the price of medical cannabis is mostly associated with a decrease in the number of felonies. Except for SEM model when using the rook contiguity of order 1 and the inverse distance matrix. The SEM sustains the idea that quantity consumed of non-medical cannabis in positively related to the total violent transgressions. The SDM presents opposite results for all matrices. Globally, there is a positive association between number of police officers and number of felonies as well as between the number of consumers and the number of total violent crimes.

[31] Both come from a plant with many chemicals. In medicine, tetrahydrocannabinol (THC) and cannabidiol (CBD) are the main chemicals used. THC creates dependency while CBD tempers the psychoactive property of THC thus, as a results medical marijuana does not render users euphoric. However, non-medical marijuana is high in THC and produce the euphoria effect proper to non-medical cannabis. Source: Canadian Center of Substance Abuse.

The positive correlation between the number of police officers and total violent criminal code violations contradict the theory of criminal deterrence advocated by Becker (1968) and developed later by Chalfin and Maccrary (2017). These effect estimates are mainly statistically insignificant except for the coefficient derived from the SDM using the inverse distance matrix which is statistically significant at 5% significance level. The direct effect estimates of the quantity consumed of recreational marijuana and the number of consumers across both models and all three matrices functional forms, even though statistically insignificant still fulfill the expectations. That is, marijuana consumers are more likely to commit a felony.

The spillover effects of my two variables of interest are strongly significant at 1% significance level using the different matrix specifications. The results show that an increase in own-province price of medical marijuana increases the number of violent criminal code violations in neighboring locations. By doing a parallel with the spillover effect from equation (1) this result makes sense. Indeed, I found earlier that an increase in the price of medical marijuana in one region leads to an increase in the quantity consumed of marijuana in neighboring states. Thus, if indeed, marijuana consumption is positively correlated with crimes, then, one must expect an increase in the number of felonies in neighboring provinces consequently. Similarly, the previous findings contradicted the bootlegging effect suggesting that people will tend to buy from neighboring provinces if there is a price increase in their own province. Thus, the current results go in the same direction by telling that if there is a rise in own-province price of non-medical marijuana, there will be a decrease in the total number of violent criminal code violations in neighboring regions[32].

7. Alternative Specification

Here, I change the functional form of all my variables. Having previously computed the percentage changes from one year to the next for each of my variables, I now take the log of their level values in order to evaluate how sensitive the results are to the functional form of my variables. I shall test again for spatial autocorrelation using all nine matrices that I have created for this study.

The results of the spatial dependence tests are straightforward for equation (2) as none of the tests using the nine different matrices detected any spatial autocorrelation[33]. This suggests that a non-spatial model suffices to explain the variation in total violent criminal code violations.

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[32] From equation (1) direct effect, there is an increase in disposable income thus, people may not have to go after cheaper cannabis due to the increase in their revenue (Vega & Elhorst, 2013)

[33] I decided to use the log of the number of police officers as dependent variable and obtained a positive result for the test of spatial dependence. The LM error test is significant at 5% significance level and its

For equation (1), I have obtained a positive spatial autocorrelation using the LM-test (error). The rook contiguity matrix of order 2, both queen contiguity matrices of order 1 and 2 and the 4-nearest neighbors' matrix exhibit spatial dependence in the residuals with 5%, 10%, 1% and 1% significance level respectively.

Table 8. shows the regression results of equation (1) using spatial error model and spatial Durbin model with all four matrices. It appears that the spatial autocorrelation coefficients corresponding to each model specification are positive and strongly statistically significant using all three matrices' functional form. The direct effect estimates of the log of medical marijuana and non-medical marijuana prices are strongly significant at 1% level when using the SEM. The price elasticities validate the economic theory. Indeed, the price elasticity of non-medical marijuana is about -2.524 with the four-neighbor's matrix. This magnitude is quite stable with all weighting matrices using the SEM. Thus, a one percent variation in the price of recreational marijuana leads to a 2.5 percent change in the opposite direction in its consumption. The SDM gives negative price elasticities of demand as well but, not statistically significant and of lower magnitudes.

As for medical marijuana, a one percent increase in its price leads to a 2.5 percent increase in the demand for non-medical marijuana on average across all SEM with the different matrices. The SDM produces the same results in terms of direction even though they are not statistically significant. In terms of magnitude, the SDM produces lower estimates and they are more sensitive to the matrix functional form. As instance, using the queen contiguity of order 1, a 1 percent increase in the price of medical marijuana leads to a 2.3 percent increase in recreational marijuana consumption. Whereas using the queen contiguity of order 2, the increase is only about 0.33 percent.

The income elasticities go in opposite directions depending on the model used. With the SEM, the results tell that non-medical marijuana is an inferior good as its demand decreases with an increase in disposable income whereas, with the SDM, any increase in income increases the demand for recreational cannabis. Finally, all specifications suggest a positive correlation between police officer strength and non-medical cannabis consumption, but these estimates are statistically insignificant.

The spillover effects show that an increase in the price of medical marijuana in a particular location leads to an increase in the demand of cannabis used for recreational purposes in neighboring regions. The magnitude of the demand varies substantially with the matrix functional form. And the spillover effect estimates of non-medical marijuana price do not validate the predictions of a bootlegging

robust value is significant at 1% significance level. Maybe the number of crimes affect to a higher extend the variation in police strength than police strength does to the variation in crime level.

behavior since an increase in the price of non-medical marijuana in one region does not leads to an increase in its demand in neighboring regions.

