A LONGITUDINAL STUDY OF SPECIAL PURPOSE LOCAL OPTION SALES TAXES AND SOCIAL INDICATORS OF CRIME ACROSS WASHINGTON COUNTIES

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Abstract

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The 19th century witnessed an unprecedented urbanization trend that increased the density and synergy of communal networks, social behaviors, and interjurisdictional legislative policies, thereby deeply reshaping social science research. Crime, once thought to stem purely from an individual's malevolent disposition, was rediscovered as an articulation of social disfunction. Criminological research has repetitively linked social disfunction in America with the competitive nature of urbanization, where the obsessive pursuit of success meets an environment with a finite amount of resources. Competition is also at the heart of modern tax policy, especially insofar as local governments are concerned. A modern American phenomenon termed 'devolution' causes federal and state governments to mandate that counties and cities provide a standard package of

social services with little or no financial support, thus forcing horizontally equivalent local jurisdictions to compete against each other for tax revenue.

Washington counties have not escaped the national pressure to compete. As a state that relies heavily on sales taxes, tax competition in Washington has become fierce, particularly at the local government level in the form of Local Option Sales Taxes (LOST) and Special Purpose Local Option Sales Taxes (SPLOST). Applying lessons from criminological and tax research, the study examines a 29-year history of social variables to understand how urbanization has shaped the socioeconomic structure of Washington counties and whether competition for tax revenue advances the legislative intent of two Washington SPLOSTs, one earmarked for criminal justice and the other for juvenile detention facilities.

The study finds that a county's propensity to impose either SPLOST is not significantly correlated with any observed measure of crime or social predictor of crime. Under the demagogic guise of criminal justice, tax policy seems informed solely by pecuniary factors: population, income, and economic activity. Results from statistical analyses based on 29 years of social trends in Washington counties indicate that millions of dollars spent annually to augment police staffing, judicial bandwidth, and jail space were not effective at preventing crime. The study results further suggest that these funds could have been much more effective at preventing crime if used to ensure that every Washington child (a) eats, (b) learns English in order to have wider access to educational and employment opportunities, and (c) graduates from college.

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ACKNOWLEDGEMENTS

This dissertation is a testament to the kindness and power of encouragement of my reading committee. I have been blessed with committee members whose sense of compassion is as deep as their intellectual acumen. There has not been a single exchange where their feedback was not accompanied by words of support and motivation. Thank you for believing that I could do this.

DEDICATION

To my mother, who lives her dream of a better life through my eyes.

To my son Matteo, the greatest love of my life.
~ Papà

Chapter 1. INTRODUCTION AND LITERATURE REVIEW

Social interdependence has become drastically more prominent in the last one hundred years with the exponential growth of urbanization. While only 40% of the American population lived in urban areas at the turn of the 19th century, that percentage nearly doubled to 79% by the turn of the 20th century and is predicted to grow to almost 90% by 2050.[1] The State of Washington has closely followed national trends with 38% of the state population living in urban areas in 1900 and 82% in the year 2000.[2]

The urbanization trend has increased the density of social networks, including the intertwining of behavioral and policy phenomena that before the 19th century were thought to be independent of each other. For example, early criminological research viewed crime as the expression of something wrong with the individual committing the crime, such as sub-standard intelligence (Goddard 1914), psychic forces (Aichhorn 1935), biological imperfections (Dugdale 1877), or "criminal bumps" on the head (Lombroso-Ferrero 1911). Only after the Great Depression, when crime rates reached peak levels in America, the research focus shifted to society as the possible explanation for criminal behavior (Burrough 2009).

Crime is but one of the phenomena that was previously thought to depend solely on the individual and was later rediscovered as fitting in a greater social science. Urbanization has also changed the way researchers study law, economics, epidemiology, ecology, anthropology, and many other disciplines deeply embedded in the relationship between people and their ecosystem.

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[1] United Nations World Urbanization Prospects (2018). *Our World in Data*. Available at https://ourworldindata.org/urbanization [Accessed 1 Jun. 2020].

[2] United States Census Bureau. *Census of Population and Housing, Population and Housing Unit Counts (2010)*. Available at: https://tinyurl.com/y23xalyb [Accessed 1 Jun. 2020].

The urbanization phenomenon has also deeply impacted the United States geopolitically and fiscally. The United States of America is a federal republic composed of states. The states are politically subdivided in counties, which are further partitioned in cities, municipalities, and unincorporated rural areas. Each of these forms of government possesses and exercises the power to tax. Therefore, a citizen of city *x* located in the United States may be subject to tax levied by the city, the county, the state, and the federal government. This jurisdictional overlap and tangency, coupled with the urbanization trend, has created unique layers of vertical and horizontal tax competition (Devereux et al. 2007). There is horizontal tax competition where two jurisdictions vertically equivalent, such as two counties, compete for the same tax revenue. There is vertical tax competition where two jurisdictions not vertically equivalent, such as the state and a county within the state, compete for the apportionment of tax revenue (Wong 1996; Rogers 2004; Zhao 2005).

A modern American phenomenon termed ‘devolution’ causes federal and state governments to mandate that counties and cities provide certain social services with little or no financial support from the central government (Shannon 1987; Pagano and Johnston 2000; Krane and Ebdon 2004). For example, local governments in the United States typically employ 45% of the general fund revenue to provide police and safety-related services, which in most other countries are funded entirely by the central government (Pagano and Johnston 2000; Krane and Ebdon 2004). Devolution is different from decentralization. The concept of decentralization allows lower governments to make decisions about the services they provide as well as how to finance them. Devolution, on the other hand, forces local governments to provide certain services and leaves them only the choice of how to finance those services (Shannon 1987; Krane et al. 2004). Therefore, devolution has brought attention to optimal strategies for local government revenue

composition, forming a branch of literature focused on revenue portfolio theory for local governments.

Decades of urbanization trends offer an unprecedented opportunity to (a) retest theories previously formulated in more isolated environments and (b) draw inferences on the validity of theories seemingly impacting different disciplines in a world in which observations are more interdependent than ever before. This study brings together lessons learned from criminological and tax research in the last century to test the validity of established theories from both disciplinary branches in the controlled environment of Washington counties and to the extent that they rest on mutual interdependent social observations. At the heart of this study is whether social indicators of crime can better inform local tax policy in Washington.

1.1 Criminological Literature

There is an ample body of empirical criminological research from the last century that has looked at the statistical relationship between crime and social variables correlated with crime. The early trend at the turn of the 19th century was to explain crime through factors wholly within the individual, such as sub-standard intelligence (Goddard 1914), psychic forces (Aichhorn 1935), biological imperfections (Dugdale 1877), or "criminal bumps" on the head (Lombroso-Ferrero 1911). The urbanization trend at the turn of the century accompanied a major change in criminological research, as studies began to focus more on social indicators of crime outside the control of the individual.

One of the masterminds of socially induced crime theory was Robert Merton, who can be viewed as the father of social anomie theory (Merton 1938). In general terms, the theory of social anomie suggests that an excessively competitive society may lead to the disintegration of ethical behavior due to the struggle for survival of the fittest. Merton argued that the rigid conformity with

traditional American values of economic success created a fictitious picture where everyone, through hard work, could achieve the American dream. This cultural indoctrination of obsessive economic success inevitably emarginated those not able to achieve the American dream through legitimate means. Therefore, Merton argued, it was the exaltation of "success-seeking" that explained crime. In the theory of social anomie, "anomie" is the result of 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 (Merton 1938; Chamlin and Cochran 1995; Savolainen 2000). In this respect, social anomie theory also implies that economic safety nets may mitigate the incidence of some types of crime (DeFronzo 1983), as they reduce social stress.

Before moving on to other emerging criminological theories, the meta-analysis of one hundred years of criminological research offers valuable insights into how social trends shaped the research approach. The early individualistic studies of Dugdale, Goddard, and others were followed by a more complex and urbanized world, which increased awareness of intricate social dynamics potentially leading to crime. The theory of social anomie picked up on these dynamics during five decades of immense social strain caused by two world wars and the Great Depression. These were major events that, at least with respect to criminological literature, promoted a more liberal and collective agenda (Pratt 2001). Not surprisingly, social anomie theory came under attack in the 1970s, when the American dream and economic success were once again at the forefront of self-identification and anomie theory was viewed as promoting an anti-American social agenda (Messner and 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 crime correlates in the greater social context, they do not call into question the very essence of American culture: economic success and the American dream.

The theory of social disorganization 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 (Shaw and McKay 1972; Sampson and Groves 1989; Bursik 1988; Bellair 1997; Taylor 1997). Shaw and McKay first formulated the 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" in the sense that they had weak social institutions—churches, schools, and adolescence organizations—unable to adequately supervise the youth. Research in traditional social disorganization theory looks at residential mobility, racial heterogeneity, strengths of social associations and networks, and socioeconomic status: all indicators at the neighborhood level. A more focused approach to the theory of social disorganization has noted that traditional social disorganization theory has failed to consider the structure of the family as indicative of that of the neighborhood (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, family, level (Sampson 1986; Cohen and Felson 1979; Nigel 2004).

Unlike the previous theories, deprivation theory suggests that crime is linked to indicators of economic deprivation, where the general lack of means leads to higher crime (Turk 1969; Lilly et al. 1995). For example, multiple studies have found a significant positive relationship between unemployment rates and property crime (Krohn 1976; Raphael and Winter-Ebmer 2001) or

poverty and crime at large (Patterson 1991; Peterson and Bailey 1988). Under the theory of deprivation, the business and economic cycles are useful indicators of crime (Wagner 1936). The theory of deprivation, however, 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 and Blau 1982). Relative deprivation research has found that economic inequality is positively associated with crime, thus suggesting that income redistribution may be a more effective measure of crime intervention than punishment (Danziger and Wheeler, 1975; Ehrlich, 1973; Carroll and Jackson 1983; Krahn et al. 1986; Vieraitis 1999). Deprivation theory can be viewed as a growth form of social anomie theory in that both theories study the social stress between those who have and those who don't as a precursor to crime. Unlike social anomie theory, however, deprivation theory does not blame a broken success-hungry society but merely suggests that the satisfaction of basic needs and avoidance of excessive social stratification of classes may be sufficient to curb criminal behavior without redesigning the very essence of the American culture driven by seeking economic success.

All socially-related theories of crime—social anomie, social disorganization, family disruption, deprivation—rest on the premise that crime needs space, time, and opportunity, where the wrong composition of social structure elements may provide a fertile ground for criminal activity. Regardless of theory, criminological studies typically also incorporate demographic data as control variables because indicators such as 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, an increased divorce rate coupled with both parents being fully employed would suggest lower property crime rates as deprivation decreases but higher non-property crime rates because of family disruption and social disorganization (Sampson 1987). None of the theories, of course, claim to offer infallible predictions but they are all grounded in data-driven statistical models (Morrow 2012). Given the large body of criminological research on point, many meta-analysis studies have summarized the results of previous research to derive conclusions about the overall body of research concerning social correlates of crime (Hsieh and Pugh 1993; Bonta et al. 1998; Pratt 2001; Pratt and Cullen 2005; Nivette 2011). The meta-analysis studies yield four key paradigms of the strongest and most stable correlates of crime across the large body of research (Figure 1.1):

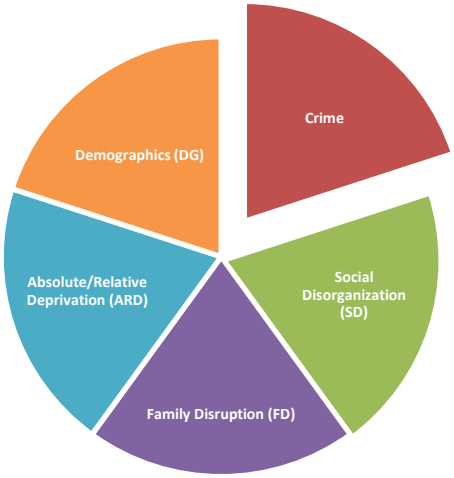

Figure 1.1. Social Correlates of Crime

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 further 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, not the crime itself (Pratt and Cullen 2005). Therefore, data pertaining to the size of the police force or the number of arrests is not useful to a study that aims to gauge future crime trends.

Second, the empirical value of an indicator of crime is not only in its nature but in its degree of change over time. For example, a 1993 study looked at whether an abrupt change in a crime

indicator is itself correlated to crime (Sampson and Laub 1993). The 1993 study looked at 500 delinquents and 500 control subjects matched by age, IQ, and neighborhood. The study then gathered exhaustive records on the subjects' life course and identified several life-turning points on a common scale. The study found that adult crime is clearly connected to childhood behavior, but perhaps more so indirectly because feeble youth associations can lead to weaker adult social bonds (e.g., labor force attachment and marital cohesion), which are mitigative of crime. Thus, the benefits of a longitudinal study are evident in its ability to, among other things, capture the impact of change over time.

Third, crime is often spatially autocorrelated (Huebner and 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, in fact, the very principle behind the *CrimeStat* software, a crime prediction software developed under the direction of the United States Department of Justice.[3]

The fourth lesson is the observation that most criminological studies look at crime correlates on a macro-level (e.g., national or state) or micro-level (e.g., neighborhood) unit of analysis (Pratt 2001). This reflection 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.

1.2 TAX LITERATURE

A 1989 study found that the package of public services provided by local governments is relatively standardized across localities; however, the way local governments finance those public

[3] *CrimeStat: Spatial Statistics Program for the Analysis of Crime Incident Locations*, U.S. Department of Justice, National Institute of Justice. Available at: https://tinyurl.com/yywq78fn.

services is quite diverse (Schneider 1989). After all, most cities must offer the same set of housekeeping functions: what will vary is the quality of the services and thus the tax price. When it comes to financing local public services, many studies have examined the optimal revenue portfolio composition for local governments (Jones and McIntosh 1974; Lockwood 2000; Zhao and Jung 2008).

