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# Empirical Evidence of the Myopic Nature of Special Purpose Local Sales Taxes to Fight Crime

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**Abstract**

**Background**: Local governments increasingly rely on sales taxes to raise revenue, often justifying the need for a local sales tax increase with a specific programmatic goal, such as better education or transportation. In Washington State, the legislature explained that a local sales tax increase was necessary to support criminal justice because criminal justice requires more police, courts, and jails.

**Objective**: Informed by decades of literature questioning the efficacy of fighting crime through police, courts, and jails, the objective of this study seeks to use empirical evidence to explain whether the social fabric offers indicators that can better define criminal justice and thus inform local tax policy so that local sales tax revenue may be used to prevent crime rather than fight it.

**Method**: The study compiled a 29-year history of 36 social variables across all 39 Washington counties to determine whether crime is predictable and what is most predictive of crime. Pearson coefficients of determination were calculated to identify cross-sectional associations between social variables and crime variables. An ARIMAX predictive model was then constructed to test the predictive power of the multivariate time series.

**Results**: The study finds that crime is predictable and social observations specific to how a child grows up are consistently predictive explanatory variables of crime. There is reason to believe that the most effective action state and local governments can take to promote criminal justice and prevent crime is to leverage their taxing power to ensure that every child (a) has access to food and basic necessities, (b) is raised in a safe and stable home, and (c) graduates from college.

**Keywords**: cultural competence, curriculum redesign, educator preparation, school leaders, ESSA

## Introduction

**In a modern schism from federalism known as devolution**, federal and state governments are increasingly entrusting counties and cities with the delivery of certain social services with little or no financial support from the central government (Krane et al., 2004; Pagano & Johnston, 2000; Shannon, 1987). Devolution is different from decentralization. Under decentralization, critical managerial and fiscal decisions are made at the top, while administration and execution are decentralized. In contrast, devolution shifts most responsibilities to local governments, which must provide a package of social and safety services while finding a way to pay for them (Krane et al., 2004;

Shannon, 1987). For example, local governments in the United States typically employ 45% of local general fund revenue to provide police and safety services, which in many other countries are fully funded by the central government (Bresser-Pereira, 2004; Krane et al., 2004; Pagano & Johnston, 2000).

Historically, property taxes have been the primary source of revenue for local governments in the United States. Since the Great Depression, however, public support for the property tax has dramatically declined. Whereas in 1902, property taxes accounted for 82% of all state and local tax revenues, by 1950, the property tax share fell to 45%, and by 2001 to 29% (A Guide to Property Taxes, 2004). This phenomenon is sometimes referred to as the property tax revolt. The property tax revolt forced local governments to provide social services without relying too heavily on property taxes, as they had in the past. Over the past five decades, local governments have struggled to make up for lost property tax revenue through other revenue sources, relying most heavily on sales taxes (Understanding the Basics of County and City Revenues, 2013).

At the local government level, sales taxes often take the form of Local Option Sales Taxes (LOST) (Afonso, 2015; Shadbegian, 1999; Zhao, 2005). Local Option Sales Taxes consist of optional local increases to the state-wide sales tax rate. The increase is optional because localities can decide whether to levy it and at what rate (within state-approved rates). LOST are levied for a local general fund but can also be levied to fund specific purposes, such as education or transportation, in which case they are commonly referred to as "Special Purpose" Local Option Sales Taxes (SPLOST). Some states, namely Tennessee, North Carolina, Georgia, and California, have spearheaded efforts to fund public schools and transportation through a SPLOST system (Brown et al., 2021; Brunner & Schwegman, 2017; Jansen, 1991; Lederman et al., 2020; Wang & Zhao, 2011; Zhao & Wang, 2015).

Devolution and the property tax revolt have had particularly detrimental effects on Washington counties and cities because in the State of Washington the income tax is unconstitutional. Therefore, the burden of lost property tax revenue has been largely borne by sales tax increases. Washington's tax system is in fact the most regressive in the nation, relying most heavily on sales taxes (Who Pays? A Distributional Analysis of the Tax Systems in all 50 States, 2018).

What is fundamentally unique about the State of Washington is that it is the first and only jurisdiction in the United States that ties one or more SPLOSTs, not to education or transportation but to criminal justice and juvenile detention facilities.

**Criminal Justice and Local Tax Policy in Washington**

Washington Senate Bill No. 6913 (1990 2nd. Ex. Sess.), which laid the foundation for the criminal justice SPLOST, began with the following statement:

The legislature finds and declares that local government criminal justice systems are in need of assistance. Many counties and cities are unable to provide sufficient funding for additional police protection, mitigation of congested court systems, and relief of overcrowded jails.

The opening statement on the Senate bill reveals two critical legislative assumptions:

1. That a criminal justice system is best supported with money.
2. That improving a criminal justice system requires more police, judicial bandwidth, and jail space.

Chapter 14 of Title 82 of the Revised Code of Washington authorized two SPLOSTs, the subject of this study. The first SPLOST allows any county to impose, without vote but subject to repeal by referendum, a 0.1% sales tax increase earmarked for criminal justice, broadly defined as “activities that substantially assist the criminal justice system, which may include circumstances where ancillary benefit to the civil justice system occurs, and which includes domestic violence services such as those provided by domestic violence programs, community advocates, and legal advocate….” (RCW 82.14.340). After collection, 10% of the tax remains in the county coffers, and 90% is shared among the county and the cities within the county in proportion to the population.

The second SPLOST allows counties with a population of less than one million to impose, subject to a majority approval of county voters, a 0.1% sales tax increase earmarked for “costs associated with financing, design, acquisition, construction, equipping, operating, maintaining, remodeling, repairing, reequipping, and improvement of juvenile detention facilities and jails” (RCW 82.14.350). Once collected, this tax remains entirely within the county coffers and is not shared with the cities in the county.

In state-issued literature, the two SPLOSTs mentioned above are typically referred to as the “Criminal Justice” SPLOST (first option) and the “Juvenile Facilities” SPLOST (second option) (Table 1).

Table 1. SPLOST Matrix

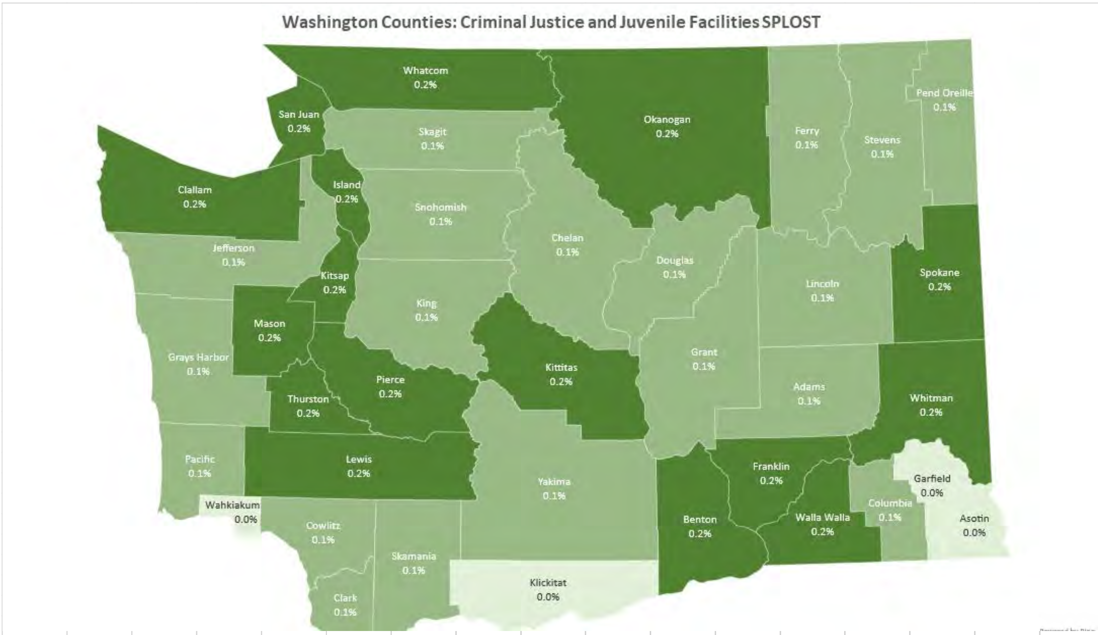
| **OPTION** | **1** | **2** |
|---|---|---|
| **AUTHORITY** | RCW 82.14.340 | RCW 82.14.350 |
| **KNOWN AS** | Criminal Justice SPLOST | Juvenile Facilities SPLOST |
| **AUTHORIZED JURISDICTIONS** | All Counties, no vote, subject only to repeal by referendum | Counties with populations of <1M, subject to a majority vote |
| **RATE OF TAX** | 0.10% | 0.10% |
| **YEAR FIRST ENACTED** | 1990 | 1995 |
| **PORTION EARMARKED** | 100.00% | 100.00% |
| **EARMARKED FUNDS MAY BE USED FOR** | Activities that directly or indirectly assist the criminal justice system | Costs associated with juvenile detention facilities and jails |