8. Conclusion and Study Limitations

The purpose of this study was to evaluate if there are spillover effects due to a variation in the price of recreational marijuana. The analysis was conducted on two equations with quantity consumed of non-medical marijuana and total violent criminal code violations as dependent variables. These equations were aimed to evaluate whether on one hand, due to an increase in the price of marijuana, agents would buy from neighboring locations with cheaper prices and on the other hand, to assess if an increase in the price of marijuana in one specific location generates a rise in total violent criminal code violations in nearby locations. The assumptions were based on the bootlegging effect instigated by Balgati and Levin (1992) and, on the assumption that marijuana use leads to violent behavior ((Niveau & dang, 2003; Moore & Stuart, 2005; Howard & Menkes, 2007).

Just like Vega and Elhorst (2013) using a binary contiguity matrix, the evidence of a bootlegging behavior could not be uncovered throughout this study. They advocated that bootlegging behavior is actually subject to opposite driving forces. On one hand, the rational consumer who wants to buy from the neighbor if the product is cheaper there than in its own location, and on the other hand, an increase in revenue that reduces the incentive to look for cheaper products due to a higher purchasing power. However, both equations complement each other. Indeed, when investigating the spillover effects, it appeared that any increase in the price of non-medical marijuana reduced the quantity consumed of recreational marijuana within the province and in neighboring locations and reduced the total violent criminal code violations as well. This suggests that quantity consumed of non-medical marijuana and violent crimes vary in the same direction due to a variation in price. The spillover effects of an increase in the price of non-medical marijuana on the quantity consumed is strongly significant using the contiguity matrices whereas it is not significant with the socio-economic matrix using the interprovincial migrations as variable. Similarly, the spillover effects of an increase in the price of non-medical marijuana on the level of crimes is strongly significant using the contiguity matrices and the inverse distance matrix. This suggests that what matters the most here is the geographical connection between provinces rather than the flux of people.

I could not capture a spatial dependence with the logarithm formulation for equation (2). Therefore, potential spillover effects could not be assessed. However, as for equation (1), the results still show no evidence of bootlegging effects and as previously, any increase in the price of non-medical marijuana in a particular province decreases the demand within the province and in neighboring provinces. The main difference is that these effect estimates are no longer significant.

Other results seem to be worth noticing. When the percentage change formulation is used, the direct effect estimates of both prices of medical and non-medical marijuana vary a lot in terms of magnitude and direction, the results with the logarithm formulation are a lot more stable. Indeed, using the latter, increasing the price of medical marijuana increases the consumption of non-medical marijuana and an increase in the price of non-medical marijuana reduces its demand. This result suggests that marijuana users might treat these two products are substitutes.

Numerous limitations can be noted from this study. First, limitations due to the identification concern attributed to spatial econometrics (Gibbons and Overman, 2012). Indeed, one of the main concern of spatial econometrics is still the construction and appropriateness of the spatial weight matrix used. For instance, one of the limitation of the binary contiguity matrix is that it ignores purchases from visiting parties considering only purchases form contiguous locations (Vega and Elhorst 2013). Elhorst (2014) Notes that inverse distance matrices may lead to unwanted empirical results because originally it is mostly adequate for infinite sample whereas empirical studies use finite samples. Moreover, it is likely to encounter a misspecification issue. Indeed, failing to find evidence of bootlegging effects with the contiguity matrix, Vega and Elhorst (2013) attributed it to a model misspecification and after estimation of the model using an inverse distance matrix, the results appeared in line with the expectations. This is one criticism of spatial econometrics accused to simply try different specifications until significant and satisfying results are obtained (Gibbons and Overman, 2012). I could not obtain the desired spillover effects even though the endogenous spatial lag attesting of the presence of spatial dependence was highly significant. Corrado and Fingleton (2012) notes that the significance of the spatial lag might be erroneous as it can actually express the impact of missing spatially dependent variables and thus wrongly predicting a potential spillover process.

Secondly, the data used are obtained from crowdsourcing, which leaves room for error. Indeed, Statistics Canada has developed an online platform that enables marijuana users to voluntarily report their metrics. Due to unregulated recreational marijuana market, the data might lack sufficient coherence to enable complex modelling. Moreover, omitted variables bias is a true concern here as many other factors not captured in my equations might affect the demand for recreational marijuana and the level of violent crimes.

Although my analysis failed to capture the expected direction of the spillover effects, there are however two interesting evidences that emerged. First, it seems to be a positive correlation between marijuana consumption and violent crimes and secondly, the SEM model strongly attests that in Canada, marijuana users treat medical and non-medical cannabis as substitute goods. These results are of prime importance in the actual institutional context. Indeed, Tuesday 1 May 2018, while a majority of Senators

(6 against 5) supported Quebec and Manitoba who wish a modification of Bill C-45 and ban the private culture of cannabis, the Federal Government through the voice of the Prime Minister Justin Trudeau however sustains that people will be allowed to grow a maximum of 4 plants of cannabis per household.

Allowing individuals to grow cannabis can be concerning on multiple levels, first, based on the finding that Canadian users tend to substitute medical cannabis to non-medical cannabis. Indeed, as noted in this study, medical and non-medical cannabis do not have the same medical properties and therefore we may expect a deterioration of the health of Canadians who consume marijuana for medical purposes. Secondly, the positive correlation found in this study between non-medical marijuana consumption and the level of violent crimes is worrying since under the law advocated by the Federal Government, everyone no matter his/her judicial record, medical condition or psychologic state will have a direct access to free non-medical cannabis. As noted by Senator Serge Joyal during an interview on ICI Radio-Canada on Thursday 3 May 2018, the Federal Government proposal seems to be difficult to implement since it shall be a major hurdle to verify that in each household only a maximum of 4 plants of cannabis are cultivated.

In order to accurately assess these concerns, after marijuana legalization and using a better dataset, new estimations have to be conducted. The results obtained thereafter will share more light on critics and worries related to marijuana legalization and its provincial implications as well as on the possible effects related to the legalization of all prohibited drugs.