Historically the property tax has been the most important source of local government revenue in the United States. Since the Reagan administration, however, public support for the property tax has dramatically decreased. While in 1970 property taxes contributed 84% of all local government tax collections, the property tax share fell to 32% by 1994 (Mackey 1997) and further down to 26.6% by 2015 (U.S. Census Bureau, 2015). 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 once did. In the last five decades local governments have struggled to make up for the lost property tax revenue through other revenue sources, such as fines, licensing fees, utility taxes, documentary fees, bonds, and sales taxes (Understanding the Basics of County and City Revenues, 2013).

The sales tax has become increasingly popular after the property tax revolt for two main reasons. First, the sales tax has a low degree of salience (Chetty et al. 2009; Finkelstein 2007; Gamage and Shanske 2011; Buchanan 1967), which makes it politically more acceptable than the property or income tax (Krishna and Slemrod 2003; Green 2014; Biegeleisen and Sjoquist 1988). Under the theory of tax salience, "salience" represents the degree of consumer response to a tax change for reasons other than the net tax liability, such as the way that taxes are displayed and the tax payment mechanism. Therefore, an invisible tax, such as a sales tax added at the register, has low salience and may not impact consumer behavior as much as expected based on the sales tax

rate (Chetty et al. 2009; Gamage and Shanske 2011; Buchanan 1967). Southern states, such as Tennessee, North Carolina, and Georgia, have spearheaded the effort to restructure local public financing relying less on property tax revenue and more on sales tax revenue. Nearly all the research concerning local sales tax policy to date, in fact, has been geographically specific to these states (Jones and McIntosh 1974; Jansen 1991; Rubenstein and Freeman 2003; Zhao 2005; Zhao and Jung 2008; Wang and Zhao 2011).

Second, the sales tax allows a jurisdiction to shift the cost incidence of critical social services to residents of neighboring jurisdictions and research has shown that taxpayers favor proposals that shift the tax incidence to someone else (Biegeleisen and Sjoquist 1988). This trend promotes horizontal tax competition (Burge and Piper 2012). Horizontal tax competition can be one of necessity, where residents of neighboring jurisdictions are forced to commute to shop or find work in another jurisdiction. It could also be a perfect competition where a jurisdiction allures business and shopping through lower sales tax rates. In both cases, the result is a tax spillover, a phenomenon where a jurisdiction collects an amount of sales tax different from the product of the sales tax rate and the income spent by its residents (Burge and Rogers 2010). The overall result is an uneven flow of tax revenue due to the spatial mobility of the revenue base. Tax spillovers preclude an equity condition known “as fiscal equivalence” (Jansen 1991; Lockwood 2000). Fiscal equivalence would be present if a body of taxpayers paying for a public service is perfectly congruent with the body of taxpayers benefitting from that public service. Fiscal equivalence, tax spillovers, and mitigation mechanisms are key elements to the theory of tax competition.

At the local government level, sales taxes often take the form of Local Option Sales Taxes (LOST) (Shadbegian 1999; Zhao 2005). Local Option Sales Taxes consist in optional local increases to the statewide sales tax rate. The increase is optional because localities can choose

whether to impose it and at what rate (within the rate limits authorized by a state). LOST are generally levied towards a local general fund, but can be levied to finance specific purposes, such as education or transportation, in which case they are commonly referred to as "Special Purpose" Local Option Sales Taxes (SPLOST). For example, Tennessee[4], North Carolina[5], and Georgia[6] have tried to finance public schools through a special local sales tax surcharge imposed by the counties. Similarly, California tried to finance public roads.[7] Generally, studies have found that SPLOST is a suboptimal method of financing critical government services because sales tax revenue flows unevenly: since the revenue base (economic spending) is mobile, sales tax revenue tends to flow where most shopping opportunities exist (Burge and Rogers 2010). While the uneven flow could be mitigated through revenue-sharing at the state level, state tax laws rarely mandate revenue sharing of local sales tax revenue. Not surprisingly, research has shown that SPLOST tied to education and transportation exacerbate inequalities among counties to the detriment of rural communities (Peevely and Ray 1989; Jansen 1991; Rubenstein and Freeman 2003; Sielke 2004; Green 2006).

Local option sales tax literature has examined the interjurisdictional tax competition whereby an increase in sales tax rates in one local jurisdiction causes consumers to spend more in neighboring lower tax jurisdictions (Wong 1996; Rogers 2004; Zhao 2005). The results were confirmed by a 2010 study which found that LOST rates are inversely and significantly related to retail sales and that higher sales tax rates in rural communities accompany a disproportionally high erosion of retail sales (Burge and Rogers 2010). From these studies we learn that market dominant,

[4] Tennessee Code Annotated § 67-6-701.
[5] North Carolina General Statutes § 105-463 *et seq.*
[6] Official Code of Georgia Annotated § *48-8-111.*
[7] California Public Utilities Code § 132300 *et seq.*

densely populated jurisdictions surrounded by rural jurisdictions are best suited to export the tax cost of their social services.

Most of the literature to date has focused on generic LOST policy without distinction as to what social services the imported LOST revenue is used to finance. In the context of SPLOST, the limited literature available has focused on the correlation between SPLOST and public education (Peevely and Ray 1989; Jansen 1991; Rubenstein and Freeman 2003; Sielke 2004; Wang and Zhao 2011) or infrastructure financing (Green 2006). One of these studies examined the correlation between LOST rates and local public education financing in Tennessee (Jansen 1991). The Tennessee study found that sales tax revenue and capacity was particularly low in rural counties, which were in turn unable to properly fund education (Jansen 1991). Another SPLOST study specific to public education in North Carolina confirmed that the adoption of an education SPLOST was aggravating inequalities across public schools within the state, recommending that the central state government adopt a sales tax revenue sharing scheme in order to mitigate tax spillovers (Wang and Zhao 2011). Every other study reached similar conclusions: that funding local services through sales tax revenue exacerbates inequalities between urban communities with market dominance and rural communities without market dominance (Peevely and Ray 1989; Rubenstein and Freeman 2003; Sielke 2004; Green 2006). Studies conducted to date do not reveal how tax spillovers can be mitigated through revenue-sharing and whether funding social services through LOST is particularly detrimental for certain services and segments of the population.

The results of the studies cited above are consistent with the nature of any sales tax system and, in that respect, do not provide surprising conclusions. For example, it seems obvious that sales tax revenue flows where most people live, work, and spend money, with the natural consequence that some jurisdictions will collect more than others. However, the studies add an important

element of reproducible, unbiased empirical evidence which sets an objective premise to the research questions.

In addition to what already mentioned, no tax study is complete without also considering that politics play a significant role in the development of tax policy. Multiple studies, in fact, have shown that many tax policy decisions are driven at least in part by political affiliation more than data-driven information (Hamideh et al. 2008; Green 2006; Afonso 2014; Luna et al. 2007; Jung 2001). Voters affiliation is often part of statistical models predicting the outcome of tax measures. Research shows that Republican voters are more likely to prefer local-option sales taxes to property taxes (Jung 2001; Zhao & Jung 2008), albeit Republican voters in general are less likely to favor any tax measure (Green 2006; Hamideh et al. 2008; Shock 2013). More specifically, Republican voters tend to prefer special purpose local option sales taxes in exchange for property tax relief (Sanders & Lee 2009; Jung 2001; Zhao & Jung 2008). This *quid pro quo*, sales tax increase in exchange for property tax relief, explains why counties with a larger share of Republican voters often reach the maximum sales tax rates (Luna et al. 2007).

1.3 THEORIES GUIDING THIS STUDY

Two tax theories and three criminological theories guide the structure, design, and data in this study. In tax literature, the theory of tax salience suggests that taxpayers are less likely to resist "invisible taxes," such as sales taxes added at the register. The theory of tax competition, on the other hand, indicates that jurisdictions will export the cost of their services if the revenue base is mobile, which is the case for the sales tax. The two tax theories, coupled with the historical trends caused by devolution and the property tax revolt, would support a dramatic shift in local government financing during the last forty years towards the sales tax. The expectation would be that winning and losing jurisdictions have emerged, where winning jurisdictions are those with a

positive tax spillover associated with high population density, large per capita income, higher than average educational attainment, lower unemployment and poverty, and a demographic structure with less children and more working adults. The losing jurisdictions, those with a negative tax spillover, would instead be rural, less densely populated, and less affluent. The tax literature would further suggest that the effects of the property tax revolt would be most prominent in Republican, market-dominant, heavily populated jurisdictions.

In criminological literature, all three socially induced crime theories—social anomie, social disorganization, and deprivation—stem from an excessively competitive society focused on success and the obsessive pursuit of the American dream, which in turn leads to the disorganization of social structure, the disruption of family values, and the stratification of social classes based on wealth. Criminological literature has therefore linked income and wealth distribution, educational attainment, unemployment, poverty, and population density to crime. The three criminological theories suggest that the increased push towards a sales tax system exacerbates the conditions of inequality that are precursors to crime. Therefore, the expectation would be that many of the same social variables indicative of higher sales tax revenue are also prognostic of crime.

1.4 The Study in a Nutshell

The criminological research discussed in Section 1.1 and the sales tax research discussed in Section 1.2 converge on the importance of competition: the inequitable partition of a finite amount of resources. Both bodies of literature have linked competition with increasing inequality and marginalization. This study rests on the premise that competition, which is at the heart of any sales tax system, is a precursor to many social "triggers" of crime and therefore a competitive tax system seems unfit to fund any measure meant to fight crime.

This study observes two special purpose local option sales taxes that are unique to Washington. The first, the Juvenile Facilities SPLOST, is earmarked for "juvenile detention facilities and jails." RCW 82.14.350. The second, the Criminal Justice SPLOST, is more broadly targeted to "activities that substantially assist the criminal justice system." RCW 82.14.340. Both taxes rest on the legislative assumption that the criminal justice and juvenile detention systems are best assisted with tax dollars and therefore sales tax revenue should bear some degree of inversely proportional relationship to crime. However, the literature suggests that the opposite is true because sales tax systems exacerbate the conditions of inequality that are precursors to crime. In simple terms, the Washington legislature assumed that crime-related SPLOSTs and crime prevention are synonyms while the literature indicates it is an oxymoron.

The study explores the relationship between crime and SPLOST revenue as well as the impact of underlying socioeconomic factors on both crime and SPLOST revenue. If the legislature's assumption is correct, the social variables indicative of higher SPLOST revenue should also be indicative of lower crime and there should be an inverse relationship between crime and SPLOST revenue (Figure 1.2). If instead SPLOST revenue and crime in Washington counties respond to socioeconomic

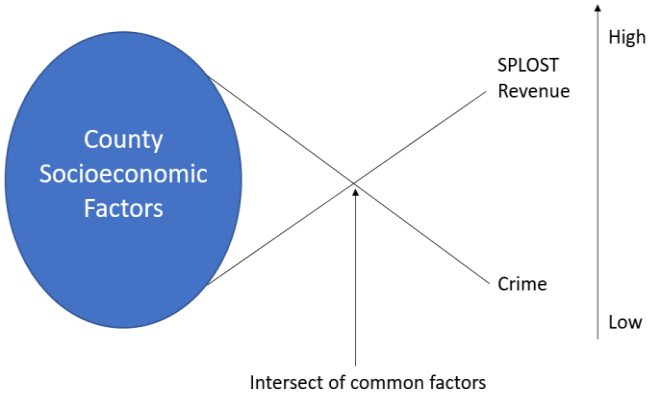

Figure 1.2. SPLOST/Crime Construct, Legislative Assumption

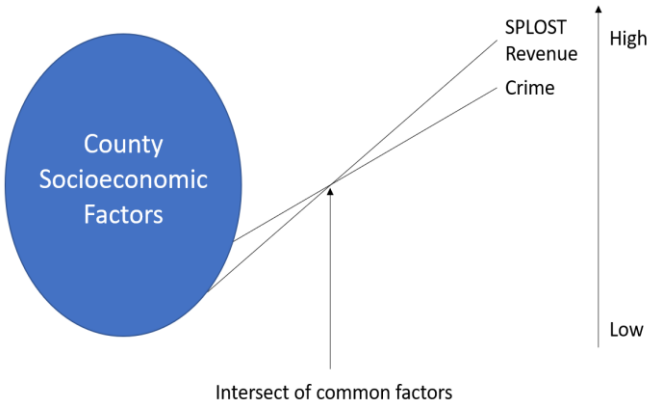

Figure 1.3. SPLOST/Crime Construct, Prior Research

factors according to the prior research, many of the same factors indicative of higher SPLOST revenue should also be indicative of higher crime, thereby defeating the legislative premise that the criminal justice and juvenile detention systems are best assisted with tax dollars (Figure 1.3).

The objective of this study is not *to forecast* SPLOST revenue or crime but to verify *whether it is possible to forecast* the flow of SPLOST revenue and the incidence of crime across Washington counties based on common socioeconomic underlying factors. If forecasting is possible, it means that society offers clues that can inform legislative policy, both in terms of criminal justice and tax policy. Statistical models can reveal which social clues are most valuable to both crime and SPLOST revenue so that the study can culminate in data-driven legislative recommendations to improve the current SPLOST design in Washington.

Chapter 2. THE CASE FOR WASHINGTON

The State of Washington has not escaped the national phenomena of urbanization, devolution, and tax revolt. The Washington Growth Management Act (GMA) of 1990, RCW 37.70A, required fast growing cities and counties to provide a comprehensive infrastructure plan on how to accommodate growth in the next 20 years. Other counties could opt in and, in doing so, received a financial incentive. The financial incentives under the GMA prompted 29 counties to reshape boundaries, incorporate new cities, and annex existing ones in an effort to urbanize (A History of Washington's Local Governments 2007). The GMA also fundamentally diminished the financial responsibility of counties towards unincorporated areas, thus pushing unincorporated areas to either incorporate or annex themselves to neighboring cities (Settle and Gavigan 1993). In the years following the GMA, some areas that remained unincorporated became pockets of low-income and unemployment (Alcorn 2019; Martinell 2017), such as, for example, White Center and Skyway in King county (A History of Washington's Local Governments 2007). The GMA continues its push for urbanization still today by promoting, whether directly or indirectly, the incorporation or annexation of unincorporated areas (Trohimovic 2002; Tovar 2014; VISION 2050; Annexation by Washington Cities and Towns 2020).