The Criminal Justice SPLOST became law in 1990. Only four counties chose to levy it immediately after the law took effect: King, Snohomish, Spokane, and Thurston. By 1996, the list had quintupled to 21 counties. By 2005, the list had grown to 32 counties. Pacific County was the latest addition to the list when it decided to impose the Criminal Justice SPLOST as of January 1, 2018.

The Juvenile Facilities SPLOST was enacted in 1995. Seven counties chose to levy it immediately after the law took effect: Benton, Franklin, Mason, Pierce, San Juan, Spokane, and Walla Walla. Kittitas and Thurston Counties joined the following year. Clallam and Okanogan County were the latest additions to the list when they decided to impose the Juvenile Facilities SPLOST as of April 1, 2018.

As of April 1, 2020, no Washington county had imposed the Juvenile Facilities SPLOST without also imposing the Criminal Justice SPLOST, although state law does not require one to be a condition of the other. Only four counties—Asotin, Garfield, Klickitat, and Wahkiakum—did not impose either SPLOST. All other counties have imposed either only the Criminal Justice SPLOST (represented in light green in Figure 1) or both (represented in bold green in Figure 1).

Figure 1. CJ and JF SPLOST Rates Map as of April 1, 2020




**Literature Review**

The Washington legislature essentially defined criminal justice as a three-dimensional expression of police staffing, judicial bandwidth, and jail space. The focus of this study is whether the social fabric of Washington counties offers indicators that can be used to better define criminal justice and shape local tax policy so that local sales tax revenue may be spent on crime prevention rather than crime control.

Over the past century, an ample body of empirical criminological research has looked at the statistical relationship between crime and social variables that correlate with crime. The early trend at the turn of the 19th century was to explain crime in terms of factors unique to the individual, such as sub-standard intelligence (Goddard, 1914), psychological powers (Aichhorn, 1925), biological imperfections (Dugdale, 1877), or "criminal bumps" on the head (Lombroso-Ferrero, 1911). The urbanization trend at the turn of the century accompanied a fundamental shift in criminological research, as studies began to focus more on social indicators of crime rather than the unique characteristics of the individual.

One of the masterminds of socially-induced crime theory was Robert Merton, who can be considered the father of social anomie theory (Merton, 1938). In general terms, social anomie theory suggests that an overly competitive society can disintegrate ethical behavior due to the struggle for survival of the fittest. Merton argued that rigid conformity to traditional American values of economic success created a fictional image in which anyone could achieve the American dream through hard work. This cultural indoctrination of obsessive economic success inevitably emarginated those unable to achieve the American dream through legitimate means. Therefore, Merton argued, the exaltation of "success-seeking" explained crime. In social anomie theory, "anomie" results from the weakening of ethical behavior as society places the largest emphasis on whether success is achieved, more so than how.

Social anomie theory rests on the premise that something is fundamentally broken in the social structure or its priorities, which fosters deviant behavior (Chamlin & Cochran, 1995; Heimer, 2019; Hövermann & Messner, 2021; Merton, 1938; Savolainen, 2000; Weiss et al., 2020). In this context, social anomie theory also implies that economic safety nets can mitigate the incidence of certain types of crime (DeFronzo, 1983; Hazra & Aranzazu, 2022; Rudolph & Starke, 2020).

The meta-analysis of one hundred years of criminological research offers valuable insights into how social trends shaped the research approach in the later part of the 20th century. The early individualistic studies of Dugdale (1877) and Goddard (1914) were followed by a more complex and urbanized world, which increased awareness of intricate social dynamics potentially leading to crime. Social anomie theory recognized these dynamics during five decades of immense social strain caused by two world wars and the Great Depression. These major events promoted a more liberal and collective agenda within criminological literature (Pratt, 2001). Unsurprisingly, social anomie theory came under attack in the 1970s, when the American dream and economic success returned to the forefront of self-identification, and anomie theory was seen as promoting an anti-American social agenda (Messner & Rosenfeld, 1997).

In the last 50 years, two new theories have emerged that are particularly relevant to this study: social disorganization theory and deprivation theory. Albeit both theories continue to identify the correlates of crime in the greater social context, they do not call into question the essence of American culture: economic success and the American dream.

Social disorganization theory rests on the statistical relationship between crime and social disorder indicators, such as increased urbanization, longer commute time, higher population density, and sparse friendship networks (Bellair, 1997; Bursik, 1988; He & Li, 2022; Hipp & Williams, 2020; Sampson & Groves, 1989; Shaw & McKay, 1972; Taylor, 1997). Shaw and McKay first formulated this theory when they studied juvenile crime across Chicago neighborhoods and found that crime was more prevalent in certain neighborhoods. They found that these neighborhoods were "socially disorganized" because they had weak social institutions—churches, schools, and youth organizations—unable to adequately supervise the youth. Research under traditional social disorganization theory addresses residential mobility, racial heterogeneity, the strength of social associations and networks, and socioeconomic status: all neighborhood-level indicators. A more focused approach to social disorganization theory has noted that traditional social disorganization theory has failed to consider the family structure as an indicator of the neighborhood structure (Sampson, 1986). In this respect, measures of family disruption, such as divorce, single parenthood, the strength of the family network, and time invested in raising children, offer additional indicators of social disruption at the micro and family levels (Cohen & Felson, 1979; Errol et al., 2021; Nigel, 2004; Sampson, 1986).

Unlike the previous theories, deprivation theory suggests that crime is related to indicators of economic deprivation, with a general lack of resources leading to higher crime (Burraston et al., 2018; De Courson &Nettle, 2021; Lilly et al., 1995; Turk, 1969). For example, multiple studies have found a significant positive relationship between unemployment rates and property crime (Krohn, 1976; Raphael & Winter-

Ebmer, 2001) or poverty and crime in general (Patterson, 1991; Peterson & Bailey, 1988). Based on deprivation theory, business and economic cycles are useful crime indicators (Taylor, 2020; Wagner, 1936). However, deprivation theory does not only take an absolute form—whether poverty or unemployment is present—but also a relative form. In its relative form, deprivation theory looks at inequality and wealth distribution rather than poverty or unemployment (Blau & Blau, 1982; Burraston et al., 2018). Relative deprivation research has found that economic inequality is positively associated with crime, suggesting that income redistribution may be a more effective crime intervention measure than punishment (Carroll & Jackson, 1983; Danziger & Wheeler, 1975; Ehrlich, 1973; Hazra & Aranzazu, 2022; Krahn et al., 1986; Rudolph & Starke, 2020; Vieraitis, 1999). Deprivation theory can be viewed as an evolution of social anomie theory, as both theories examine social stress between those who have and those who do not have as a precursor to crime. However, unlike social anomie theory, deprivation theory does not blame a broken success-hungry society. Deprivation theory merely suggests that meeting basic needs and avoiding excessive social stratification of classes may be sufficient to curb criminal behavior without redesigning the nature of American culture, driven by the pursuit of economic success.