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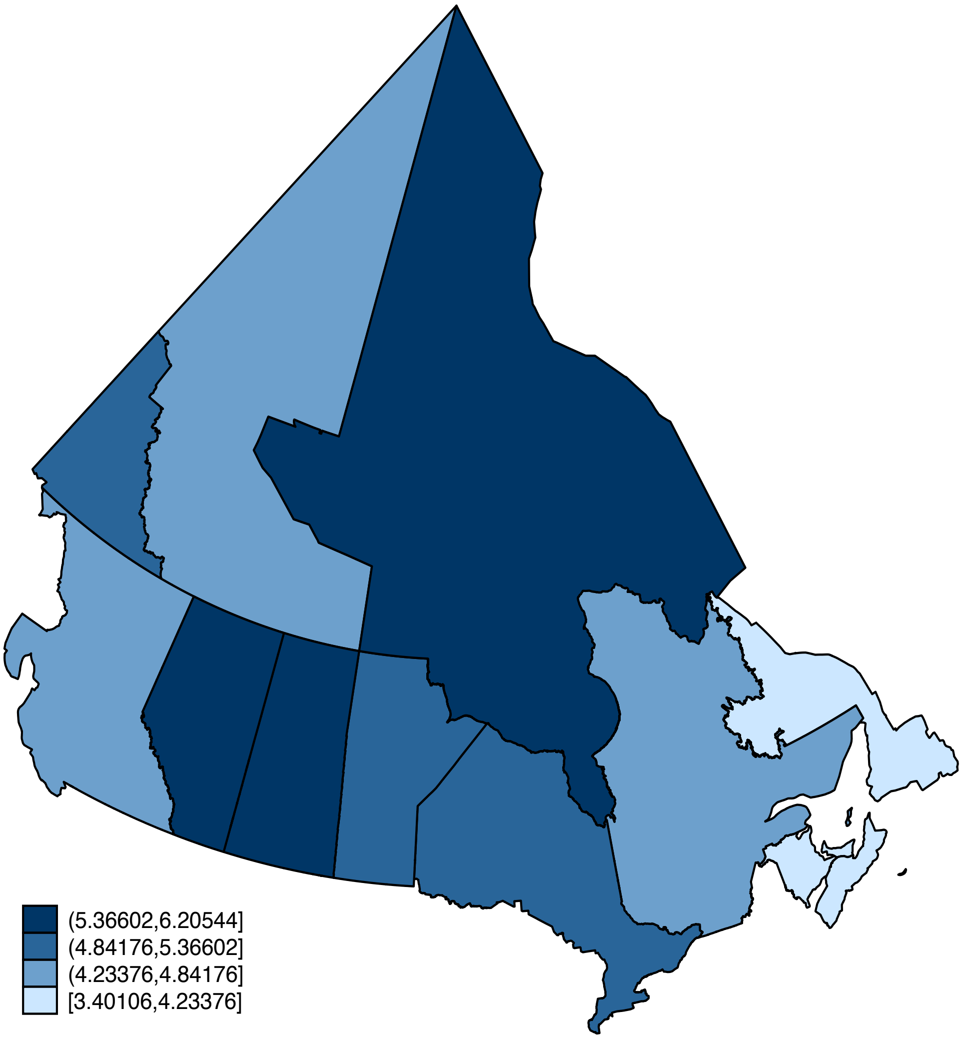
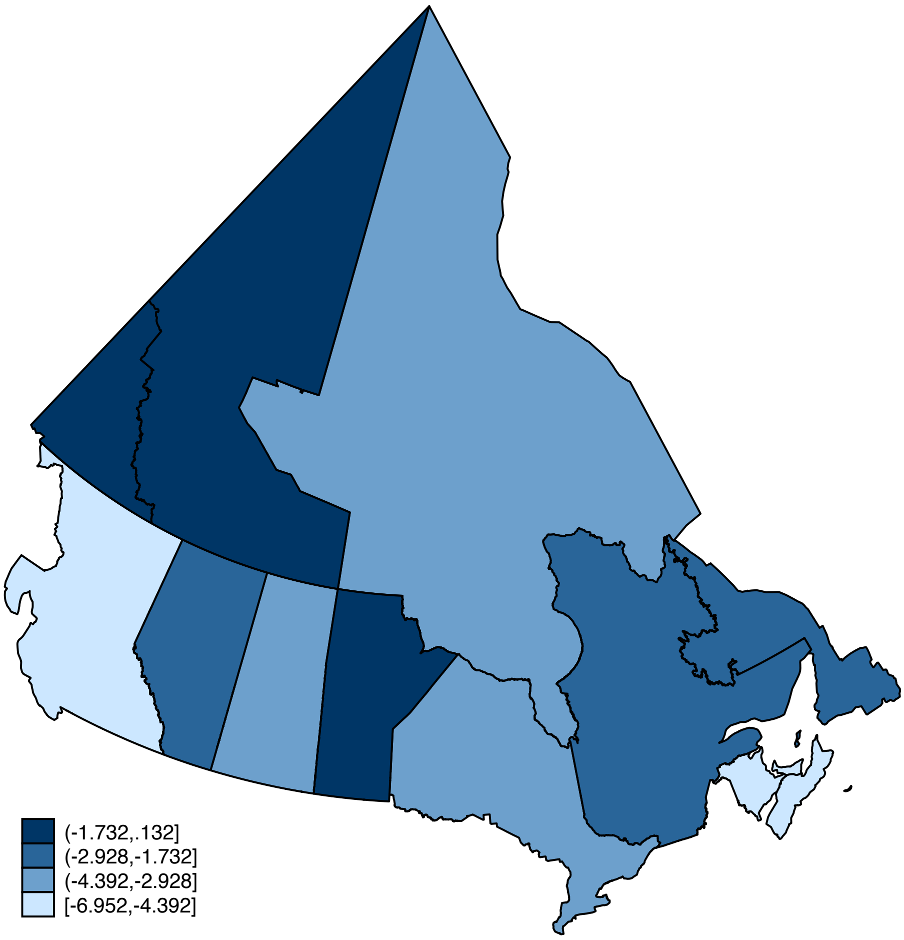
Figures:

Figure 2
Average quantity consumed of cannabis, 2011-2016



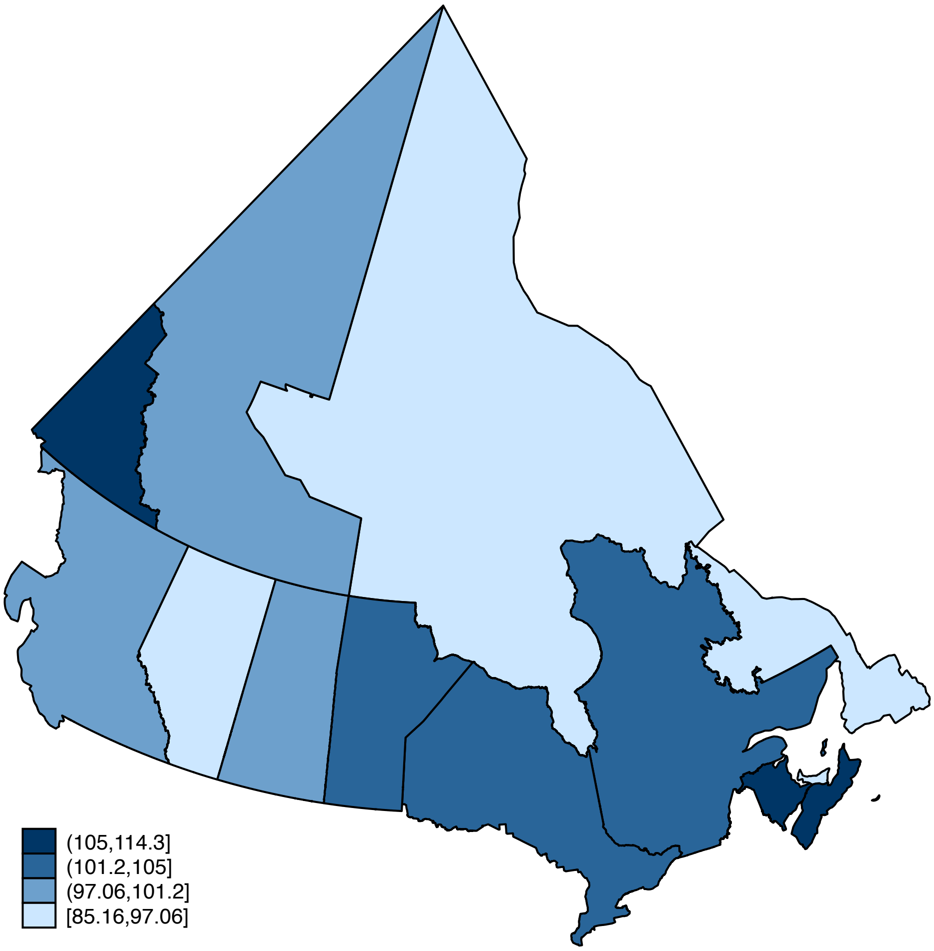
Canadian provinces and territories
Source:Own calculations based on Cannabis Stats Hub, Economy

Figure 3
Average total violent criminal code violations, 2011-2016



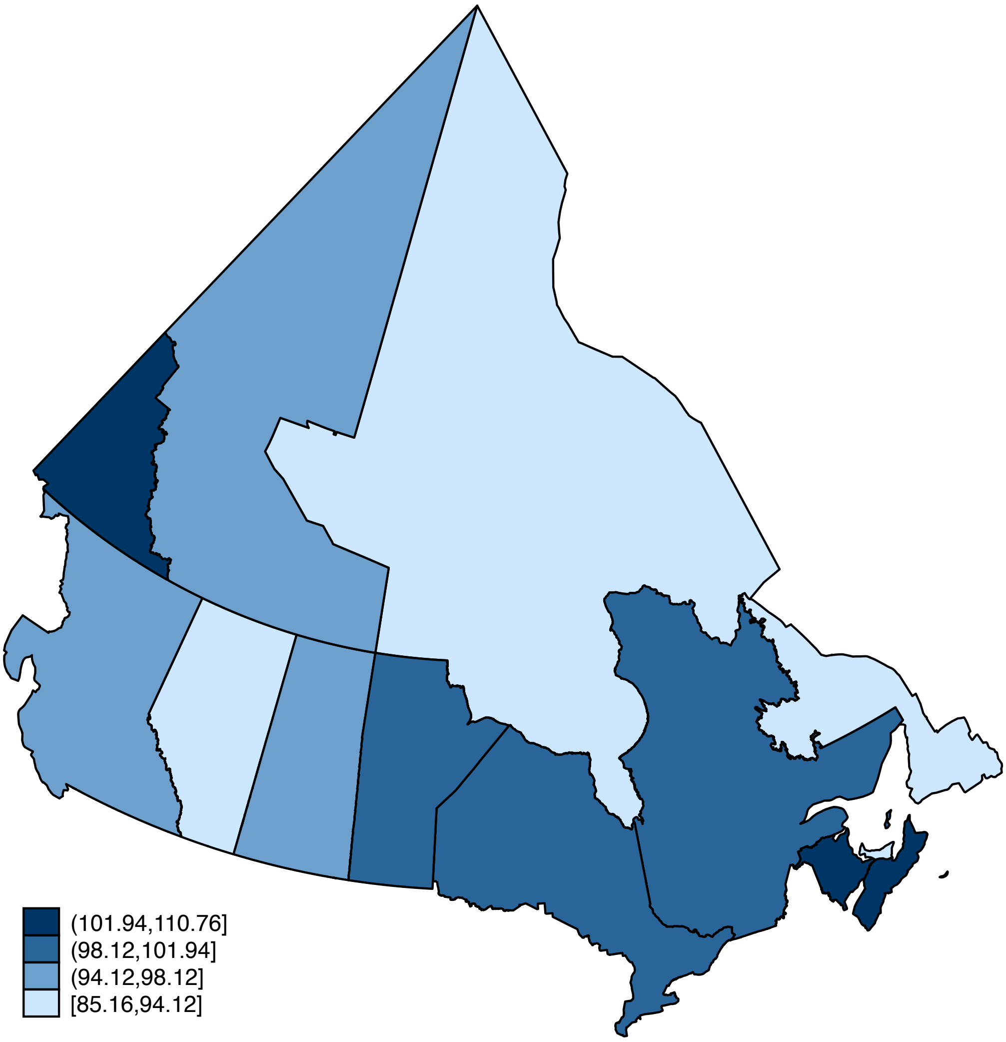
Canadian provinces and territories
Source:Own calculations based on CANSIM table 252-0051