Just as urbanization was taking off after the passing of the GMA, one man, Tim Eyman, became the standard bearer of the Washington tax revolt, filing numerous initiatives to curb or eliminate taxes that were being used to finance urbanization. Some of Mr. Eyman’s initiatives were

successful, resulting in a cap on property tax rate increases,[8] a temporary repeal of the motor vehicle excise tax,[9] and a reduction to the automobile tab fee.[10]

Three decades after the passing of the GMA and the repeal of virtually every tax-limiting initiative by the state judiciary, the fiscal landscape in Washington remains that of a state relying most heavily on sales taxes, offering a unique opportunity to study the intersect of criminological and tax theories discussed in Chapter 1 for two main reasons. First, the State of Washington has never levied an income tax and has therefore historically always been funded through property and sales taxes, thus severely altering the state's portfolio flexibility. The tax system in Washington is in fact the most regressive in the nation, as it relies most heavily on sales taxes.[11] Second, the State of Washington is the first and only jurisdiction in the United States that ties one or more SPLOST not to education or transportation, but to criminal justice and juvenile detention facilities. As discussed in Section 1.3, the expectation is that a tax system relying heavily on the sales tax, which is inherently competitive, exacerbates the conditions of inequality that are precursors to crime.

2.1 The Local Option Sales Tax Landscape in Washington

In the context of a state revenue portfolio that relies most heavily on sales taxes, it is not surprising that the State of Washington offers local governments multiple opportunities to levy special purpose local option sales taxes to pay for unfunded mandates. The Washington SPLOST system, however, came under indirect attack in the fall of 1993 with Initiative 601 and 602. First, Initiative 601 imposed a supermajority requirement for all new tax legislation. Second, the

[8] Initiative 747, held invalid on constitutional grounds in *Washington Citizens Action v. State,* 171 P.3d 486, 162 Wn.2d 142 (2007).
[9] Initiative 695, held invalid on constitutional grounds in *Amalgamated Transit Union Local 587 v. State,* 11 P.3d 762, 142 Wn.2d 183 (2000).
[10] Initiative 776, held invalid on constitutional grounds in *Pierce County v. State,* 148 P.3d 1002, 159 Wn.2d 16 (2006).
[11] The Institute on Taxation and Economic Policy; Washington State Department of Revenue.

provisions of both initiatives, when combined, would have severely altered the state's ability to collect and spend taxes beyond a formula based on population and personal income. Initiative 602 did not pass, but Initiative 601 did, thus providing a moratorium on most new taxes from 1993 until it was overturned in February 2013, when the Washington State Supreme Court in *League of Educ. Voters v. State*, 295 P.3d 743, 176 Wn.2d 8089 (2013), held that legislation requiring a supermajority vote for new taxes was in violation of Article II of the Washington Constitution.

Chapter 14 of Title 82 of the Revised Code of Washington today offers local governments numerous opportunities to impose local option sales taxes, each of which functions differently in terms of tax rate, method of levy and accounting, jurisdiction allowed to impose it, and other mechanical aspects of administration. For example, under RCW 82.14.030(1) any county or city may impose a LOST of up to 0.5% by resolution of the governing body and without the people's vote. This LOST is not earmarked for a specific purpose and therefore feeds entirely into the jurisdiction's general fund. The second paragraph under RCW 82.14.030 allows counties to impose an additional 0.5% LOST, and cities within those counties to impose an additional 0.425% LOST. In this instance, however, the counties and cities must share revenue according to a complex mechanism.

All other local option sales taxes under RCW 82.14 are special purpose local option sales taxes—optional local sales taxes earmarked for specific purposes. Under RCW 82.14.400, for example, some cities and counties may impose a 0.1% SPLOST earmarked towards "[c]osts associated with financing, design, acquisition, construction, equipping, operating, maintaining, remodeling, repairing, reequipping, or improvement of zoo, aquarium, and wildlife preservation and display facilities …." Currently, no Washington city imposes this SPLOST, while Pierce is the only county that does.

The politics surrounding local option sales taxes become evident with a close look at the legislative history of RCW 82.14.400. The language of that section in fact suggests that the SPLOST was designed specifically for Pierce county, as it is available only to counties with (a) a national park, (b) a metropolitan park district, and (c) population of more than 500,000 but less than 1,500,000.[12] As of today, Pierce county is the only Washington county fitting these requirements as it houses most of Mount Rainier National Park, a few metropolitan districts, and population of 904,980.[13] The only other county with the requisite population, Snohomish County, lacks a metropolitan park district and a national park. Mt. Baker-Snoqualmie is in fact a national forest, a subtle distinction among federal lands that proves meaningful for purposes of the SPLOST under RCW 82.14.400.[14] When RCW 82.14.400 was introduced as House Bill 1547 in 1999 the House of Representative's own bill analysis stated that only "one metropolitan park district, the Metropolitan Park District of Tacoma" existed.[15] Although, as of today, there are 21 metropolitan park districts in Washington, the other qualifying criteria imposed by RCW 82.14.400 (population and presence of a national park) have managed to effectively restrict this SPLOST solely to Pierce county for the last two decades.

Under RCW 82.14, counties and cities are offered three optional sales tax surcharges earmarked for public safety. The first option permits any county to impose, without vote but subject to repeal by referendum, a 0.1% SPLOST earmarked to fund 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

[12] RCW 82.14.400(a).
[13] U.S. Census Bureau. *Population Estimate as of July 1, 2019*. Available at: https://tinyurl.com/y3bn3ssg [Accessed 1 Jun. 2020].
[14] Contrast National Parks with National Forests under 26 U.S.C. § 5207.
[15] Final Bill Report, House Bill 1547, 56th Legislature, 1999, Regular Session.

domestic violence services such as those provided by domestic violence programs, community advocates, and legal advocate….” RCW 82.14.340. Once collected, 10% of the tax remains in the county coffers and 90% is shared among the county and the cities within the county ratably based on population.[16]

The second option is more complicated as it offers a “county option” and a “city option.” The county option allows any county to impose, subject to a majority approval of county voters, up to a 0.3% SPLOST, one third of which must be used to fund either criminal justice or fire protection. RCW 82.14.450(1). Once collected, 40% of the tax remains in the county coffers and 60% is shared among the county and the cities within the county ratably based on population.[17] The city option allows any city to impose, subject to a majority vote, a 0.1% SPLOST, one third of which must be used to fund criminal justice programs. RCW 82.14.450(2). Once collected, 85% of the tax remains in the city coffers and 15% is distributed to the county.[18]

The third option permits counties with populations of less than one million to impose, subject to a majority approval of county voters, a 0.1% SPLOST earmarked to fund “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 in the county coffers and is not shared with the cities within the county.[19]

In state-issued literature, the three above-mentioned SPLOSTs are typically referred to as the criminal justice (first option), public safety (second option), and juvenile facilities (or detention) (third option) SPLOST (Table 2.1. SPLOST Matrix).

[16] Minus a 1% administrative fee for the Washington State Department of Revenue.
[17] See Footnote 16.
[18] See Footnote 16.
[19] See Footnote 16.

Table 2.1. SPLOST Matrix

Option	1	2 (County Option)	2 (City Option)	3
Authority	RCW 82.14.340	RCW 82.14.450(1)	RCW 82.14.450(2)	RCW 82.14.350
Commonly Referred to as	Criminal Justice SPLOST	Public Safety SPLOST	Public Safety SPLOST	Juvenile Facilities SPLOST
Authorized Jurisdictions	All Counties, no vote, subject only to repeal by	All Counties, subject to majority vote	All Cities, subject to majority vote	Counties with populations of <1M, subject to majority
Rate of Tax	0.10%	0.30%	0.10%	0.10%
Year First Enacted	1990	2003	2003	1995
Portion Earmarked for Criminal Programs	100.00%	33.33%	33.33%	100.00%
Revenue sharing?	10% county; 90% county and cities based on population	60% county; 40% county and cities based on population	85% city; 15% county	No
Earmarked Funds may be used for	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	Criminal justice (same as RCW 82.14.340) and/or fire protection.	Criminal justice (same as RCW 82.14.340) and/or fire protection.	Costs associated with financing, design, acquisition, construction, equipping, operating, maintaining, remodeling, repairing, reequipping, and improvement of juvenile detention facilities and jails

This study observes only data pertaining to the Criminal Justice and Juvenile Facilities SPLOST for four reasons. First, both these SPLOSTs, unlike the public safety SPLOST, are entirely earmarked towards their intended purpose. Secondly, both these SPLOST are available only to counties and do not offer a city option, thus maintaining the county as the unit level of analysis. Third, the public safety SPLOST may be used for fire protection, which is entirely beyond the scope of this study. Fourth, the public safety SPLOST is only a recent addition to the SPLOST landscape as it was first passed in 2003. For these reasons, the rest of the analysis will focus solely on the two optional 0.1% surcharges under RCW 82.14.340 and RCW 82.14.350.

The Criminal Justice SPLOST became law in 1990.[20] Only four counties chose to impose it immediately after it became law: King, Snohomish, Spokane, and Thurston. In 1993, Grays Harbor joined the list. By 1996, the list had tripled to 21 counties. By the year 2005, the list had grown to 32 counties. Pacific county was the latest addition to the list when it chose to impose the Criminal Justice SPLOST effective January 1, 2018.

[20] Senate Bill 6913, 51st Legislature, 1990, 2nd Special Session.

The Juvenile Facilities SPLOST became law in 1995.[21] Seven counties chose to impose it immediately after it became law: Benton, Franklin, Mason, Pierce, San Juan, Spokane, and Walla Walla. Kittitas and Thurston county joined the following year. Clallam and Okanogan county were the latest additions to the list when they chose to impose the Juvenile Facilities SPLOST effective April 1, 2018.

By April 1, 2020, no Washington county imposes the Juvenile Facilities SPLOST without also imposing the Criminal Justice SPLOST, although state law does not require that one be a condition to the other. Only four counties—Asotin, Garfield, Klickitat, and Wahkiakum—do not impose either SPLOST. All other counties impose either only the Criminal Justice SPLOST (represented in light green in Figure 2.4. CJ and JD SPLOST Rates Map) or both (represented in bold green in Figure 2.4. CJ and JD SPLOST Rates Map).

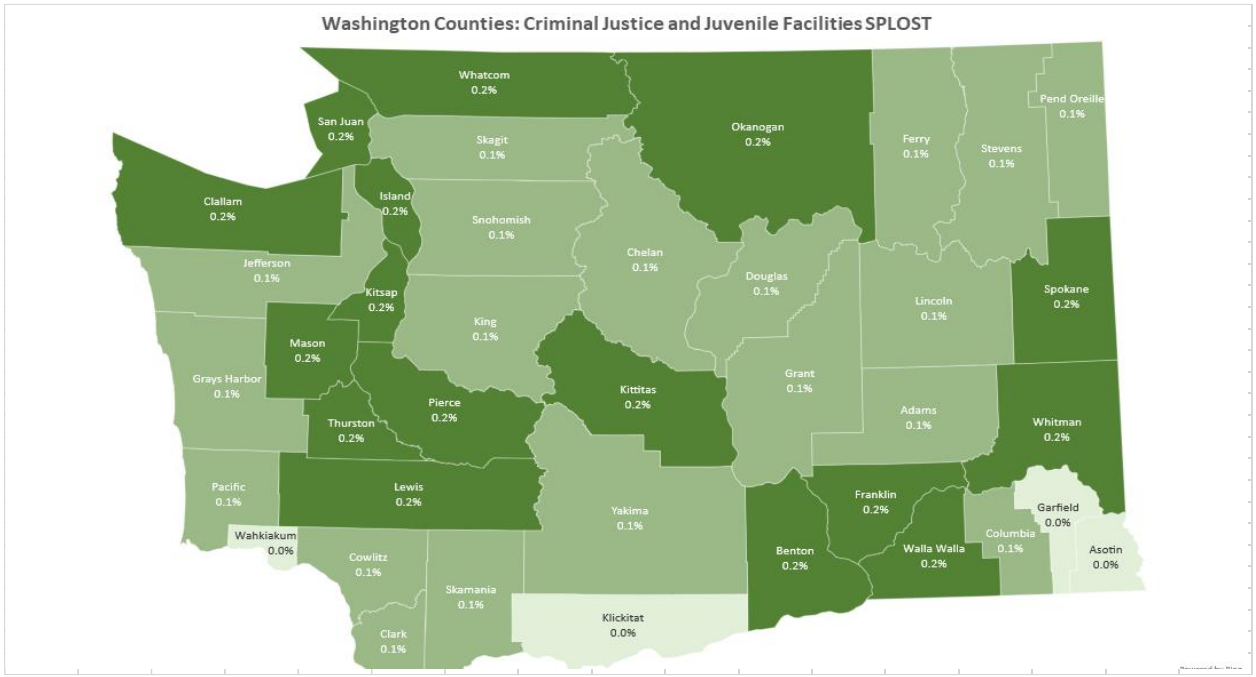

Figure 2.4. CJ and JD SPLOST Rates Map

[21] House Bill 2110, 54th Legislature, 1995, 2nd Special Session.

2.1 MECHANICS OF SPLOST ADMINISTRATION IN WASHINGTON

The Criminal Justice and the Juvenile Facilities SPLOSTs are administered by the Washington State Department of Revenue, which is paid a 1% administrative fee. The taxes are collected in the same manner as the general retail sales tax. Each SPLOST is assigned a specific accounting code under the State Auditor's Office (SAO) Budget, Accounting and Reporting System (BARS) to ensure that funds are distributed according to the apportionment prescribed under the respective section in the Revised Code of Washington.

Although the BARS system has been used for a long time, local revenue data became most accessible in 2009 when the SAO launched its new Local Government Finance Reporting System (LGFRS) portal, which allows users to retrieve local revenue data by BARS account and therefore quickly zoom in on a given revenue type. Before 2009, data pertaining to local revenue distributions was disseminated directly by the Washington Department of Revenue (DOR), first bimonthly and then annually, but DOR's data was often presented in inconsistent formats and configurations, which made navigating and comparing data a tedious process.