All socially-related theories of crime—social anomie, social disorganization, family disruption, and deprivation—rest on the premise that crime needs space, time, and opportunity, where the wrong composition in the social fabric may provide fertile ground for criminal activity. Regardless of theory, criminological studies also typically incorporate demographic data as control variables because indicators of ethnic heterogeneity, youth population, population growth, gender, and age distribution provide important clues as to whether the socioeconomic milieu impacts certain segments of the population differently (Nivette, 2011).

Criminological theories are naturally interwoven. For example, increased divorce rates coupled with full employment of both parents would suggest lower property crime rates as deprivation decreases but higher non-property crime rates due to family disruption and social disorganization (Sampson, 1987). None of the theories claim to offer infallible predictions, but they are all based on data-driven statistical models (Morrow, 2012). Given the large body of criminological research on point, meta-analysis studies have synthesized the results of previous research to derive conclusions about the overall body of research on social correlates of crime (Bonta et al., 1998; Hsieh & Pugh, 1993; Nivette, 2011; Pratt, 2001; Pratt & Cullen, 2005). The meta-analysis studies yield four key paradigms of the strongest and most stable correlates of crime in the extensive research literature:

1. Indicators of social disorganization (SD).
2. Indicators of family disruption (FD).
3. Indicators of absolute or relative deprivation (ARD).
4. Demographics (DG).

Criminological literature offers four additional lessons that are important to this study. First, policing and arrest measures are among the weakest indicators of crime as they predict the use of public resources in fighting crime but not the crime itself (Pratt & Cullen, 2005). Therefore, data on the size of police forces or the number of arrests are not useful in estimating future crime trends.

Second, the empirical value of a crime indicator lies not only in its nature but also in its degree of change over time. For example, a 1993 study examined whether an abrupt change in a crime indicator was itself correlated with crime (Sampson & Laub, 1993). The 1993 study examined 500 delinquents and 500 control subjects matched by age, IQ, and neighborhood. The study then gathered detailed records of the subjects' life course and identified several life-turning points on a common scale. The study found that weak relationships in youth can lead to weaker social bonds in adulthood (e.g., weaker labor force attachment and marital cohesion). Thus, the benefits of a longitudinal study are evident in its ability to capture the impacts of change over time.

Third, crime is often spatially autocorrelated (Huebner & Bynum, 2016; Levine, 2013), and this autocorrelation principle, coupled with longitudinal data and spatial association, dramatically improves the predictive power of a statistical model. This is the very principle behind the *CrimeStat* software, a crime prediction software developed under the direction of the United States Department of Justice.

The fourth lesson is the observation that most criminological studies examine crime correlates at a macro-level (e.g., national or state) or micro-level (e.g., neighborhood) unit of analysis (Pratt, 2001). This consideration and this study's own data collection efforts lead to the belief that the lack of county-level longitudinal studies on crime indicators is at least partially explained by the scarcity of uniform and consistent criminological data at the county level.

**Data and Unit of Analysis**

This study assesses data pertaining to the two 0.1% Criminal Justice and Juvenile Facilities SPLOSTs. As the county is the relevant unit of analysis, data available at the macro level were specifically excluded in favor of micro and meso-level indicators. The data selection in this study was driven by the literature review and its mere availability. For example, the most reliable source of consistently and uniformly reported data strictly related to adult crime at the county level is the number of criminal charges filed in each superior court. Similarly, the only indicators of juvenile crime consistently reported at the county level are the number of cases and arrests. However, these observations have limitations. Not all arrests result in criminal charges, and not all charges result in a conviction. Nevertheless, the study selected the best available observations consistently and uniformly reported at the county level for adult and juvenile crime. On this basis, eight measures of crime and 28 measures of the socioeconomic fabric were compiled for each county in Washington for annual lags from 1990 to 2018 (Table 2). The study focused on data from 1990 onward because the Criminal Justice SPLOST became effective in 1990, while the Juvenile Facilities SPLOST became effective in 1995.

Table 2. Archival Data

| **CRIME DATA** | | **SOCIAL DATA** |
|---|---|---|
| · CD CJ VC: Homicide Charges per 100,000 People | | · FD: % of Total Births to Unmarried Teenage Mothers (15-19) |
| · CD CJ VC: Sex Crimes Charges per 100,000 People | | · FD: % of Total Births to Unmarried Mothers |
| · CD CJ VC: Assault Charges per 100,000 People | | · FD: Children in Foster Care Placement per 1,000 People |
| · CD CJ VC: Robbery Charges per 100,000 People | | · FD: Divorce per 1,000 People |
| · CD CJ NVC: Non-violent Property Crimes Charges per 100,000 People | | · SD: Population Density (PPL/Sq mi) |
| · CD CJ: Total Criminal Complains per 100,000 People | | · SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men) |
| · CD JF: Total Juvenile Arrests per 100,000 People | | · SD: Average Reported Poor Mental Health Days |
| · CD JF: Total Juvenile Cases per 100,000 People | | · SD: Income Inequality Ratio (80th Percentile Income/20th Percentile) |
| | | · SD: Residential Segregation Index - Black/White |
| | | · SD: Residential Segregation Index - non-white/White |
| | | · SD: High School Graduation Rate |
| | | · SD: % Population with Some College Education |
| | | · SD: % Population with a College Degree |
| | | · ARD: % Unemployed |

| | | |
|---|---|---|
| | | · ARD: % Total Adults without Health Insurance |
| | | · ARD: % Children without Health Insurance |
| | | · ARD: % of Total Population in Poverty |
| | | · ARD: % Children under 18 in Poverty |
| | | · ARD: % Children Participating in Basic Food Program |
| | | · ARD: % Homeowners |
| | | · ARD: % Severe Housing Problems |
| | | · DG: Per Capita Income |
| | | · DG: Median Household Income |
| | | · DG: % less than 18 years of age |
| | | · DG: % Female |
| | | · DG: % Not Proficient in English |
| | | · DG: % Rural |
| | | · DG: Political Party Affiliation |

## Methodology

The availability of a 29-lag time series across 36 variables lends itself to the ARIMAX forecasting model. ARIMAX is a combination of autoregressive (AR) integrated (I) moving average (MA) statistical procedures with explanatory variables (X).

ARIMAX (*p, d, q*)

Where

*p*=AR term, order of autoregression

*d*=degree of differencing to render the time series stationary

*q*=MA term, order of the moving average

X=explanatory variables

An ARIMAX model can combine autoregression and the moving average of a variable's trend along with the cointegration of multiple explanatory variables. When the ARIMAX model is well-fitted, its forecasting power is far superior to regression, autoregression, or moving average alone, as ARIMAX brings together all three elements.

Fitting an ARIMAX model requires four key elements:

1. Rendering the data stationary.
2. Finding the degree of dependency between an observation and its lagged observations.
3. Finding the degree of dependency between an observation and the residuals from its lagged observations.
4. Identifying and incorporating the explanatory variables.

**Rendering the Data Stationary**

A stationary time series is a series whose properties do not depend on fixed-length cycles or seasonality. One of the common methods to render non-stationary data stationary is differencing, which consists of computing the difference between consecutive observations. The degree *d* in the I element of the ARIMA model indicates the level of differencing required to render the time series stationary. An ARIMA model with I(0) means that the data is already stationary.