Figure 4
Average price index of medical cannabis, 2011-2016



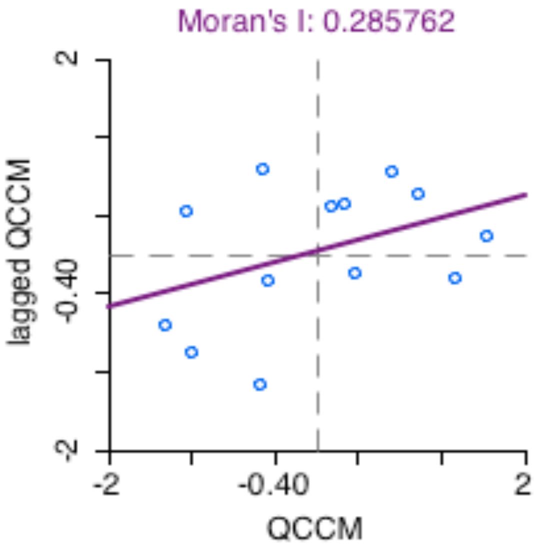
Canadian provinces and territories
Source:Own calculations based on CANSIM table 388-0011

Figure 5
Average price index of non-medical cannabis, 2011-2016



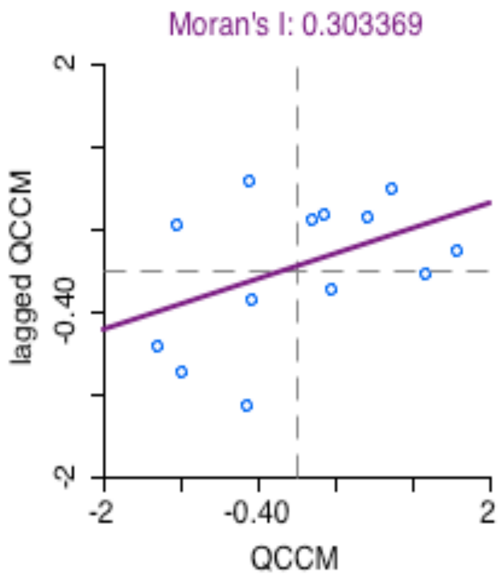
Canadian provinces and territories
Source:Own calculations based on CANSIM table 388-0011

Figure 6
Moran's I scatter plot (rook contiguity of order 1)



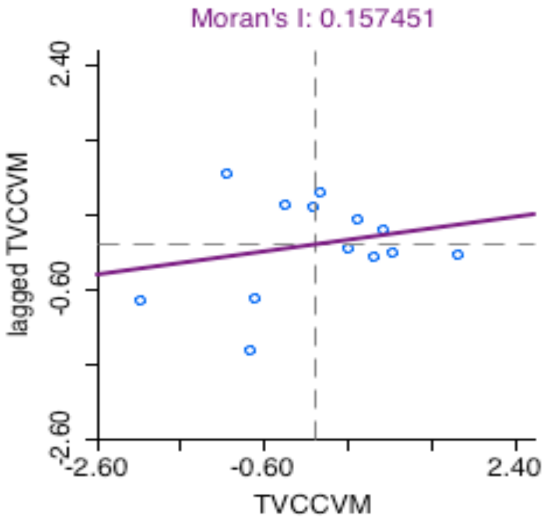
Note: p-value = 0.057 with 999 permutations

Figure 7
Moran's I scatter plot (queen contiguity of order 1)



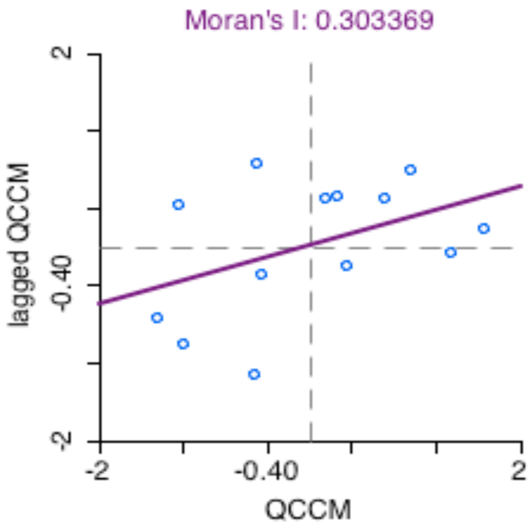
Note: p-value = 0.041 with 999 permutations

Figure 8
Moran's I scatter plot (rook contiguity of order 1)



Note: p-value = 0.114 with 999 permutations

Figure 9
Moran's I scatter plot (queen contiguity of order 1)