The first number in the BARS code in the state's chart of accounts indicates whether the account is a revenue (number 3) or expenditure (number 5) account. For revenue accounts, the second number indicates the main source: 1 for taxes, 2 for licenses and permits, 3 for federal funds, 4 for utility charges, 5 for court-imposed fines, 6 for miscellaneous revenue, 7 for capital projects, 8 and 9 for everything else. Therefore, all BARS accounts beginning with 31 are tax revenue accounts. The third number in the sequence indicates the type of tax: 1 for property tax, 2 for timber harvest taxes, 3 for retail sales and use taxes, etc. The remaining numbers in the BARS account are used to link the revenue source with a specific section of the Revised Code of Washington (Table 2.2).

Table 2.2. SPLOST Budget, Accounting and Reporting System (BARS) Codes

	Criminal Justice SPLOST	Juvenile Facilities SPLOST
BARS Code	313.71.00	313.72.00

Table 2.3. Financial Responsibility of State, County, City

Jurisdiction	Law Enforcement	Courts	Adult and Juvenile Corrections
State	Washington State Patrol and specialized law enforcement – state and inter-state highways, state lands	▪ Supreme and Appeals Courts ▪ Attorney General ▪ Administrative Office of the Courts ▪ Office of Public Defense	▪ Prison (felony > year sentence) ▪ Community supervision and detainment of violators of community supervision ▪ Juvenile Rehabilitation (felony > year sentence)
County	Sheriff Departments – Unincorporated county lands and roads; some city contracts Dispatch/911 system, including city contracts	▪ Superior and juvenile court (felons) ▪ District court of limited jurisdiction (misdemeanors and infractions) ▪ City contracts for court services, prosecutor, public defense, clerk, probation	▪ Jail (felony and misdemeanant pretrial detainees, those with <year sentence) ▪ Pretrial release programs ▪ Alternatives to incarceration ▪ Juvenile detention (<year felons and misdemeanors) ▪ Juvenile probation
City	Police Departments – Incorporated cities and streets Dispatch/911 system or contract	▪ Contract with county District Court or provide Municipal Court of limited jurisdiction (misdemeanors and infractions) traffic violation bureaus (traffic/ parking infractions), prosecutor, public defense, probation	▪ Jail for adult misdemeanant defendants by contract or in city owned facility ▪ Pretrial release programs ▪ Alternatives to incarceration

Source: Berk, 2014.

On the expenditure side, each level of government is responsible for a different aspect of criminal justice (Table 2.3). Washington counties fund approximately 18% of criminal justice needs through special purpose local option sales taxes and spend most SPLOST revenue on the court system and court-related services (Figure 2.5).

Source: Berk, 2014.

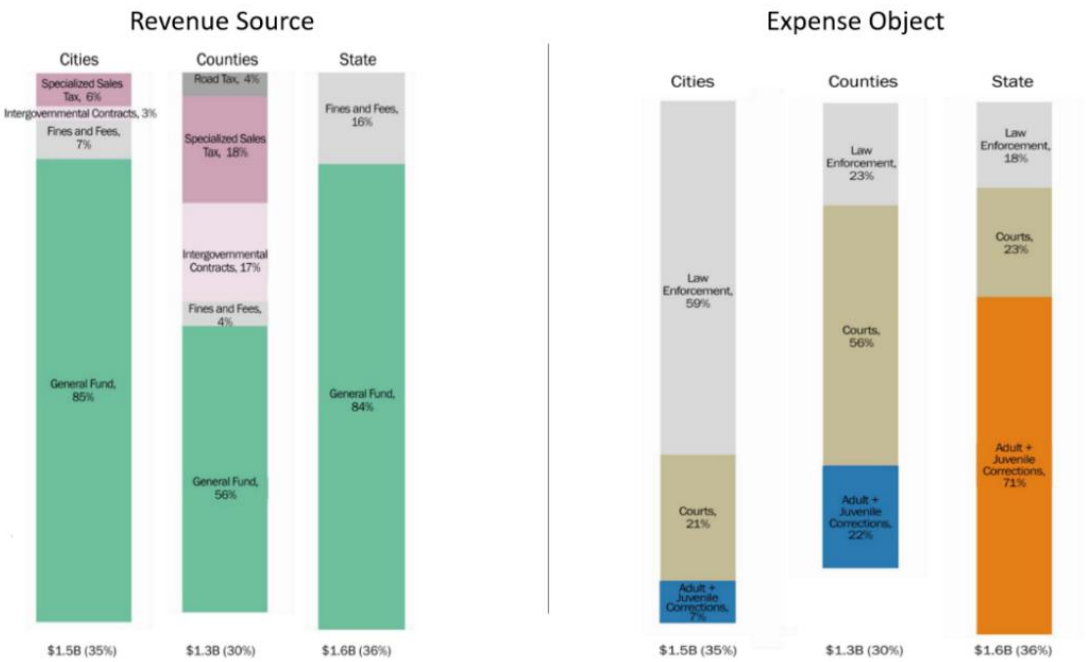

Figure 2.5. Criminal Justice Revenue Sources and Expense Objects

In the state accounting system, BARS expense accounts are unfortunately not tied to specific revenue sources but to programmatic goals, rendering it impossible to trace how money is spent and what impact it may be having. This is particularly true because each expense object receives funding through multiple sources, of which the SPLOST is only one. For example, the Criminal Justice SPLOST can be pay for items expensed through BARS accounts 512 (superior courts and juvenile courts), 515 (legal services and indigent defense), 521 (law enforcement), 523 (detention facilities), 524 (protective inspection services), 528 (dispatch services), or 565 (domestic violence). Similarly, while the Juvenile Facilities SPLOST is earmarked towards "costs associated with financing, design, acquisition, construction, equipping, operating, maintaining, remodeling, repairing, reequipping, and improvement of juvenile detention facilities and jails," there is no expenditure BARS account specifically designated to juvenile detention facilities. Funds from this SPLOST could be used to pay for items expensed through BARS accounts 523 (detention facilities) or 527 (juvenile services).

2.2 Aim of The Study

This study will advance the theory of tax competition at the local government level by testing its validity in a new context: a highly regressive state tax system where Washington counties compete through special purpose local option sales taxes to fund criminal justice services and juvenile detention facilities. Informed by prior criminological and tax research, this study is modeled after that portion of the SPLOST literature focused on public education financing in order to (a) identify the most likely factors that inform a county's decision to impose a SPLOST and (b) observe whether funding criminal justice and juvenile detention facilities through a SPLOST system is financially detrimental to certain counties. Considering the consistent findings of all previous SPLOST studies that horizontal sales tax competition favors market dominant

jurisdictions, the expectation is that the current SPLOST system in Washington financially emarginates rural counties. If the study finds that that earmarked tax revenue is not flowing where the need is most critical, it will leverage predictive analytics to offer ameliorative recommendations. The results of this study will also inform the phenomenon of devolution in Washington insofar as the state may wish to mandate local governments to provide other critical services without first receiving adequate resources.

Chapter 3. RESEARCH QUESTIONS AND DESIGN

At the heart of this study is whether social indicators of crime can better inform local tax policy in Washington, which is the first and only state to permit local governments to finance critical justice needs through SPLOSTs. In this respect, the study aims to answer two main research questions to reach a conclusion:

Research Question 1	Whether there is a detectable trend in the distribution of sales tax revenue across the state and, if a trend can be identified, whether a predictive statistical model can be fitted to estimate future SPLOST revenue patterns.
Research Question 2	Whether there is enough explanatory information in the data collected to fit a statistical model predictive of the dispersion of adult crime and juvenile detention.
Conclusion Question	Whether, based on the results from the previous two research questions, the anticipated spatial flow of SPLOST revenue espouses the likely need.

3.1 RESEARCH DESIGN

Research constructs can be defined on four main premises: (a) basis of overall approach; (b) data source; (c) length of observation; and (d) analytical method (Shadish et al. 2002). The research approach can take the form of an experimental or observational design. In the first type, the thing being measured is a byproduct of the experiment, typically accompanied by a control group. In the second type, the variable already exists and is simply being observed. The data source further divides studies in archival and non-archival research. In archival research, the observations are collected by independent sources and stored in collections. The opposite is true for non-archival research where the observations do not predate the study and are collected for the study itself. The

length of time over which observations are collected further distinguishes longitudinal studies from cross-sectional studies. While a cross sectional study is a snapshot view of the relationship among observations at one point in time, a longitudinal study involves repeated observations of the same variables at constant time intervals. At last, the analytical method of research depends on whether the researcher is measuring a variable or describing it. Any attempt to measurement requires a quantitative method, whereas a descriptive objective is best achieved through a qualitative method.

The research construct is a result of the questions the researcher wishes to answer. For example, a medical study on the efficacy of a new drug against AIDS may be constructed as an experimental, non-archival, longitudinal, quantitative study. On the other hand, a study on the relationship between student evaluations and quality of teaching based on the age of the teacher would likely be an observational, archival, cross-sectional, qualitative study.

The present study is observational, archival, longitudinal, and quantitative. It is observational because the data the study analyzes predates the study and already exists in social nature. It is archival because the data necessary for this study is routinely collected by multiple governmental and non-governmental organizations. The study is longitudinal because the passage of time is essential in capturing the cointegration across multivariate time series and building a statistical model able to leverage the observations' own temporal trends. Because the aim of the study is to measure the relationship among trends over time, the study employs quantitative research methods.

3.2 Level of Analysis and Unit of Observation

The term "level of analysis" in social science research refers to the scale of measurable observations concerning a research target (Yurdusev 1993). That research target is known as the "unit of analysis" (Babbie 2016). Together, the level and unit of analysis determine a set of criteria that observations must meet in order to be relevant and useful to the study (Table 3.4).

Table 3.4. Level of Analysis and Unit of Analysis

E.g., Level of Analysis	E.g., Unit of Analysis
Macro	National
Meso	State
Micro	County
	City
	Neighborhood

As this study aims to observe the relationship between criminological and fiscal trends at the county level, the unit of analysis is the county. As such, macro-level data, such as national or state observations would homogenize the distribution of the very attributes the study aims to observe at the county level. On the other hand, micro and meso levels of analysis offer the most relevant observations capable of capturing differences among each unit (Serpa and Ferreira 2019) (Figure 3.6).

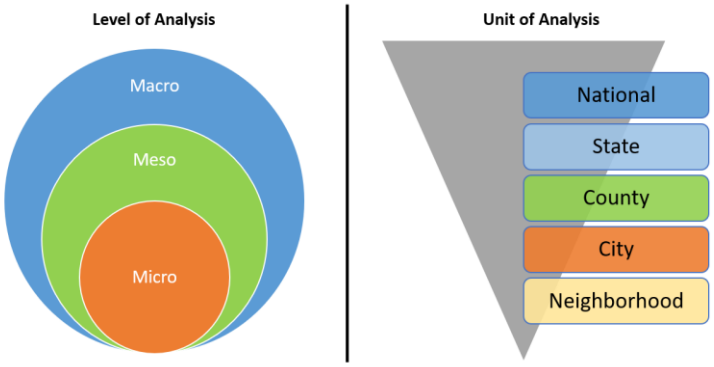

Figure 3.6. County Level and Meso Unit of Analysis

The data collection process in the study was informed by the relevant levels and unit of analysis. In this respect, data available only at the macro level was specifically excluded in favor of micro and meso level indicators. At the micro level, the study collected measures describing individuals or communities, such as drinking habits and mental wellbeing. At the meso level, the study collected a mix of measures scaled based on the unit of analysis, such as county-level population density, educational attainment, and unemployment.

3.3 Data Collection

The selection of data for this study was severely influenced by the availability of observations (a) collected at the county-level, (b) archived on a consistent basis over time, and (c) reported

uniformly. For example, archival data on income inequality is abundant at the national and state level but very limited at the county level. Similarly, crime data is plentiful at the national and state level but there is no consistent measure of crime expressed on a county basis. Most crime data is expressed in terms of arrest statistics, which research has shown to be least useful. In addition, data is often reported by police precincts, which are not organized according to county boundaries.

There are also many instances where data has been collected at the county level only in recent years. Similarly, there are instances where some counties report certain pieces of information while others do not. For example, incorporating commute time, dietary habits, or pollution into the study could have been useful but the data is simply not available for all Washington counties for a sufficiently long period of time. Another example is homelessness. There is currently no uniform reporting system of homelessness at the county level in Washington. Homelessness data is available only in certain counties and, even then, only for more recent years.

The choice of data in this study was informed by the literature review as well as its mere availability. The selected data spans across 29 years (1990-2018) and 46 variables[22] that can be grouped in three main domains:

1. Crime data (8 variables);
2. Society (29 variables); and
3. Revenue (9 variables).

The study focuses on data from 1990 and onward because the Criminal Justice SPLOST became law in 1990[23] while the Juvenile Facilities SPLOST became law in 1995[24].

[22] See Appendix A.
[23] Senate Bill 6913, 51st Legislature, 1990, 2nd Special Session.
[24] House Bill 2110, 54th Legislature, 1995, 2nd Special Session.

3.3.1 *Crime Data*

The most reliable source of data consistently and uniformly reported, and strictly related to crime at the county level, is the quantity of criminal complaints filed in each superior court. Just like every other piece of data, the observations have limitations. Not all arrests result in a criminal complaint and not all complaints result in a conviction. Therefore, while counting complaints is a more accurate measure of crime than counting arrests, complaints do not equate crime. Nevertheless, criminal complaints are the best available observations consistently and uniformly reported at the county level during the time period of this study.

The following variables[25] in this domain capture crimes prosecuted as adults, all of which are expressed in the study on the scale of 1:100,000 residents (CJ variables):

1. CJ VC: Homicide. Violent crime cases where the primary charge involves murder, manslaughter, excusable homicide, or justifiable homicide.
2. CJ VC: Sex Crimes. Violent crime cases where the primary charge involves sexual exploitation of a minor, incest, rape, statutory rape, or indecent liberties.
3. CJ VC: Assault. Violent crime cases where the primary charge involves assault or intent to cause another person physical harm, including malicious harassment and coercion.
4. CJ VC: Robbery. Violent crime cases where the primary charge involves theft of property using force, violence, or fear of injury to a person or his or her property.
5. CJ NVC: Property Crimes. Non-violent crime cases where the primary charge involves theft of property, possession of stolen property, extortion, burglary, criminal trespass and taking a motor vehicle without permission.