To test the time series for stationarity, a random sample of four counties (Chelan, Kitsap, Spokane, Yakima) was selected, and the Dickey and Fuller (1979) stationarity test was applied to each observed crime measure. For all variables and all four counties, the p-value of the Dickey and Fuller stationarity test could not be rejected until 1 degree of differencing was added to render the data stationary.

**Autoregression and Moving Average**

The literature consistently suggests that crime is spatially autocorrelated (Huebner & Bynum, 2016; Levine, 2013; Chamlin, 1988), and this autocorrelation principle is the lynchpin of the *CrimeStat* software, a crime prediction software developed under the direction of the United States Department of Justice. Autocorrelation means that a future observation is predictable based on past observations, implying that a statistical relationship exists between past and future lags.

The autoregressive and moving average elements of an ARIMAX model capture autocorrelation in two distinct ways. The autoregressive element forecasts future values based on past values; the moving average element leverages the residuals (the errors) in the previous forecasts to improve the quality of future forecasts. The combination of the two elements extrapolates the predictive power of an autocorrelated time series.

The degree of dependency *p* between an observation and its lagged values is known as autoregression and can be expressed as AR(*p*); it represents the lingering effects of preceding values on future values. An AR (0) would mean that lag observations are completely random and not dependent on each other.

Observations with no correlation are referred to as white noise, and the resulting forecast is called a random walk.

The degree of dependency *q* between an observation and the residuals from its lagged observations is known as the moving average and can be expressed as MA(*q*). An MA(2) would indicate that the residual values of two previous lags times a coefficient can forecast the next lag. This is known as the order of the moving average. As more lag residuals are needed to forecast an observation through the MA model, the order *q* of the moving average increases.

In ARIMAX models with AR and MA terms, the terms that best fit the model are determined by running the model on multiple AR and MA terms and selecting the one with the lowest error score. In this study, Schwarz's Bayesian Criterion (SBC) was used as the measure of prediction error to select the best AR and MA terms (Schwarz, 1978). A model was run for four randomly selected counties (King, Jefferson, Lewis, Whatcom) on multiple AR and MA terms to verify whether the autocorrelation terms in the time series are consistent across all counties. SBC scores were calculated on each iteration, and the terms yielding the lowest SBC score were selected as the best fit (Table 3). The result was that no AR and MA terms would fit every county for every observed measure. Instead, the model must be fitted on a county-by-county level as each county's crime patterns follow different autocorrelation terms.

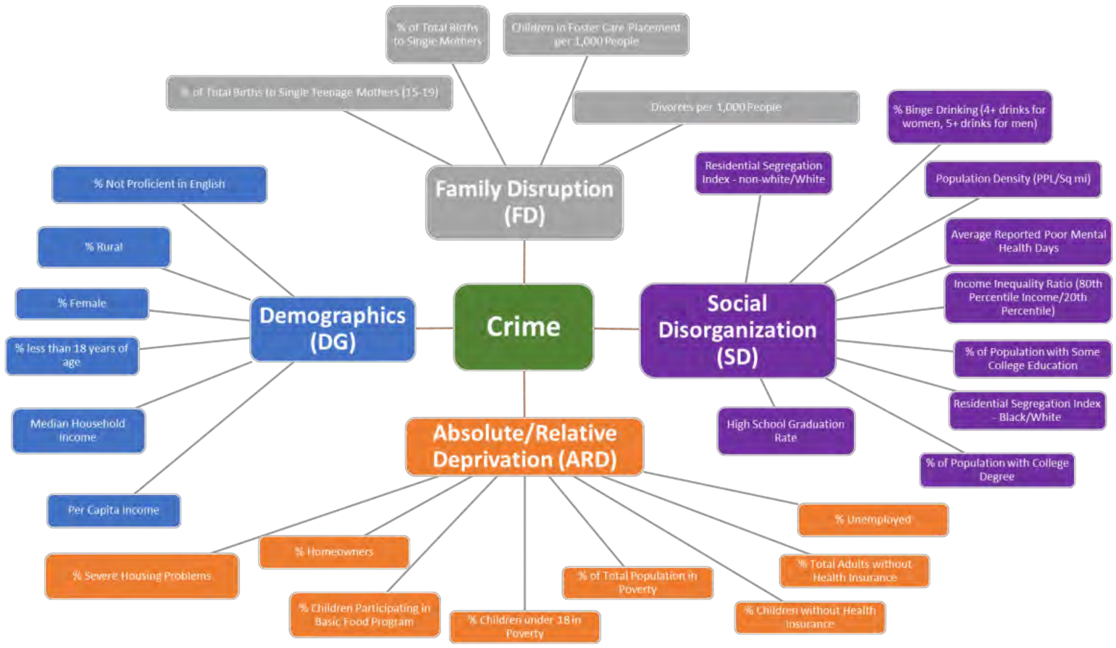
Table 3. AR(*p*) and MA(*q*) Terms: Select Counties

| | **King** | | **Jefferson** | | **Lewis** | | **Whatcom** | |
|---|---|---|---|---|---|---|---|---|
| | **AR(*p*)** | **MA(*q*)** | **AR(*p*)** | **MA(*q*)** | **AR(*p*)** | **MA(*q*)** | **AR(*p*)** | **MA(*q*)** |
| Homicide Charges | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Sex Crimes Charges | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Assault Charges | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 |
| Robbery Charges | 1 | 3 | 1 | 2 | 1 | 1 | 1 | 1 |
| Property Crimes Charges | 1 | 3 | 1 | 2 | 1 | 1 | 1 | 1 |
| Total Charges | 1 | 3 | 1 | 2 | 1 | 1 | 1 | 1 |
| Total Juvenile Arrests | 1 | 4 | 1 | 4 | 1 | 1 | 1 | 1 |
| Total Juvenile Cases | 1 | 4 | 1 | 4 | 1 | 1 | 2 | 2 |

**Incorporating Explanatory Variables**

Criminological research indicates that crime is not only the result of previous crime but is closely related to indicators of the social fabric that provide space and opportunity for crime (Figure 2).

Figure 2: Crime and Social Variables, Radial Cluster




Pearson coefficients of determination were calculated to identify cross-sectional associations between each observed social variable and each measure of adult and juvenile crime. (Table 4).

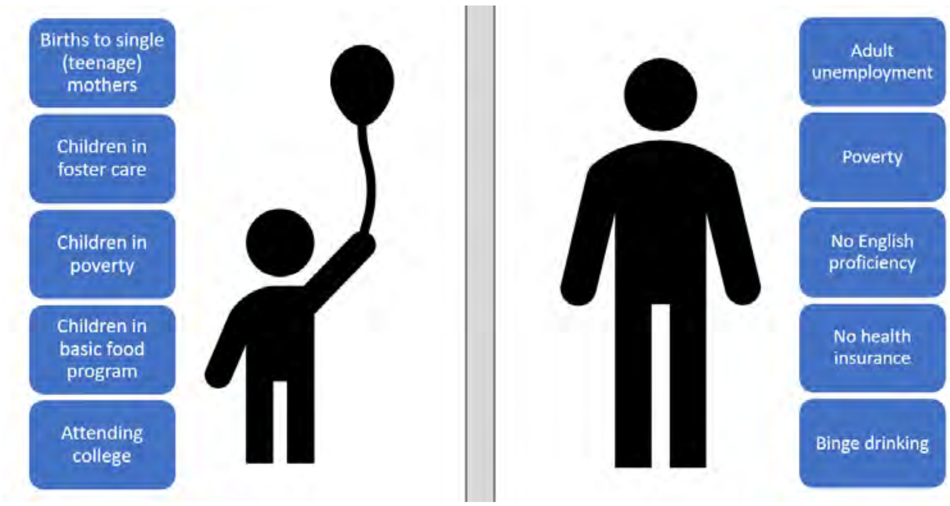
Table 4. Pearson Coefficients of Determination, Social Variables