Note: p-value = 0.041 with 999 permutations

Tables

Table 1: Summary statistics of the matrices

Matrix	Links	No	Provinces
rooknorm_1	Max links	5	Northwest Territories Nunavut
	Min links	2	Newfoundland and Labrador Prince Edward Island Nova Scotia Yukon
rooknorm1_2	Max links	10	Nunavut
	Min links	3	Prince Edward Island Nova Scotia
queen_1	Max links	6	Northwest Territories Nunavut
	Min links	2	Newfoundland and Labrador Prince Edward Island Nova Scotia Yukon
queen_2	Max links	5	Newfoundland and Labrador Quebec Manitoba Saskatchewan
	Min links	1	Prince Edward Island Nova Scotia
matcom	Max links	12	Newfoundland and Labrador Nova Scotia New Brunswick Quebec Ontario Manitoba Saskatchewan Alberta British Columbia Northwest Territories
	Min links	10	Prince Edward Island
matmig	Total links	156	All provinces
distnorm	Total links	156	All provinces
Kmat_3	Total links	39	All provinces
Kmat_4	Total links	52	All provinces

Notes: Maximum and minimum number of neighbors obtained according to the matrix type. For instance, the first row shows that Nunavut shares a border with five provinces. "Total links" is used whenever every province has all other locations as neighbors. For instance, based on the fourth to last row, it appears that, every province has a trading relationship with all the others (12*13=156).

Table 2: Summary statistics of key variables

Variables	Means	Minimum	Maximum
A. Dependent variables			
Quantity consumed[34]	4.717 (1.678)	2.550	8.366
Total violent criminal code violation	-3.036 (6.038)	-19.290	10.910
B. Independent variables			
Price index medical	100.791 (9.432)	73.800	122.900
Price index non-medical	97.783 (9.944)	68.600	119.900
Household disposable income	2.485 (2.295)	-10.014	5.797
Police strength	-0.870 (2.910)	-8.656	10.151
Number of consumers	3.764 (.961)	-10.014	5.797
Total observations		65	

Notes: The values in brackets represent the standard deviations. The variables are in percentage changes per province.
Source: Own Calculations

Table 3: Spatial clustering, Moran's I

Matrices	Moran's I Equation (1)	Moran's I Equation (2)
rooknorm_1	-.347***	-.217**
rooknorm1_2	-.108	-.113
queen_1	-.321***	-.202*
queen_2	-.288***	-.150
matmig	-.140*	-.073
matcom	-.058	-.067
distnorm	-.035**	-.131*
kmat_3	-.334***	-.104
kmat_4	-.142	-.107

*p<0.1; **p<0.05; ***p<0.01
Source: Own calculations

[34] This variable is used in a second equation as an explanatory variable in order to assess the variation in Total Violent Criminal Code Violations

Table 4.1: Spatial dependence tests results, equation (1) (model SAR)

LM-Tests	rooknorm_1	queen_1	queen_2	kmat_3	matmig
LM Error	9.443***	8.598***	6.940***	9.616***	3.005*
LM Error Robust	19.168***	16.388***	12.730***	17.532***	4.184**
LM Lag	0.000	0.000	0.000	0.000	0.000
LM Lag Robust[35]	9.725***	7.789***	5.790**	7.917***	1.179

Notes: Only are reported the results from the matrices that have shown spatial dependence. *p<0.1; **p<0.05; ***p<0.01
Source: Own calculations

Table 4.2: Spatial dependence tests results, equation (2) (model SAR)

LM-Tests	rooknorm_1	queen_1	distnorm
LM Error	3.955**	3.295*	3.146*
LM Error Robust	20.959***	16.552***	7.079***
LM Lag	0.000	0.000	0.000
LM Lag Robust	17.003***	13.257***	3.933**

Notes: Only are reported the results from the matrices with at least one conclusive LM-test. *p<0.1; **p<0.05; ***p<0.01
Source: Own calculations

[35] The result of the robust LM Lag matters only when the LM Lag itself is significant.

Table 5.1: Spatial regression results, equation (1) model SDM

	(1)	(2)	(3)	(4)	(5)
	rooknorm_1	queen_1	queen_2	kmat_3	matmig
W_QCCP	.862***	.876***	.839***	.792***	.884***
(ρ)	(.026)	(.027)	(.036)	(.037)	(.030)
Direct effect					
PIM	-.104	-.107	.061	.175	-.000[36]
	(.202)	(.197)	(.378)	(.441)	(.433)
PIN	.112	.123	-.041	-.194	-.044
	(.201)	(.192)	(.390)	(.458)	(.440)
HDI	.143**	.147***	.184**	.157**	.166**
	(.056)	(.054)	(.074)	(.072)	(.079)
POLP	-.004	.002	.002	.007	-.000[37]
	(0.18)	(.020)	(.024)	(.022)	(.019)
Indirect effect					
PIM	.741***	.848***	1.047	.420	.164
	(.230)	(.216)	(.786)	(.640)	(.653)
PIN	-.714***	-.766***	-.883	-.462	-.619
	(.228)	(.209)	(.636)	(.603)	(.663)
HDI	.436**	.501**	.618*	.371*	.811
	(.197)	(.207)	(.367)	(.215)	(.562)
POLP	-.014	.004	.002	.018	-.000[38]
	(.059)	(.070)	(.080)	(.052)	(.093)
Log-likelihood	-32.537	-29.976	-43.042	-44.9480	-34.1770
AIC	81.074	75.952	102.084	105.896	84.354

Notes: All variables are in percentage changes. The endogenous variable is the quantity consumed of non-medical cannabis per province. Each specification regresses the endogenous variable on its price, the price of medical cannabis, the disposable income and police strength using the spatial Durbin model with a rook contiguity matrix of order 1, queen contiguity matrices of order 1 and 2, a 3-nearest neighbor's matrix and an interprovincial migration based matrix respectively. All matrices are normalized. Robust standard errors in brackets. *p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

[36] The exact value is -.0004624
[37] the real value is -.0000887
[38] the exact value is -.0008599