[25]All collected by the Washington Administrative Office of the Courts and compiled by the Washington State Statistical Analysis Center.

6. CJ: Total. Total number of superior court filings for all offenses.

Because funds raised by the Juvenile Facilities SPLOST are earmarked for "costs associated with financing, design, acquisition, construction, equipping, operating, maintaining, remodeling, repairing, reequipping, and improvement of juvenile detention facilities and jails," the study also captures two additional variables[26] measuring county-level juvenile detention, both expressed on the scale of 1:100,000 residents (JD variables):

7. JD: Total Juvenile Arrests. Total number of juvenile arrests for all suspected offenses.[27]
8. JD: Juvenile Dispositions. Total number of juvenile sentences for all offenses.

3.3.2 *Social Data*

The social data relevant to this study has been aggregated according to the four realms of social indicators of crime that are most predominant in criminological literature, shown previously in Figure 1.1:

1. Indicators of social disorganization (SD variables):
   - SD: Population Density (PPL/Sq mi).[28] Total population divided by county area in square miles.
   - SD: % Binge Drinking.[29] Percentage of resident population who drinks excessively based on thresholds established by the National Institute on Alcohol Abuse and

[26] Data collected by the Federal Bureau of Investigation through its two Uniform Crime Reporting Systems: the Summary Reporting System (SRS) and National Incident-Based Reporting System (NIBRS).
[27] While criminological research indicates that arrest data is not predictive of crime, this variable is specific to juvenile arrest because the tax under RCW 82.14.350 is earmarked for juvenile detention facilities. In this respect, the reason or legitimacy of the arrest is less relevant as the variable is not used an indicator of crime but as a predictor of juvenile detention population.
[28] Data collected through the Washington State Office of Financial Management, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[29] Data collected through the Behavioral Risk Factor Surveillance System of the United States Centers for Disease Control and Prevention, and compiled by County Health Rankings, a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.

Alcoholism (NIAA). NIAA defines binge drinking as a pattern of drinking that brings blood alcohol concentration (BAC) levels to 0.08 g/dL. This typically occurs after 4 drinks for women and 5 drinks for men in a 2-hour window.

- SD: Average Reported Poor Mental Health Days.[30] Reported average number of days respondents felt mentally unhealthy based on self-assessment surveys.
- SD: Income Inequality Ratio (80th Percentile Income/20th Percentile).[31] Ratio of household income at the 80th percentile measured against household income at the 20th percentile. A higher inequality ratio indicates greater division between the top and bottom ends of the income spectrum.
- SD: Residential Segregation Index - Black/White.[32] An index of dissimilarity in the racial distribution of the population ranging from 0 (complete integration) to 100 (complete segregation). The index score can be interpreted as the percentage of either black or white residents that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area.
- SD: Residential Segregation Index - non-white/White.[33] An index of dissimilarity in the racial distribution of the population ranging from 0 (complete integration) to 100 (complete segregation). The index score can be interpreted as the percentage of either non-white or white residents that would have to move to different geographic areas in order to produce a distribution that matches that of the larger area.

[30] See Footnote 29.
[31] Data collected through the American Community Surveys administered by the United States Census Bureau, and compiled by County Health Rankings, a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.
[32] See Footnote 31.
[33] See Footnote 31.

- SD: High School Graduation Rate.[34] Percentage of high school students who graduate, whether on time or not.
- SD: % of Population with College Degree.[35] Percentage of adults 25 or older who received a bachelor's degree or higher.

2. Indicators of family disruption (FD variables):
   - FD: % of Total Births to Unmarried Teenage Mothers (15-19).[36] Percentage of total births to unmarried mothers age 15 to 19.
   - FD: % of Total Births to Unmarried Mothers.[37] Percentage of total births to unmarried mothers, of any age.
   - FD: Children in Foster Care.[38] Number of children under 18 years of age in foster care placement, expressed on the scale of 1:1,000 children.
   - FD: Divorce Rate.[39] Number of divorces expressed on the scale of 1:1,000 residents.
3. Indicators of absolute or relative deprivation (ARD variables):
   - ARD: % Unemployed.[40] Percentage of people ages 16 and over who are without a job but are actively looking for one.

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[34] Data collected by the Washington State Office of Superintendent of Public Instruction, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[35] Data collected by the United States Department of Agriculture Economic Research Service.
[36] Data collected by the Washington State Department of Health Data Center for Health Statistics, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[37] See Footnote 36.
[38] Data collected by the Washington State Department of Social and Health Services Research and Data Analysis, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[39] See Footnote 36.
[40] Data collected by the Labor Market and Economic Analysis Branch of the Washington State Employment Security Department, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.

- ARD: % Total Adults without Health Insurance.[41] Percentage of the population ages 18 to 64 that has no health insurance coverage.
- ARD: % Children without Health Insurance.[42] Percentage of the population under the age of 19 that has no health insurance coverage.
- ARD: % of Total Population in Poverty.[43] Percentage of the population with income levels below federal poverty thresholds established by the United States Office of Management and Budget. For example, a family of two adults and two children in 2018 would be in poverty with household income equal to, or less than, $25,465.[44]
- ARD: % Children under 18 in Poverty.[45] Percentage of children under the age of 18 who live in families with income levels below federal poverty thresholds established by the United States Office of Management and Budget.
- ARD: % Children Participating in Basic Food Program.[46] Percent of children under the age of 18 receiving benefits from the U.S. Department of Agriculture Supplemental Nutrition Assistance Program (SNAP), called Basic Food in Washington.
- ARD: % Homeowners.[47] Percentage of owner-occupied and owner-vacant housing units.

[41] Data collected through the Small Area Health Insurance Estimates Program of the United States Census Bureau, and compiled by County Health Rankings, a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.
[42] See Footnote 41.
[43] United States Census Bureau. *Poverty Rates by County (1960-2010)*. Available at: https://tinyurl.com/yybtz9a2 [Accessed 18 Mar. 2019].
[44] Semega, J.; Kollar, M.; Creamer, J.; Mohanty, A. (2019). *Income and Poverty in the United States: 2018*. Washington, DC: United States Census Bureau.
[45] Data collected through the Small Area Income and Poverty Estimates Program of the United States Census Bureau, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[46] See Footnote 38.
[47] Data compiled by the Federal Reserve Bank of St. Louis through its Federal Reserve Economic Data portal.

- ARD: % Severe Housing Problems.[48] Percentage of households with one or more of the following housing problems: (a) housing unit lacks complete kitchen facilities or plumbing facilities; (c) household is overcrowded (more than one person per room); or (d) household spends 50% or more of its income on housing.

4. Demographics (DG variables):

- DG: Per Capita Income.[49] Income from all sources of the entire resident population divided by the resident population.
- DG: Median Household Income.[50] The annual income level at which half of all households in the county have more income and half have less.
- DG: % less than 18 years of age.[51] Percentage of the population younger than 18.
- DG: % Female.[52] Percentage of the population that is female.
- DG: % Not Proficient in English.[53] Percentage of the population age 5 and over that self-reports speaking English "not well" or "not well at all."
- DG: % Rural.[54] Percentage of the population living in census tracts with a population under 2,500.

[48] Data tabulated for the United States Department of Housing and Urban Development (HUD) Comprehensive Housing Affordability Strategy by the United States Census Bureau, and compiled by County Health Rankings, a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.
[49] Data collected through the United States Department of Commerce Bureau of Economic Analysis, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[50] See Footnote 28.
[51] Data collected through the Small Area Demographic Estimates of the Washington State Office of Financial Management, and compiled by Washington KIDS COUNT, a partnership between the Children's Alliance and the Washington State Budget & Policy Center.
[52] Data prepared by the Population Estimates Program of the United States Census Bureau, and compiled by County Health Rankings, a collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute.
[53] See Footnote 31.
[54] See Footnote 52.

- DG: Relevant Previous Presidential Election Turnout.[55] Party receiving the majority of electoral votes in the immediately preceding presidential election (1988-2016).

3.3.3 *Revenue Data*

While revenue data has been consistently collected at county level, it has been inconsistently compiled and presented through different state agencies. Until 2000 the Washington Department of Revenue reported local sales and use tax distributions on a bimonthly basis. From 2001 the Department of Revenue began offering annual reporting summaries. Since 2009 local revenue data has been compiled with much more detail through the new Local Government Finance Reporting System (LGFRS) portal of the Office of the Washington State Auditor. The following variables in this domain are all scaled on the basis of $1:1,000 residents (RC variables):

1. RC: Total Taxable Retail Sales. The amount of reported taxable retail sales in all incorporated and unincorporated areas of the county.
2. RC: Total Tax Revenue. The amount of total tax revenue available to the county from all sources, such as property tax, sales and use tax, numerous excise taxes, and penalties and interest on delinquent taxes. It includes incorporated and unincorporated areas.
3. RC: SALTAX. General fund sales and use tax revenue raised by the county. It includes incorporated and unincorporated areas. It does not include sales and use tax earmarked for special purposes.
4. SPLOST CJ: RCW 82.14.340. If a county imposes the SPLOST under RCW 82.14,340, the amount of revenue raised. It includes incorporated and unincorporated areas.

[55] Official poll results certified by the Washington Secretary of State.

5. SPLOST JD: RCW 82.14.350. If a county imposes the SPLOST under RCW 82.14,350, the amount of revenue raised. It includes incorporated and unincorporated areas.

In addition, the revenue domain of this study incorporates two binary and two latent variables:

6. RC: SPLOST CJ. This is a binary variable that indicates whether the county has adopted the Criminal Justice SPLOST. A value of 1 indicates the county imposes the SPLOST, while zero indicates no SPLOST.
7. RC: SPLOST JD. This is a binary variable that indicates whether the county has adopted the Juvenile Facilities SPLOST. A value of 1 indicates the county imposes the SPLOST, while zero indicates no SPLOST.
8. RC: Degree of Reliance on Sales Tax. This is a latent variable computed by comparing county revenue from general fund sales and use taxes with total county tax revenue.
9. RC: Presumed SALTAX Spillover. This is a latent variable computed by measuring each observation of a county's taxable retail sales per 1,000 residents against the state average of taxable retail sales for the same year per 1,000 residents. A value equal to 1 indicates that the county's taxable retail sales are identical to state average for that year.

3.3.4 *Tabulation*

Data for all Washington counties and for all variables listed above was collected for annual lags for the period from 1990 to 2018. The data was then tabulated to yield a set of 46 observations for each of 29 lags and each of 39 counties (52,026 observations).

Table 3.5. Data Tabulation Matrix

County	***Year***	***CJ/JD (8 Var.)***	***SD (10 Var.)***	***FD (4 Var.)***	***ARD (8 Var.)***	***DG (7 Var.)***	***RC (9 Var.)***
$County_x$	1990	VALUE	VALUE	VALUE	VALUE	VALUE	VALUE
$County_x$	…	VALUE	VALUE	VALUE	VALUE	VALUE	VALUE
$County_x$	2018	VALUE	VALUE	VALUE	VALUE	VALUE	VALUE

Chapter 4. A KERNEL MODEL TO EXPLAIN SPLOST REVENUE

4.1 THE KERNEL REGRESSION MODEL

The first research question is whether there is a detectable trend in the distribution of sales tax revenue across the state and, if a trend can be identified, whether a predictive statistical model can be fitted to estimate future SPLOST revenue patterns. The model used to answer this question is the Kernel regression model proposed by Nadaraya and Watson (Bierens, 1994). While many variations of the Kernel model are available, this study applies the Locally Weighted Scatterplot Smoothing (LOWESS) method introduced by Cleveland (1979) because it offers the benefit of understanding the learning sample temporally, rather than as a single dataset.

The Kernel regression model uses a kernel function to weigh the observations depending on their distance from the predicted observation. The closer the values of the explanatory variables from the learning sample are to the values of the observation being predicted, the higher the weight. This type of regression does not assume a linear relationship between independent and dependent variables and is useful only insofar as it can confirm whether adding certain variables to the model increases its forecasting quality.

$$y = g(x_i) + \epsilon$$

where

y = dependent variable

x_i = weighted explanatory variables

g = non-linear regression slope

ϵ = error term

To identify the best explanatory variables for the Kernel model, the study first addressed several ancillary questions to understand the historical trend of sales tax revenue and the relationship between the flow of sales tax revenue and the social structure of Washington counties during the observed time series.

4.2 Identifying Historical Trends in Sales Tax Reliance

The literature suggests that local governments have been relying more heavily on sales taxes in the last five decades. The objective of the first ancillary research question is to verify whether Washington counties have been following this national trend and, if so, to what extent. If an upward trend can be identified, three subsequent expectations emerge. First, that some counties have tried to leverage the sales tax more aggressively than others. Second, that the tax portfolio of Washington counties today relies more heavily on sales taxes than ever before. Third, that the increased reliance on the sales tax has augmented tax spillovers. Understanding the relationship between these elements can reveal if they are connected to each other, to what extent, and whether they are useful to forecast future SPLOST revenue.

The degree of reliance on sales tax is a latent variable computed by comparing each county's total tax revenue (all revenue from BARS accounts beginning with 31) with the respective general fund sales and use tax revenue (BARS code 313). Data from 1990 through 2018 was tabulated for all counties to display a degree of reliance on the general sales and use tax ranging from 0 (no reliance) to 100 (total reliance). All observations were grouped by year to test whether an upward monotonic trend can be identified in the time series applying the trend test proposed by Mann (1945) and Kendall (1975). The Kendall's tau, the correlation coefficient expressing the presence of a trend from 0 to 1, was 0.437 at a 95% confidence interval ($P<0.005$, 95% CI, $N=1131$) with a

Sen's slope, the magnitude of the trend, of 0.001. These values indicate a slow but steady and reliable upward trend statewide ().