| *Values in bold are different from 0 with a significance level of alpha=0.05* | Homicide Charges | Sex Crimes Charges | Assault Charges | Robbery Charges | Non-Violent Property Charges | Total Criminal Complaints | Juvenile Arrests | Total Juvenile Cases |
|---|---|---|---|---|---|---|---|---|
| FD: Births to Single Teenage Mothers (15-19) | **0.043** | **0.088** | **0.037** | **0.011** | **0.062** | **0.119** | **0.099** | **0.131** |
| FD: Births to Single Mothers | **0.023** | **0.078** | **0.168** | **0.006** | **0.060** | **0.165** | **0.063** | **0.193** |
| FD: Children in Foster Care | **0.049** | **0.098** | **0.036** | 0.001 | **0.037** | **0.042** | **0.060** | **0.027** |
| FD: Divorces per 1,000 ppl | 0.002 | 0.000 | **0.029** | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 |
| SD: Population Density | **0.082** | **0.070** | **0.031** | **0.014** | **0.049** | **0.066** | **0.044** | **0.061** |
| SD: Mental and Substance Abuse Disorder Deaths | **0.019** | **0.055** | **0.095** | **0.008** | **0.020** | **0.083** | **0.043** | **0.040** |
| SD: % Binge Drinking | 0.002 | **0.029** | **0.062** | **0.015** | **0.062** | **0.111** | **0.303** | **0.160** |
| SD: Average Reported Poor Mental Health Days | **0.004** | **0.036** | **0.029** | 0.000 | **0.025** | **0.052** | **0.016** | 0.000 |
| SD: Income Inequality Ratio | 0.000 | **0.004** | **0.006** | **0.007** | **0.010** | **0.018** | **0.116** | **0.039** |
| SD: Residential Segregation Index - Black/White | 0.001 | **0.020** | **0.007** | **0.019** | **0.031** | **0.030** | **0.005** | 0.001 |
| SD: Residential Segregation Index - non-white/White | **0.017** | **0.008** | 0.002 | **0.003** | **0.018** | **0.006** | **0.023** | 0.003 |
| SD: High School Graduation Rate | 0.000 | **0.006** | **0.005** | 0.002 | **0.013** | **0.032** | 0.001 | **0.006** |
| SD: % Population with Some College Education | **0.013** | **0.003** | 0.001 | 0.003 | **0.006** | 0.002 | **0.051** | 0.000 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| SD: % Population with a College Degree | **0.074** | **0.161** | **0.106** | **0.009** | **0.139** | **0.230** | **0.114** | **0.160** |
| ARD: % Unemployed | **0.044** | **0.079** | **0.059** | **0.003** | **0.017** | **0.046** | **0.029** | **0.016** |
| ARD: % Total Adults without Health Insurance | **0.028** | **0.022** | **0.033** | **0.005** | **0.028** | **0.046** | **0.150** | **0.116** |
| ARD: % Children without Health Insurance | **0.076** | **0.025** | 0.002 | **0.005** | 0.000 | 0.000 | 0.000 | **0.025** |
| ARD: % of Total Population in Poverty | **0.071** | **0.029** | **0.065** | 0.002 | **0.022** | **0.065** | **0.049** | **0.047** |
| ARD: % Children in Poverty | **0.094** | **0.087** | **0.121** | **0.005** | **0.042** | **0.105** | **0.035** | **0.153** |
| ARD: % Children in Basic Food Program | **0.035** | **0.062** | **0.141** | **0.027** | **0.059** | **0.136** | **0.070** | **0.122** |
| ARD: % Homeowners | **0.020** | **0.025** | 0.001 | **0.014** | 0.000 | 0.002 | **0.060** | 0.000 |
| ARD: % Severe Housing Problems | 0.002 | **0.027** | **0.010** | 0.001 | **0.014** | **0.013** | 0.000 | **0.041** |
| DG: Per Capita Income | **0.053** | **0.027** | **0.007** | **0.010** | **0.022** | **0.008** | **0.017** | 0.000 |
| DG: Median Household Income | **0.107** | **0.043** | 0.001 | **0.004** | **0.033** | **0.015** | 0.002 | **0.012** |
| DG: % less than 18 years old | **0.015** | **0.015** | 0.001 | **0.026** | **0.033** | **0.033** | **0.294** | **0.088** |
| DG: % Female | **0.020** | **0.006** | 0.000 | **0.008** | 0.002 | 0.002 | **0.013** | **0.004** |
| DG: % Not Proficient in English | **0.004** | 0.000 | **0.019** | **0.026** | **0.006** | **0.031** | **0.312** | **0.072** |
| DG: % Rural | **0.116** | **0.050** | 0.001 | **0.016** | 0.000 | 0.001 | **0.118** | **0.020** |
| DG: Relevant Previous Presidential Election Turnout | **0.020** | **0.021** | **0.037** | 0.001 | **0.018** | **0.042** | **0.096** | **0.059** |

While some social variables are statistically significant for only some observed measures of crime, others are significant across the board. Social observations specific to how a child grows up—births to single mothers, children in foster care, children in poverty, children in basic food programs—are consistently significant to each observed measure of crime. A generalization can be made that unstable family dynamics and poverty among children are perhaps precursors to other social variables that also significantly impact crime, such as adult unemployment, binge drinking, college education, and adults without health insurance (Figure 3).

Figure 3: Most Important Explanatory Variables, Children and Adults




Besides identifying social indicators that are consistently significant to crime, criminological research points out another critical element of crime prediction: crime is intercorrelated. Intercorrelation refers to the fact that other crimes accompany incidences of crime, and therefore a predictive model must account for crime as an explanatory factor of crime itself. Hence, all observed adult and juvenile crime measures are expected to be statistically significant to each other with a strong positive association. If this is the case, each observed crime measure will also serve as an explanatory variable *x* in the ARIMAX model for *y*. The expectation is confirmed by a high and always positive correlation among all the observed crime measures (Table 5).

Table 5: Pearson Correlation Matrix, Crime Measures

| *Values in bold are different from 0 with a significance level of alpha=0.05* | Homicide Charges | Sex Crimes Charges | Assault Charges | Robbery Charges | Non-Violent Property Charges | Total Criminal Complaints | Juvenile Arrests | Total Juvenile Cases |
|---|---|---|---|---|---|---|---|---|
| Homicide Charges | **1** | **0.222** | **0.122** | **0.068** | **0.123** | **0.158** | -0.054 | **0.110** |
| Sex Crimes Charges | **0.222** | **1** | **0.369** | **0.109** | **0.307** | **0.475** | **0.145** | **0.309** |
| Assault Charges | **0.122** | **0.369** | **1** | **0.279** | **0.463** | **0.695** | **0.188** | **0.301** |
| Robbery Charges | **0.068** | **0.109** | **0.279** | **1** | **0.277** | **0.335** | **0.119** | 0.048 |