Table 5.2: Spatial regression results, equation 2 model SDM

	(1) rooknorm_1	(2) queen_1	(3) distnorm
W_TVCCV (ρ)	.314** (.127)	.331** (.129)	.487*** (.125)
Direct effect			
PIM	-4.913** (2.227)	-4.781** (2.234)	-5.647*** (2.075)
PIN	5.122** (2.327)	4.986** (2.333)	5.857*** (2.165)
POLP	.511 (.323)	.515 (.324)	.572** (.336)
QCCP	-.109 (.618)	-.111 (.640)	-.173 (.743)
NCP	2.439 (1.650)	2.382 (1.630)	2.889 (1.783)
Indirect effect			
PIM	5.576*** (2.022)	5.422***(2.029)	5.988*** (2.257)
PIN	-5.968*** (2.046)	-5.820***(2.051)	-6.662*** (1.994)
POLP	.186 (.159)	.206 (.175)	.474 (.349)
QCCP	-.079 (.322)	-.087 (.360)	-.291 (.925)
NCP	1.150 (1.170)	1.235 (1.284)	3.000 (3.069)
Log-likelihood	-190.289	-190.194	-188.315
AIC	398.577	398.388	394.629

Notes: All variables are in percentage changes. The endogenous variable is the total violent criminal code violations per province. Each specification regresses the endogenous variable on medical marijuana and non-medical marijuana prices, police strength, quantity consumed of recreational marijuana and the number of consumers. The spatial Durbin model uses different matrices functional forms: a rook contiguity matrix of order 1, queen contiguity matrices of order 1 and an inverse-distance matrix. All matrices are normalized. Robust standard errors in brackets *p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

Table 6.1: Spatial regression results, equation (1) model SEM

	rooknorm_1	queen_1	queen_2	kmat_3	matmig
W_QCCP	.880***	.909***	.815***	.808***	.833***
(λ)	(.134)	(.171)	(.047)	(.037)	(.031)
PIM	.204	.098	.392**	.389***	.483***
	(.486)	(.822)	(.161)	(117)	(.116)
PIN	-.222	-.112	-.418**	-.414***	-.508***
	(.504)	(.856)	(.164)	(.119)	(.119)
HDI	.077**	.073**	.109***	.121***	.121***
	(.031)	(.031)	(.035)	(.034)	(.034)
POLP	.008	.013	.005	.022	.006
	(.010)	(.012)	(.022)	(.023)	(.019)
Log-likelihood	-37.786	-35.789	-45.950	-39.646	-34.6113
AIC	87.571	83.578	103.899	91.293	81.223

Notes: All variables are in percentage changes and all matrices are normalized. The endogenous variable is the quantity consumed of non-medical cannabis per province. Each specification regresses the endogenous variable on its price, the price of medical cannabis, the disposable income and police strength using the spatial error model with a rook contiguity matrix of order 1, queen contiguity matrices of order 1 and 2, a 3-nearest neighbor's matrix and an interprovincial migration based matrix respectively. Robust standard errors in brackets*p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

Table 6.2: Spatial regression results, equation (2) model SEM

	rooknorm_1	queen_1	distnorm
W_TVCCV (λ)	.301** (.662)	.310** (.147)	.442*** (.152)
Direct effect			
PIM	.672 (.662)	.683 (.682)	.589 (.907)
PIN	-.700 (.710)	-.706 (.727)	-.611 (.957)
POLP	.427 (.347)	.433 (.341)	.506 (.317)
QCCP	.221 (1.369)	.189 (1.402)	.278 (1.786)
NCP	2.834 (2.066)	2.675 (2.018)	2.450 (1.962)
Log-likelihood	-194.136	-194.025	-192.945
AIC	402.271	402.050	399.890

Notes: All variables are in percentage changes and all matrices are normalized. The endogenous variable is the total violent criminal code violations per province. Each specification regresses the endogenous variable on medical marijuana and non-medical marijuana prices, police strength, quantity consumed of recreational marijuana and the number of consumers. The spatial error model uses different matrices functional forms: a rook contiguity matrix of order 1, queen contiguity matrices of order 1 and an inverse-distance matrix. Robust standard errors in brackets *p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

Table 7.1: Model comparison, equation (1)

	non-spatial	rooknorm_1		queen_1		matmig	
	OLS	SEM	SDM	SEM	SDM	SEM	SDM
W_QCCP		.880***		.909***		.833***	
(λ)		(.134)		(.171)		(.031)	
W_QCCP			.862***		.876***		.887***
(ρ)			(.026)		(.027)		(.030)
Direct effect							
PIM	.408***	.204	-.104	.098	-.107	.483***	-.000
	(.062)	(.486)	(.202)	(.822)	(.197)	(.116)	(.433)
PIN	-.437***	-.222	.112	-.222	.123	.508***	-.044
	(.053)	(.504)	(.201)	(.504)	(.192)	(.119)	(.440)
HDI	.065	.077**	.143**	.077**	.147***	.121***	.166**
	(.053)	(.031)	(.056)	(.031)	(.054)	(.034)	(.079)
POLP	-.005	.008	-.004	.008	.002	.006	-.000
	(.047)	(.010)	(.180)	(.010)	(.020)	(.019)	(.019)
Indirect effect							
PIM			.741***		.848***		.164
			(.230)		(.216)		(.653)
PIN			-.714***		-.766***		-.619
			(.228)		(.209)		(.663)
HDI			.436**		.501**		.811
			(.197)		(.207)		(.562)
POLP			-.014		.002		-.000
			(.059)		(.080)		(.093)
Log-likelihood	-83.638	-37.786	-32.537	-.35.789	-29.976	-34.611	-34.177
AIC	177.276	87.571	81.074	83.578	75.952	81.223	84.354