The Mann-Kendall trend test confirmed the presence of a steady upward trend at the overall state level. County-level time series visualizations confirm that the upward trend is valid for each individual county over the observed time period, albeit at different paces (Figure 4.8).

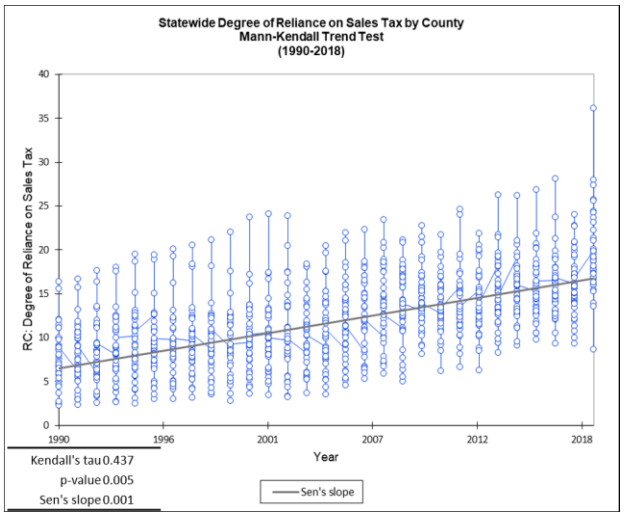


Figure 4.7. Statewide Degree of Reliance on Sales Tax, Historical Trend Test

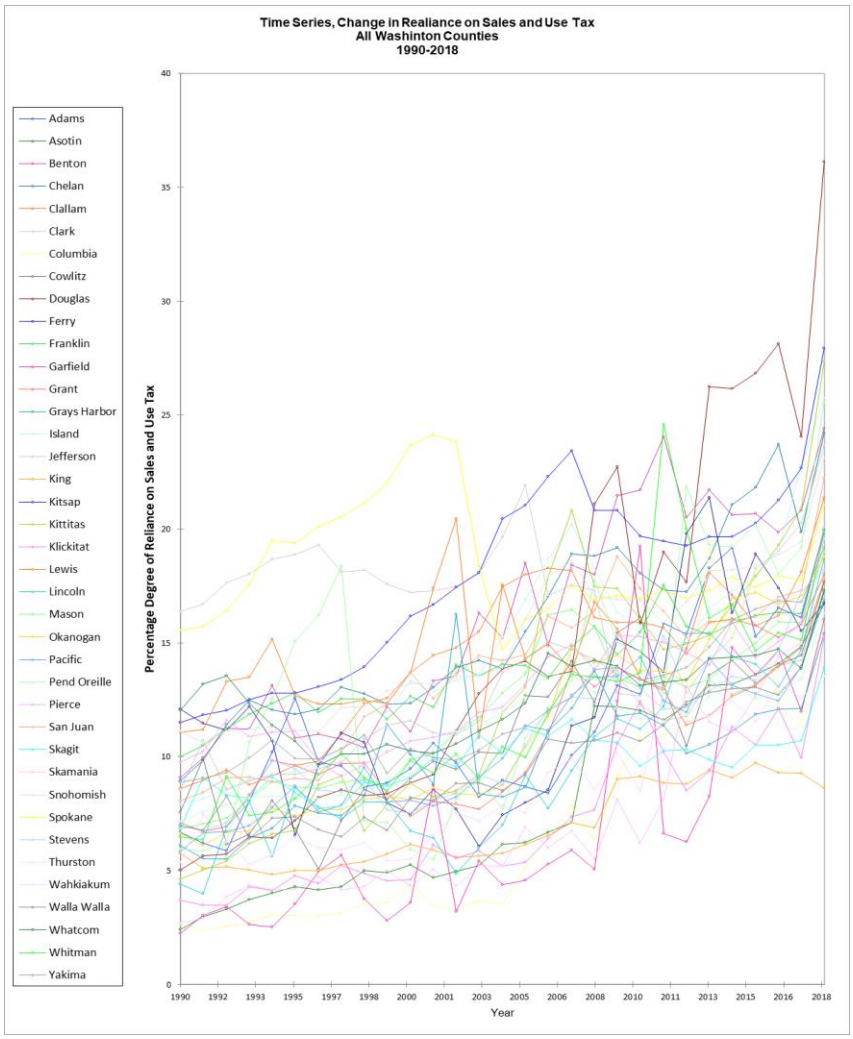


Figure 4.8. Reliance on Sales Tax by County, Time Series Visualization

Comparing 1990 with 2018 data, the degree of reliance on the general sales and use tax has increased for each Washington county, from a minimum of 135 percent increase (Spokane County) to a maximum of 724 percent increase (Skamania County). There is no single instance, among all 39 counties, of decreased reliance on sales and use tax revenue from 1990 through 2018 (Figure 4.9).

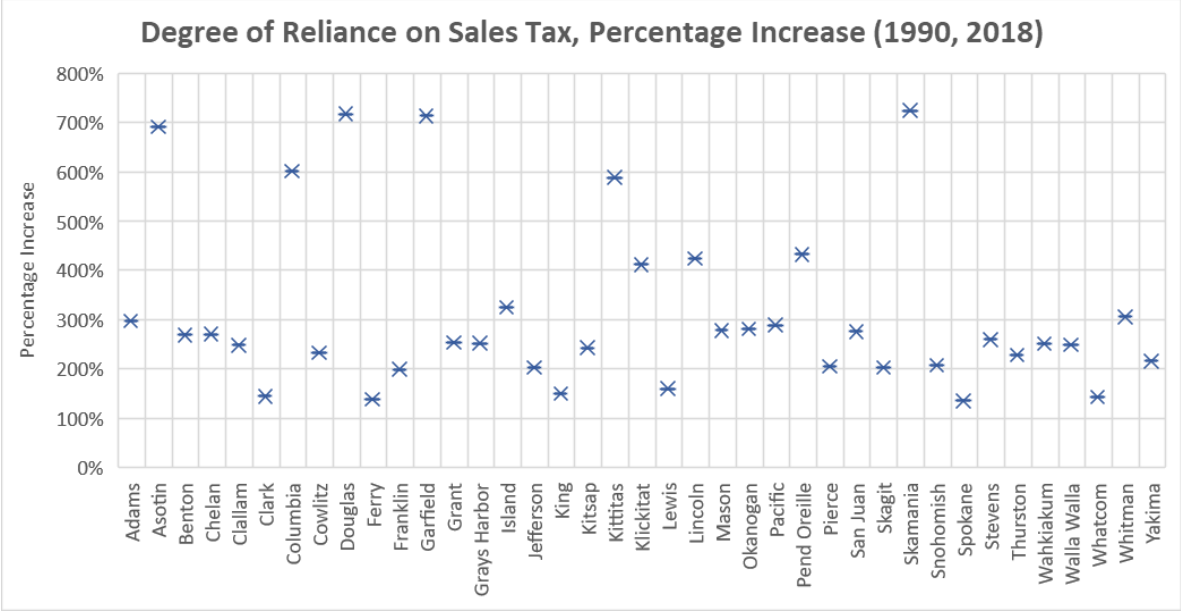


Figure 4.9. Degree of Reliance on Sales Tax, Percentage Increase by County

As of 1990, the counties relying the least on the general sales tax were Asotin and Garfield, while those relying the most were Clark and Spokane (Figure 4.10). By 2018, King county has become the one relying the least on the general sales and use tax, while Douglas has reached by far the highest degree of reliance among all Washington counties (Figure 4.11). As of 2018, the general fund revenue portfolio of all Washington counties comprises 15-25% sales tax, 50-70% property tax, and 15-30% other taxes (Figure 4.12). Therefore, while property taxes remain the main source of general fund revenue at the county level, the modern portfolio is balanced, sometimes evenly, with a combination of sales and other taxes.

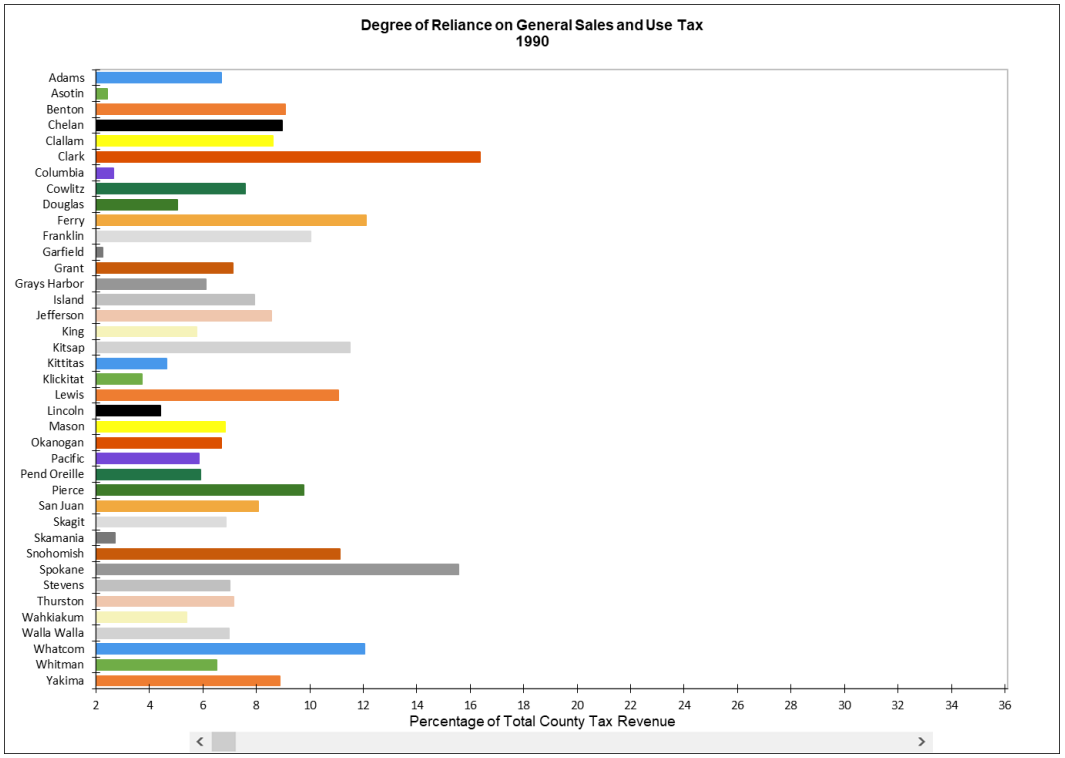


Figure 4.10. Degree of Reliance on Sales Tax by County (1990)

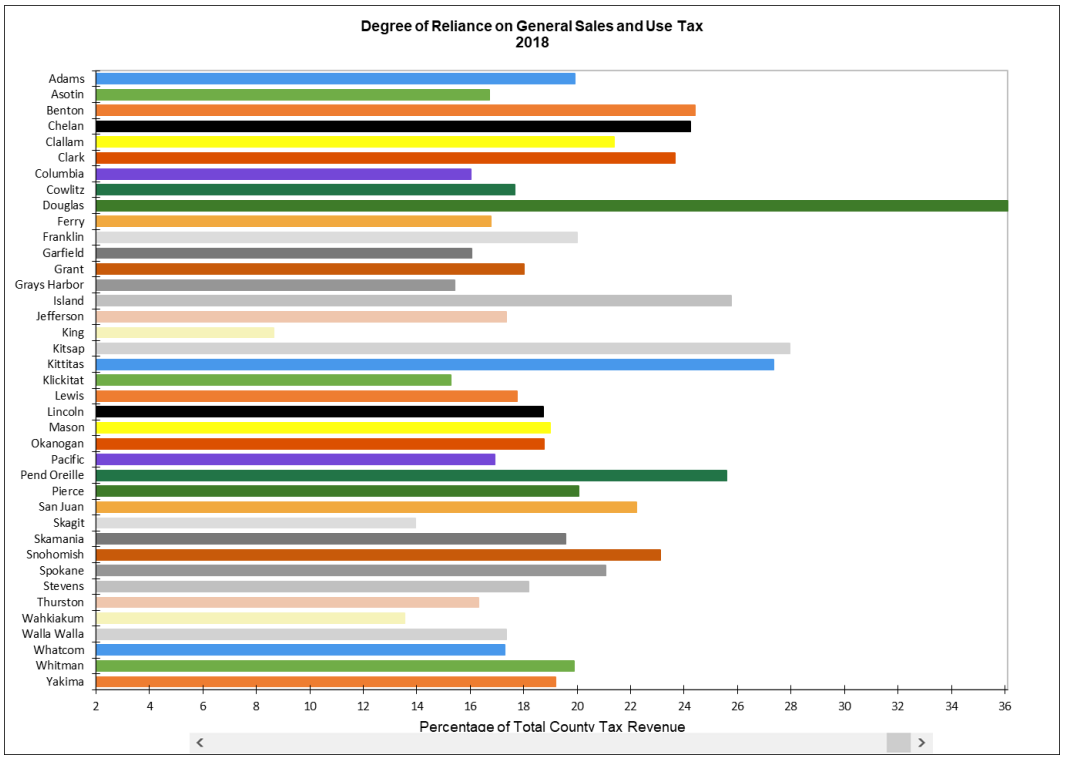


Figure 4.11. Degree of Reliance on Sales Tax by County (2018)