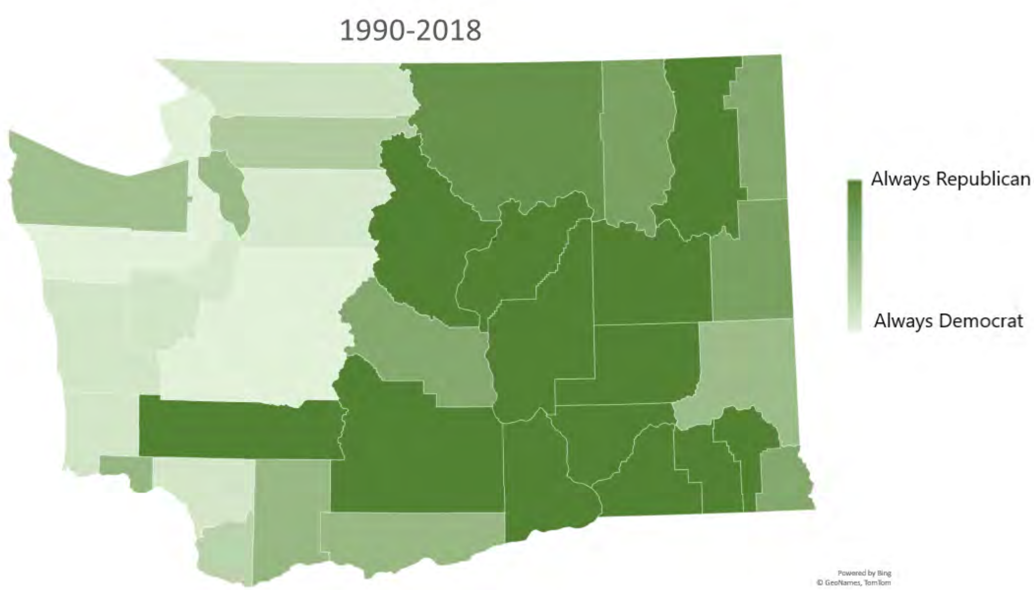
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Non-Violent Property Crimes Charges | **0.123** | **0.307** | **0.463** | **0.277** | **1** | **0.766** | **0.264** | **0.284** |
| Total Criminal Complaints | **0.158** | **0.475** | **0.695** | **0.335** | **0.766** | **1** | **0.364** | **0.382** |
| Total Juvenile Arrests | -0.054 | **0.145** | **0.188** | **0.119** | **0.264** | **0.364** | **1** | **0.431** |
| Total Juvenile Cases | **0.110** | **0.309** | **0.301** | 0.048 | **0.284** | **0.382** | **0.431** | **1** |

**Exploring the Impact of Political Affiliation**

Many tax policy decisions are driven, at least in part, by political affiliation (Afonso, 2014; Green, 2006; Hamideh et al., 2008; Jung, 2001; Luna et al., 2007). Thus, political affiliation is often a component of statistical models that predict the outcome of tax measures. While Republican voters are less likely to favor any tax measure (Green, 2006; Hamideh et al., 2008; Shock, 2013), research shows that they prefer local option sales taxes over property taxes (Jung, 2001; Zhao & Jung, 2008), especially when the sales tax is levied in exchange for property tax relief (Jung, 2001; Luna et al., 2007; Sanders & Lee, 2009; Zhao & Jung, 2008).

If a statistical relationship exists between a county's political affiliation and taxable retail sales or a county's propensity to impose the Criminal Justice or Juvenile Facilities SPLOST, the political affiliation can also be fitted into the ARIMAX model. Data of each county's presidential election turnout over the 29 years of this study was tabulated as binary values, where 1 indicates that the county's majority vote in the immediately preceding presidential election was for the Republican candidate and 0 for the Democrat candidate (Figure 4).

Figure 4. Political Affiliation



At the 95% confidence interval, the biserial correlation shows that, while political affiliation is statistically significant with many social variables observed in this study, it is not associated or only negligibly associated with any measure related to sales tax revenue as far as Washington counties are concerned (Tables 6 and 7).

Table 6. Correlation Matrix: Political Affiliation/Sales Tax Variables

| Variables | correlation |
|---|---|
| RC: Total Taxable Retail Sales per 1,000 People | **-0.074** |
| Presumed SALTAX Spillover Index | **-0.170** |
| RC: Total Tax Revenue per 1,000 People | **-0.170** |
| RC: General Fund Sales and Use Tax Revenue (SALTAX) per 1,000 People | **-0.083** |
| RC: Degree of Reliance on Sales Taxes | **0.072** |
| SPLOST CJ: Criminal Justice SPLOST? | 0.047 |
| SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000 People | -0.043 |
| SPLOST JD: Juvenile Detention SPLOST? | **-0.072** |
| SPLOST JD: RCW 82.14.350 Revenue (Juvenile Detention) per 1,000 People | -0.063 |

*Values in bold are different from 0 with a significance level of alpha=0.05*

Table 7. Correlation Matrix: Political Affiliation/Other Social Variables

| Variables | correlation |
| --- | --- |
| CJ VC: Homicide Charges per 100,000 People | **0.143** |
| CJ VC: Sex Crimes Charges per 100,000 People | **0.144** |
| CJ VC: Assault Charges per 100,000 People | **0.192** |
| CJ VC: Robbery Charges per 100,000 People | 0.029 |
| CJ NVC: Property Crimes Charges per 100,000 People | **0.134** |
| CJ: Total Criminal Complaints per 100,000 People | **0.204** |
| JD: Total Juvenile Arrests per 100,000 People | **0.309** |
| JD: Total Juvenile Cases per 100,000 People | **0.243** |
| FD: % of Total Births to Single Teenage Mothers (15-19) | **0.174** |
| FD: % of Total Births to Single Mothers | **0.239** |
| FD: Children in Foster Care Placement per 1,000 People | 0.014 |
| FD: Divorces per 1,000 People | **-0.220** |
| SD: Population Density (PPL/Sq mi) | **-0.389** |
| SD: Mental and Substance Abuse Disorder Deaths per 100,000 People | -0.031 |
| SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men) | **-0.321** |
| SD: Average Reported Poor Mental Health Days | **-0.242** |
| SD: Income Inequality Ratio (80th Percentile Income/20th Percentile) | -0.061 |
| SD: Residential Segregation Index - Black/White | 0.065 |
| SD: Residential Segregation Index - non-white/White | 0.054 |
| SD: High School Graduation Rate | **0.074** |
| SD: % Population with Some College Education | **-0.104** |
| SD: % Population with a College Degree | **-0.345** |

| | |
|---|---|
| ARD: % Unemployed | 0.042 |
| ARD: % Total Adults without Health Insurance | **0.260** |
| ARD: % Children without Health Insurance | **0.141** |
| ARD: % of Total Population in Poverty | **0.348** |
| ARD: % Children under 18 in Poverty | **0.320** |
| ARD: % Children Participating in Basic Food Program | **0.239** |
| ARD: % Homeowners | 0.000 |
| ARD: % Severe Housing Problems | **-0.179** |
| DG: Per Capita Income | **-0.151** |
| DG: Median Household Income | **-0.166** |
| DG: % less than 18 years of age | **0.234** |
| DG: % Female | **-0.172** |
| DG: % Not Proficient in English | **0.295** |
| DG: % Rural | **0.119** |

*Values in bold are different from 0 with a significance level of alpha=0.05*

In general terms, Republican counties prosecute more crimes, as evidenced by a positive relationship between political affiliation and adult charges across all observed crimes except for robbery. Similarly, Republican counties experience more juvenile arrests and significantly more juvenile charges than Democrat counties. Republican counties are substantially less densely populated and less correlated with binge drinking or mental disorders. The demographic variables also suggest that people in Republican counties have more children, including more births to single mothers, but are less likely to divorce. While high school graduation rates are similar across the board regardless of political affiliation, Republican counties have fewer people with college degrees and far more adults and children in poverty and without health insurance. Ultimately, Republican counties in Washington are more rural, male-dominant, and are home to more people who are not proficient in English.

The biserial correlation paints a detectable profile between political affiliation and a county's social structure and crime output. However, there is no statistical significance between revenue composition and party affiliation. In other words, the local tax portfolio of Washington counties is not statistically associated with how a county population votes in presidential elections.

**Empirical Testing**

Fitting an ARIMAX model requires trial and error. The quality of the ARIMAX model is determined by (a) whether the residuals are autocorrelated, (b) whether the model forecast can taper off the residuals close to zero, and (c) the width of upper and lower bound forecast at a 95% confidence interval assuming an identical replication of the explanatory variables for the next 29 years.