Notes: Results from three models appear here, the non-spatial Ordinary Least Squares (OLS) model, the spatial Durbin model (SDM), the spatial error model (SEM). The endogenous variable is the quantity consumed of recreational cannabis. All models regress the endogenous variable on its price, the price of medical cannabis, the disposable income and police strength. The spatial models make use of similar matrices: rook contiguity matrix of order 1, queen contiguity matrix of order 1 and interprovincial migration based matrix. Standard errors and robust standard errors for OLS and spatial models respectively are in brackets. *p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

Table 7.2: Model comparison, equation (2)

	Non-spatial	rooknorm_1		queen_1		distnorm	
	OLS	SEM	SDM	SEM	SDM	SEM	SDM
W_TVCCV			.314**		.331**		.487***
(ρ)			(.127)		(.129)		(.125)
W_TVCCV		.301**		.310**		.442***	
(λ)		(.662)		(.147)		(.152)	
Direct effect							
PIM							
	.852*	.672	-4.913**	-.706	-4.781**	.589	-5,647***
PIN	(.483)	(.662)	(2.227)	(.682)	(2.234)	(.907)	(2.075)
	-.897*	-.700	5.122**	-.706	4.986**	-.611	5.857***
POLP	(.463)	(.710)	(2.327)	(.727)	(2.333)	(.957)	(2.165)
	.530*	.427	.511	.433	.515	.506	.572**
QCCP	(.266)	(.347)	(.323)	(.341)	(.324)	(.317)	(.336)
	-.086	.221	-.109	.189	-.111	.278	-.173
NCP	(.822)	(1.369)	(.618)	(1.402)	(.640)	(1.786)	(.743)
	2.227	2.834	2.439	2.675	2.382	2.450	2.889
	(1.832)	(2.066)	(1.650)	(2.018)	(1.630)	(1.962)	(1.783)
Indirect effect							
PIM			5.576***		5.422***		5.988***
			(2.022)		(2.029)		(2.257)
PIN			-5.968***		-5.820***		-6.662***
			(2.046)		(2.051)		(1.994)
POLP			.186		.206		.474
			(.159)		(.175)		(.349)
QCCP			-.079		-.087		-.291
			(.322)		(.360)		(.925)
NCP			1.150		1.235		3.000
			(1.170)		(1.284)		(3.069)
Log-likelihood	-196.61	-194.14	-190.29	-194.03	-190.19	-192.95	-188.32
AIC	405.21	402.27	398.58	402.05	398.89	399.89	394.63

Notes: Results from three models appear here, the non-spatial Ordinary Least Squares (OLS) model, the spatial Durbin model (SDM), the spatial error model (SEM). The endogenous variable is total violent criminal code violations. All models regress the endogenous variable on medical and non-medical cannabis prices, police strength, quantity consumed of non-medical marijuana and the number of consumers. The spatial models make use of similar matrices: rook contiguity matrix of order 1, queen contiguity matrix of order 1 and inverse-distance matrix. Standard errors and robust standard errors for OLS and spatial models respectively are in brackets*p<0.10; **p<0.05; ***p<0.01
Source: Own calculations

Table 8: SEM and SDM regressions results, equation (1)
Variables in logarithm form

	non-spatial	kmat_4		queen_1		queen_2		rooknorm1_2	
	OLS	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM
W_lnqcc		.732***		.571***		.569***		.698***	
(λ)		(.085)		(.090)		(.084)		(.060)	
W_lnqcc			.6856***		.528***		.518***		.189***
(ρ)			(.098)		(.103)		(.100)		(.060)
Direct effect									
Lnpm	2.351***	2.483***	1.019	2.510***	2.302	2.387***	.333	2.427***	.506
	(.155)	(.313)	(2.972)	(.273)	(3.200)	(.251)	(3.980)	(.352)	(3.608)
Lnpn	-2.38***	-2.524***	-1.029	-2.53***	-2.330	-2.44***	-2.240	-2.46***	-.532
	(.142)	(.316)	(2.958)	(.269)	(3.183)	(.245)	(3.952)	(.348)	(3.591)
Lnhdi	.091	-.014	.009	-.037	.024	-.005	.074	-.020	.014
	(.105)	(.060)	(.089)	(.089)	(.074)	(.082)	(.074)	(.086)	(.090)
lnpol	.241***	.096*	.139*	.166**	.202**	.124	.201*	.112	.174
	(.082)	(.056)	(.083)	(.084)	(.092)	(.095)	(.106)	(.086)	(.106)
Indirect effect									
Lnpm			1.947		.008		2.521		1.998
			(2.845)		(3.160)		(3.749)		(3.565)
Lnpn			-1.757		-.070		-2.240		-1.928
			(2.897)		(3.124)		(3.813)		(3.536)
Lnhdi			.006**		.023		.079		.0367
			(.234)		(.076)		(.094)		(.181)
Lnpol			.270		.191		.209		.324
			(.251)		(.130)		(167)		(.236)
Log-likelihood	188.94	209.04	210.35	200.22	199.98	197.85	202.42	203.24	204.61
AIC	-367.89	-406.07	-404.71	-388.44	-383.96	-383.70	-388.85	-394.49	-393.21

Notes: All specifications regress the log of quantity consumed of recreational marijuana on its price, the price of medical marijuana, the disposable income and police strength. The first model is a non-spatial model namely, Ordinary Least Square (OLS) while others are spatial models, spatial Durbin model (SDM) and spatial error model (SEM). The last two make use of normalized matrices: a 4-nearest neighbor's matrix, a queen contiguity matrix of order 1, a queen contiguity matrix of order 2, a rook contiguity matrix of order 2. Standard errors and robust standard errors corresponding to the OLS and spatial models respectively are in brackets. *p<0.10; **p<0.05; ***p<0.01
Due to space constraint, the last two rows values are rounded off to two decimal digits.
Source: Own regressions