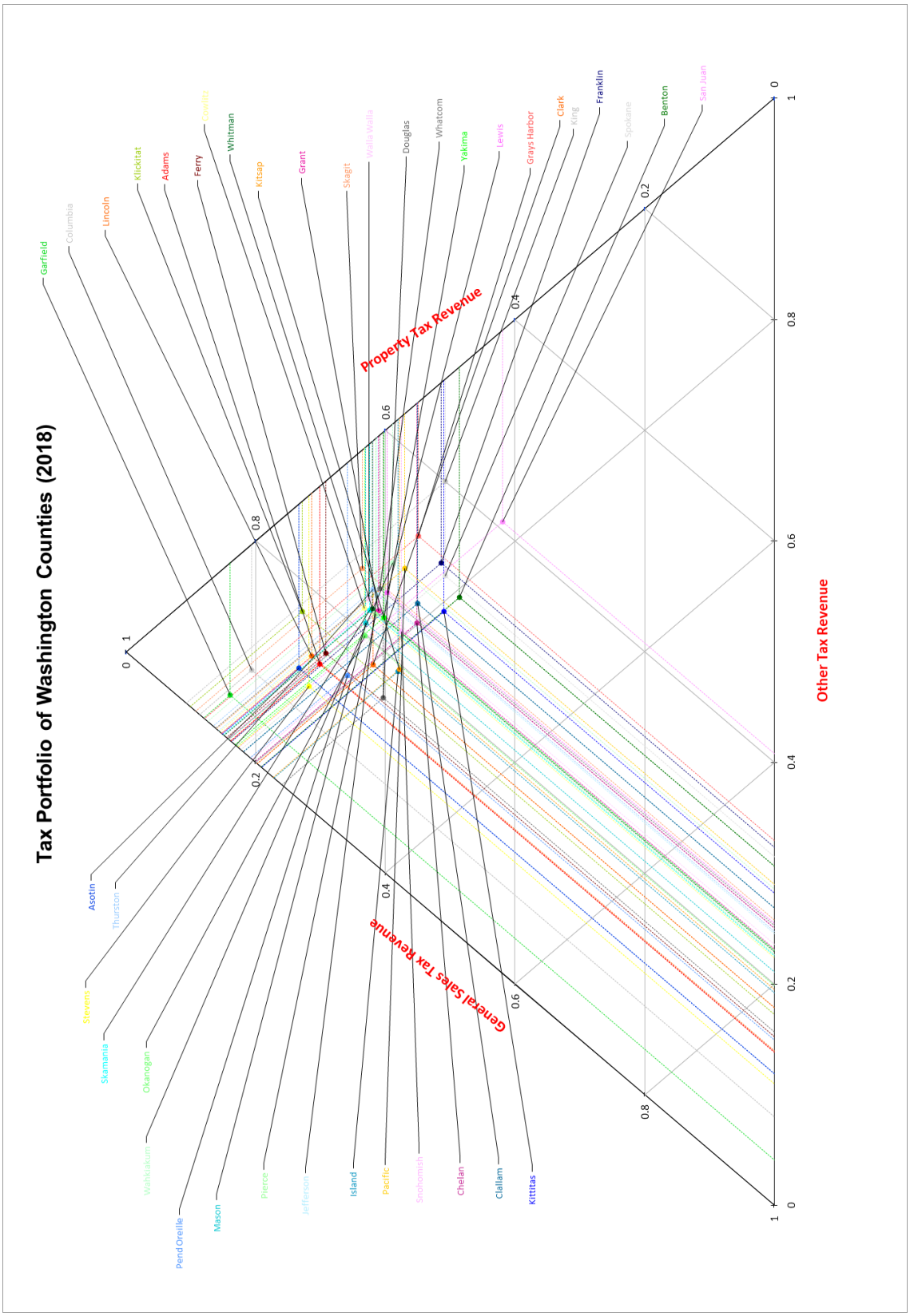


Figure 4.12. Tax Portfolio of Washington Counties (2018)

4.3 Winners and Losers in Sales Tax Spillovers

Section 4.2 showed that, while all Washington counties rely more on sales taxes today than in 1990, the upward trend has been more aggressive in some counties. The expectation is that this increased reliance on the sales tax has augmented tax spillovers. If that is indeed the case, there should be a positive association between the degree of reliance on sales tax, tax spillovers, and taxable retail sales and the Kernel model can leverage that association.

The literature defines fiscal equivalence as a condition present when a body of taxpayers paying for a public service is perfectly congruent with the body of taxpayers benefitting from that public service. Tax spillovers preclude fiscal equivalence because jurisdictions can export the cost of public services to taxpayers outside the jurisdiction (Jansen 1991; Lockwood 2000). The degree of tax spillover depends on how the jurisdiction's tax collections compare to an expected range. In this study, the presumed tax spillover is a latent variable computed by measuring each observation of a county's taxable retail sales per 1,000 residents against the state average of taxable retail sales for the same year per 1,000 residents. Expressing taxable retail sales on the scale of 1,000 residents is important to neutralize the effects of the size of a county's population, thereby expressing all values on a common scale. A value equal to 1 indicates that the county's taxable retail sales are identical to the state average for that year. A value above 1 indicates that the county reports taxable retail sales above the state average, thus resulting in a positive tax spillover into county coffers. A negative tax spillover, indicated by a value between 0 and 1, indicates that the county is losing sales tax revenue to other jurisdictions. This working definition presumes fiscal equivalence at the state level, thus ignoring interstate tax spillovers.

Over all counties and observed periods, the tax spillover index has been as low as 0.248 (Wahkiakum 1999) and as high as 1.512 (King 2000), indicating that in those years Wahkiakum

and King counties were at the opposite spectrum of losing and gaining sales tax revenue on a competitive basis.

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Presumed SALTAX Spillover	1131	0.248	1.512	0.758	0.255

From the minimum and maximum values in the observed sample, it emerges that some counties are experiencing a significant negative tax spillover, while others are collecting far more sales tax revenue than the statewide standard for 1,000 residents. The distribution of the observations indicates a low variance (0.065), with a positive skewness (0.553) and kurtosis (0.106). The low variance shows that most of the observations are close to the mean (0.758) and to each other. The positive skewness and kurtosis indicate that the right tail (positive spillover) of the distribution is longer than the left (Figure 4.13).

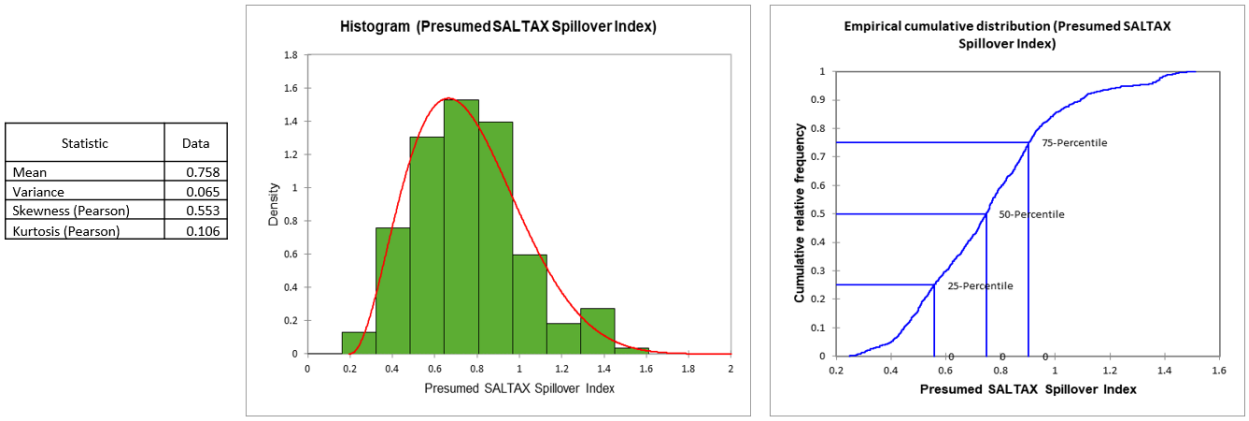


Figure 4.13. Sales Tax Spillover, Normal Distribution and Interquartile Range

In sum, most Washington counties in most years observed experienced a negative tax spillover (loss of sales tax revenue), while few counties reaped all that lost sales tax revenue in the form of large positive tax spillovers. In fact, only 8% of 1,131 observations fell above 1, meaning that for 92 instances where counties lose sales tax revenue, there are only 8 instances of counties benefitting. The only four counties that have maintained a positive tax spillover for the duration

of the study were Chelan (1990: 1.17, 2018: 1.21), King (1990: 1.35, 2018: 1.38), San Juan (1990: 1.41, 2018: 1.44), and Skagit (1990: 1.13, 2018: 1.12) (Figure 4.14 and Figure 4.15).

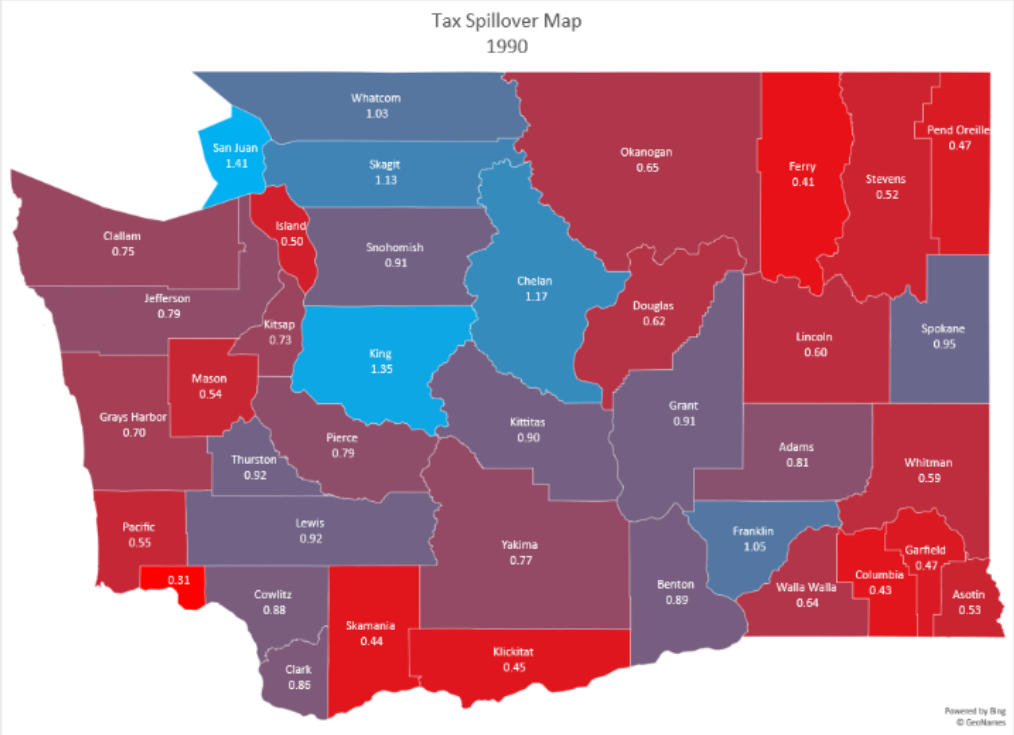


Figure 4.14. Sales Tax Spillover Map (1990)

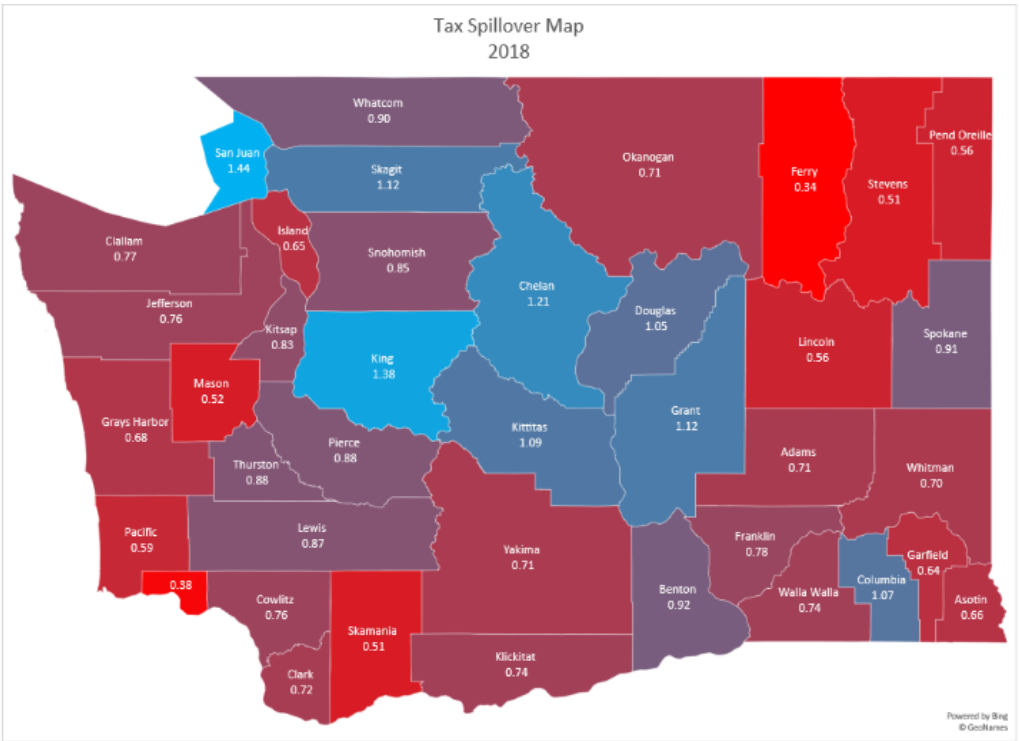


Figure 4.15. Sales Tax Spillover Map (2018)

The literature suggests that counties that can export the cost of public services will do so because taxpayers favor measures that shift the tax incidence to someone else (Biegeleisen and Sjoquist 1988). The ancillary research question is whether there is a correlation between the extent of tax spillover, the degree of reliance on the sales tax, and taxable retail sales, anticipating that positive tax spillovers are accompanied by heavier reliance on the sales tax (a less diversified portfolio) and more taxable retail sales.

At a 95% confidence interval there is a very strong, consistently positive association between tax spillovers and taxable retail sales in all Washington counties (Figure 4.16). The correlation *r*, which measures a linear dependence between two variables, is 0.868 statewide and the r^2 coefficient, which measures the proportion of the variance, is 0.754 statewide. This indicates that tax spillovers are excellent indicators of the flow of taxable retail sales and therefore crucial to the Kernel model.