The descriptive statistics have shown that applying the same ARIMAX model to each county is impossible as each county's crime patterns follow different autocorrelation terms. Thus, the ARIMAX model was fitted separately for each observed measure to four randomly selected counties (Benton, Douglas, Pierce, Stevens) based on consistent differencing term and explanatory variables but county-specific AR and MA terms.

ARIMAX ($p_c$, *0*, $q_c$)

Where

$p_c$=county specific AR term

*0*=degree of differencing to render the time series stationary

$q_c$=county specific MA term

X=explanatory variables

**Results**

Given the small number of homicide and robbery charges, forecasting is not reliable for those crimes. Similar limitations, albeit to a lesser extent, apply to sex crimes and assault. However, the ARIMAX model is very well-fitted to explain non-violent property crimes, total adult charges, juvenile arrests, and juvenile cases in all four counties (Figures 5-8).

Figure 5: Nonviolent Property Crimes ARIMAX Visualization

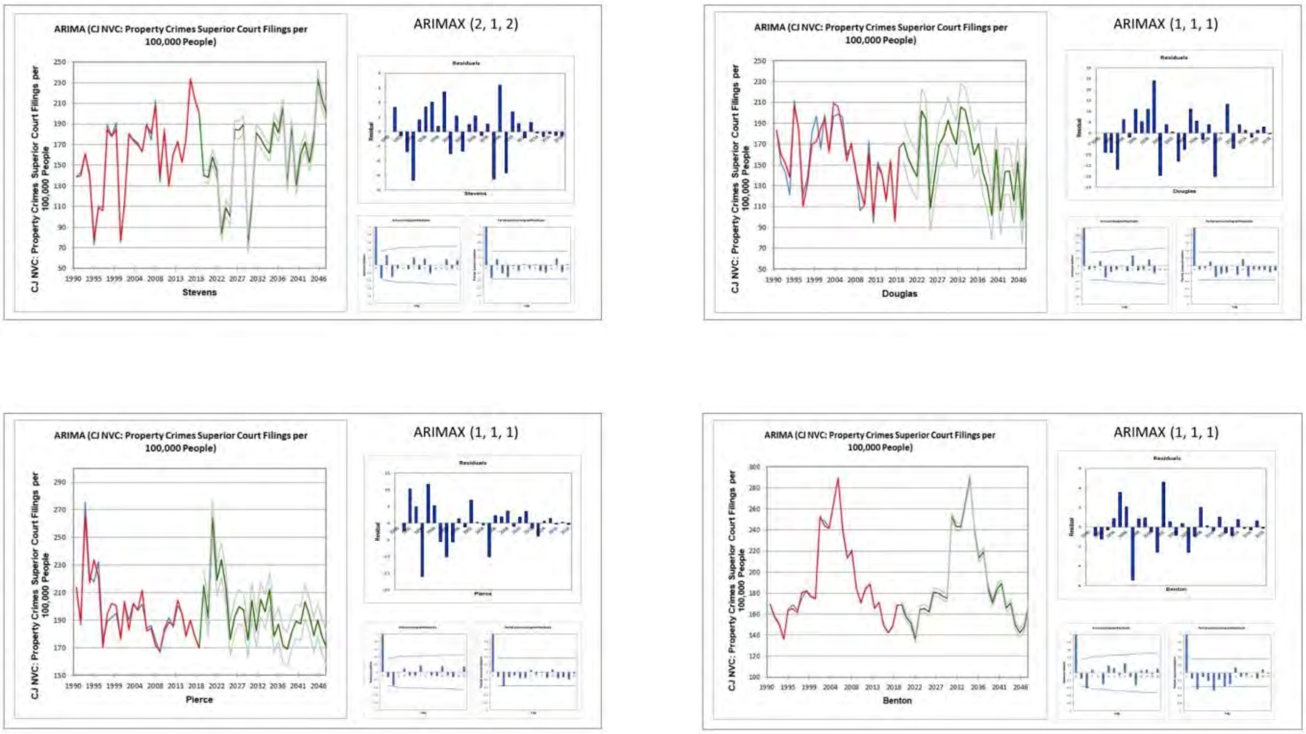



Figure 6: Total Adult Charges ARIMAX Visualization

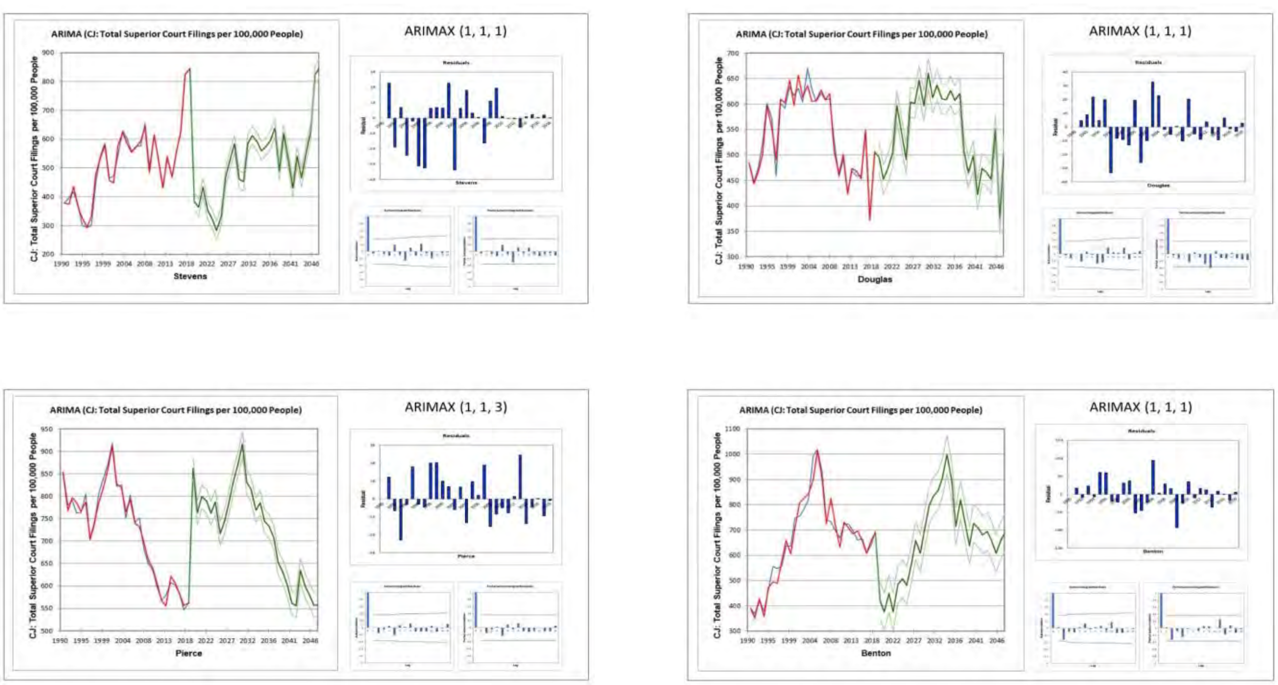


Figure 7: Juvenile Arrests ARIMAX Visualization

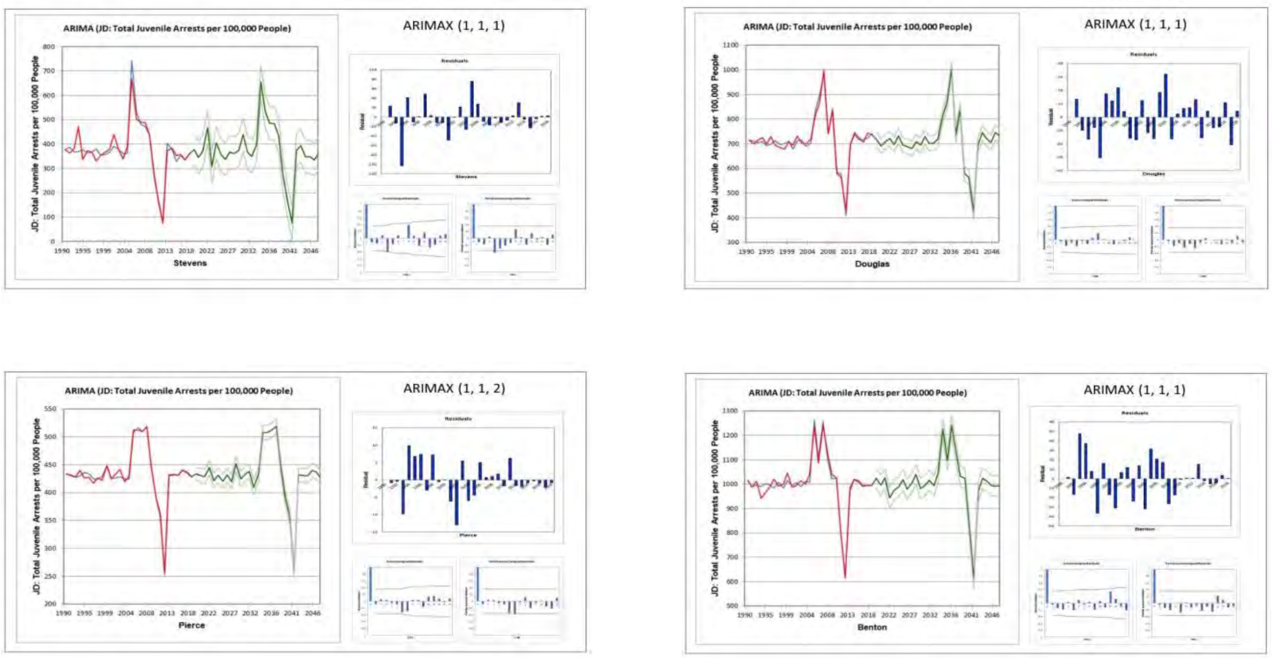
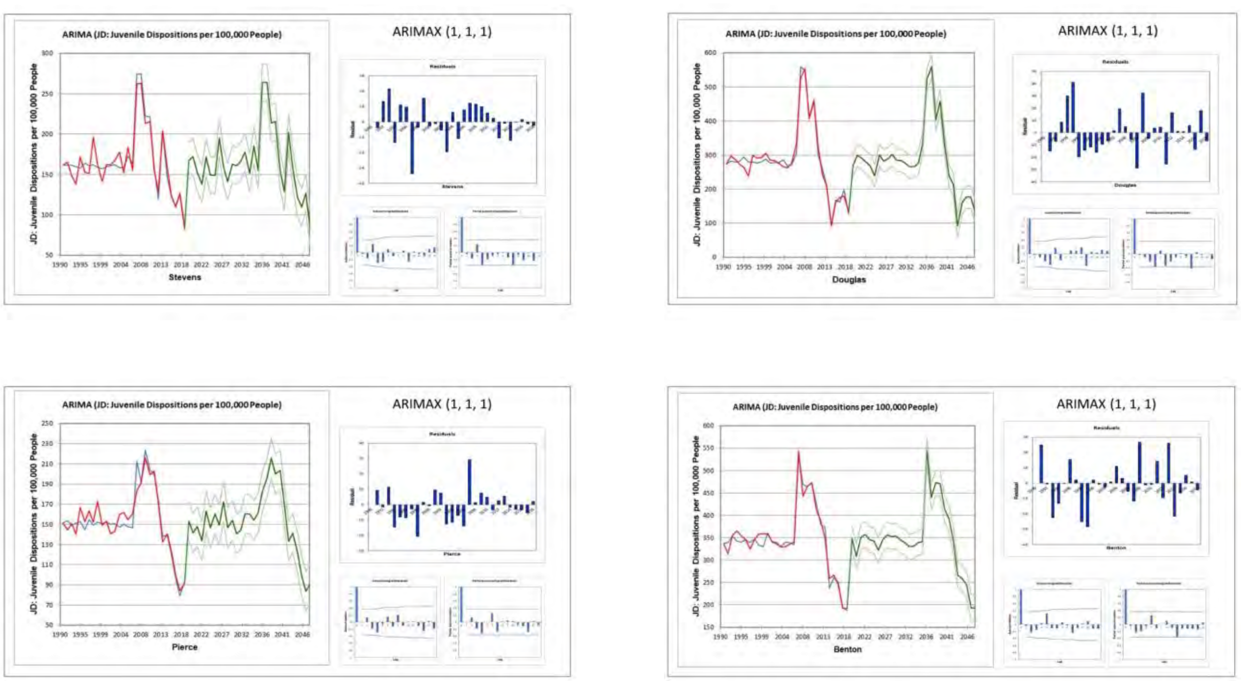



Figure 8: Total Juvenile Cases ARIMAX Visualization



Although the ARIMAX models exhibited consistent goodness of fit, the models did not equally fit across all observed crime measures. Four patterns emerged:

1. Adult crimes occurring less often are more difficult to forecast with the data in this study.
2. The data in this study are more robust with respect to non-violent property crimes than any other observed crime measure.
3. While the ARIMAX model has limitations in forecasting individual categories of adult crime, it performs well in predicting the total number of adult criminal charges without regard to the type of offense.
4. As for the observed juvenile measures, the model fits equally well for total juvenile arrests and total juvenile cases, suggesting a cointegration of the two observed time series.

## Summary and Conclusions

The real significance of the ARIMAX models is not that future crime can be predicted but that it can be prevented. The models show that crime is an expression of identifiable clues embedded in the socioeconomic fabric of each county. As long as the Washington legislature understands criminal justice as a three-dimensional expression of more police, more courtrooms, and more jail space, they will not successfully influence the multitude of social clues that predict crime. Legislative policy, both in terms of criminal justice and tax policy, should be informed by demographics, wealth distribution, poverty, educational attainment, and unemployment, rather than police staffing, congested court systems, and jail sizes.

Social variables specific to how a child grows up—births to single mothers, children in foster care, children in poverty, children in basic food programs—are consistently predictive of crime and possibly precursors to other variables predictive of crime later in life, such as adult unemployment, lack of college education, lack of health insurance, income inequality, per capita income, binge drinking, etc. In 2018 alone, Washington counties and cities collected more than $175 million in Criminal Justice SPLOST and $60 million in Juvenile Facilities SPLOST. There is reason to believe that the most effective action counties could take to advance criminal justice is to leverage their taxing power to guarantee that every child (a) has access to food and primary necessities, (b) is raised in a safe and stable home, and (c) graduates from college.

### Areas of Further Research

The main limitation of this study should also stimulate future and further research. The core limitation is that the empirical selection of a single state and counties within its borders may severely limit the generalizability of the findings. Future research should therefore replicate and extend this work in two directions. First, research should explore whether the social indicators that best predict crime differ regionally. Second, future research should question the aggressive advance of SPLOST by exploring whether empirical evidence supports the legislative premise and the intended outcomes.

### Geolocation Information

The data supporting this study's findings are specific to the State of Washington and its 39 counties.

**Declaration of Interest Statement**

There are no relevant financial or non-financial competing interests to report.

**Data Availability Statement**

The dataset compiled for this study consists of publicly available data. The dataset is available upon reasonable request from the corresponding author, F.A.

**List of Acronyms**

ARD: Absolute or Relative Deprivation

CD: Crime Data

CJ: Criminal Justice

DG: Demographics

FD: Family Disruption

JF: Juvenile Facilities

LOST: Local Option Sales Tax

NVC: Non-violent Crime

SD: Social Disorganization

SPLOST: Special Purpose Local Option Sales Tax

VC: Violent Crime

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