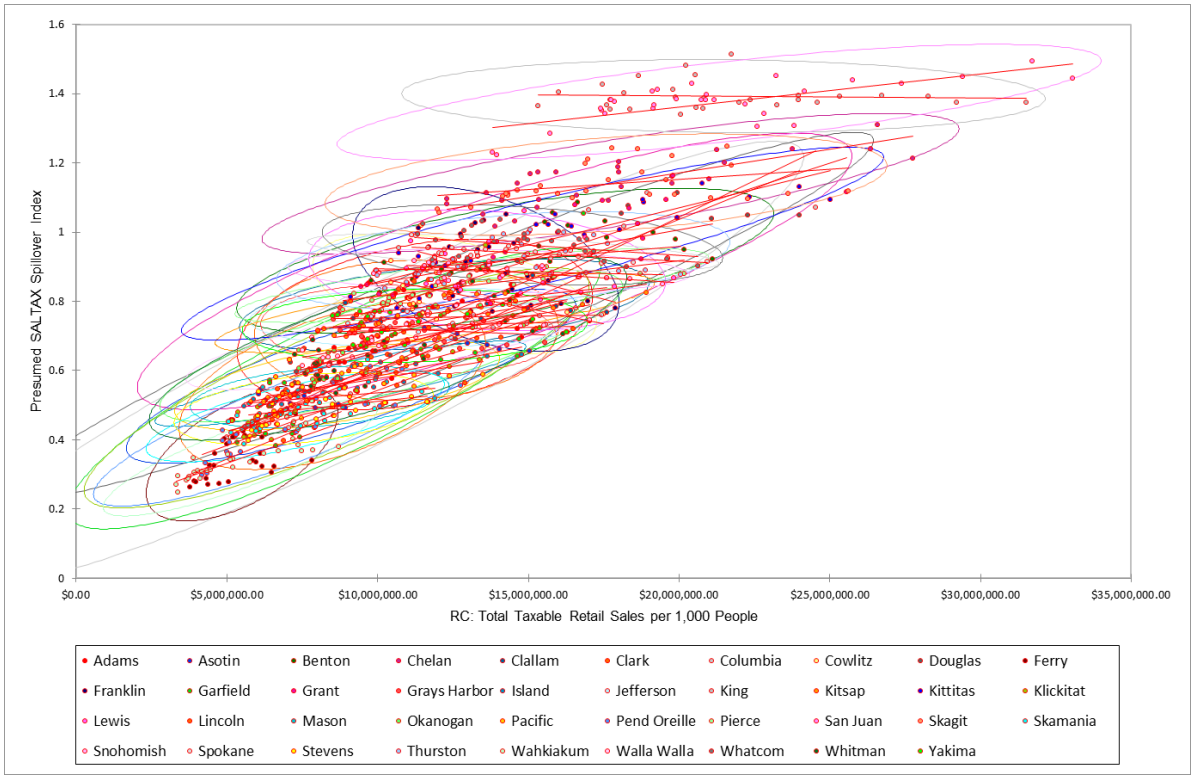


Figure 4.16. Retail Sales and Spillover, Scatterplot and Regression by County

The statistical relationship between taxable retail sales and the degree of reliance on the sales tax is far less strong albeit still evident for all Washington counties except Spokane (Figure 4.17). Statewide the correlation *r* is 0.524 and the r^2 coefficient is 0.275. This indicates that a county's degree of reliance on the sales tax is useful to the Kernel model, but not as much as the degree of tax spillover.

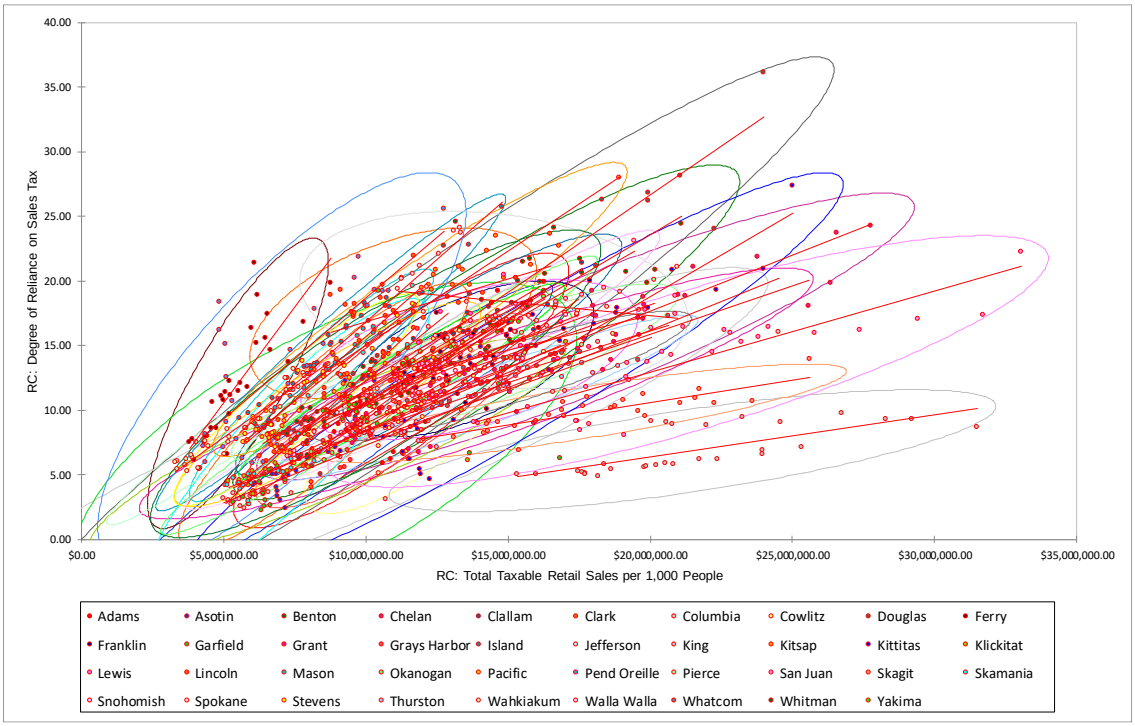


Figure 4.17. Retail Sales and Sales Tax Reliance, Scatterplot and Regression by County

4.4 Sales Tax as a Mobile Revenue Base Favoring Urban Areas

Previous sales tax research has consistently shown that rural jurisdictions are more prone to experience negative tax spillovers, leading to the conclusion that the sales tax inherently exacerbates financial inequalities between densely populated and rural areas. Rural areas tend to experience negative tax spillovers because of lower population density and per capita income. This study measures rurality in two different ways. First, the annual population for each county was divided by the county area in square miles, thus arriving at a yearly measure of population density.

Second, data was collected pertaining to the percentage of each county's population living in census tracts with less than 2,500 residents, thus measuring intra-county rurality. While Section 4.3 has found a positive statistical association between sales tax spillovers, the degree of reliance on the sales tax, and taxable retail sales, it is anticipated that measures of population density and income are also strong indicators of taxable retail sales.

Five quantitative variables were included in an Analysis of Covariance (ANCOVA) regression model with one respondent variable and four explanatory variables. ANCOVA is particularly effective in this instance because it tests each explanatory variable separately to see what influence it has on the model coefficient for the respondent variable, thereby ranking explanatory variables by importance so that only the best indicators are included in the Kernel model.

$$y = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \epsilon$$

where

y = respondent variable*

x_i = explanatory variables**

p = number of quantitative variables

j = each quantitative variable separately

β = coefficient

ϵ = error term

***Respondent Variable**
y=RC: Taxable Retail Sales per 1,000 People

****Explanatory Variables**
x_1=DG % Rural
x_2=SD Population Density (PPL/Sq Ml)
x_3=Median Household Income
x_4=Per Capita Income

While there was a statistically significant relationship between all explanatory variables and the respondent variables, the percentage of a county's population living in rural areas was more determinant of taxable retail sales than population density. Similarly, per capita income was more

determinant than median household income. The percentage of a county's population living in rural areas and per capita income were therefore the best correlates of taxable retail sales (Figure 4.18).

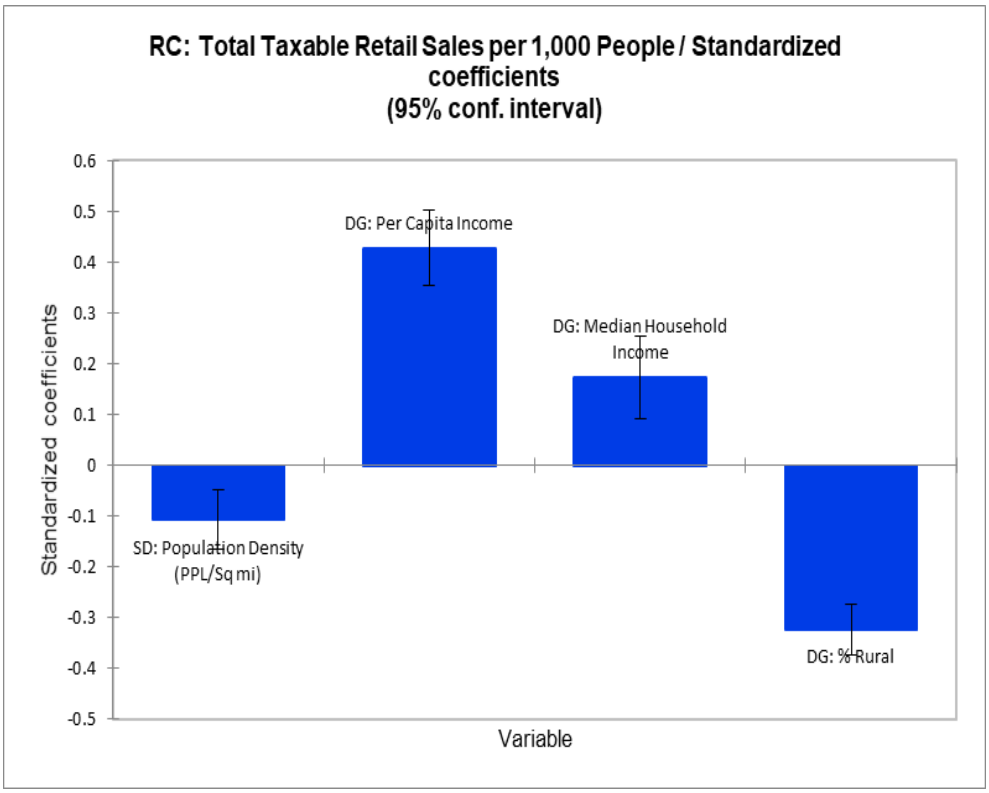


Figure 4.18. Taxable Retail Sales, ANCOVA r^2 by Variable

Consistent with expectations, the relationship between per capita income and taxable retail sales was directly proportional, while the relationship between rurality and taxable retail sales was inversely proportional (Figure 4.19 and Figure 4.20).

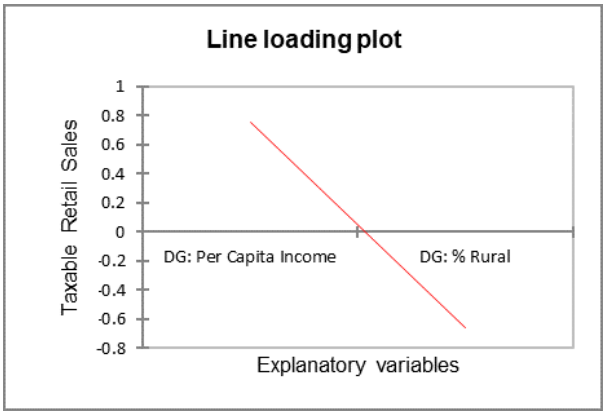


Figure 4.19. Line Loading Plot

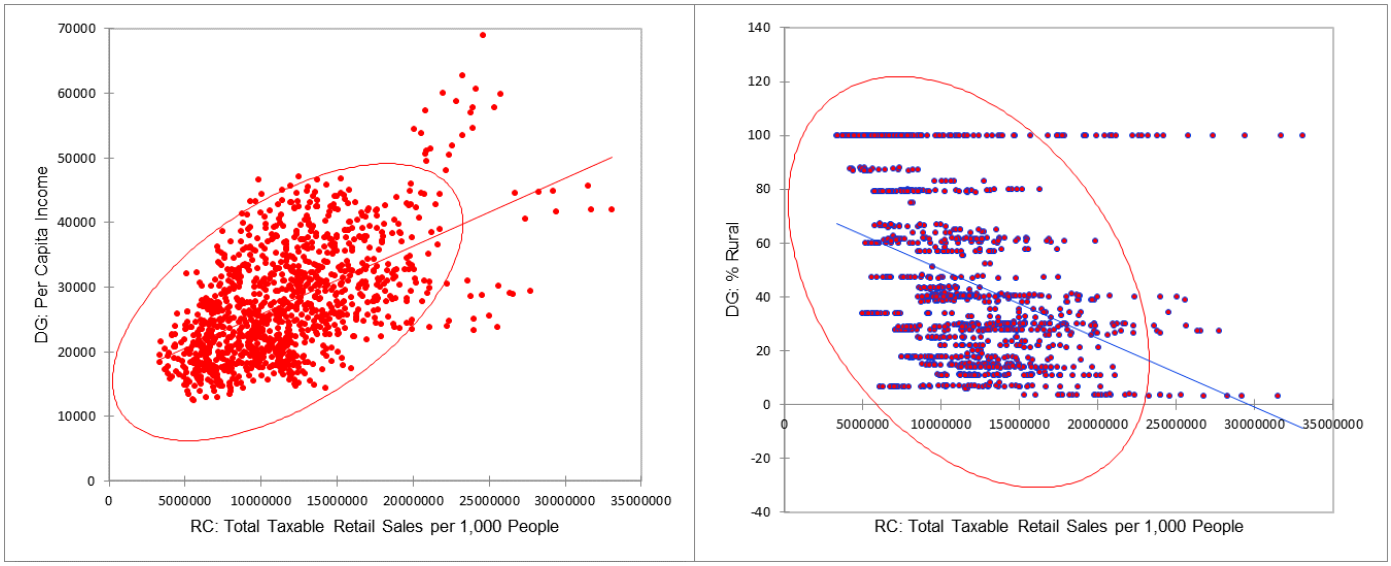


Figure 4.20. Correlation Scatterplots for Figure 4.18

The explanatory power of the ANCOVA model was 0.427 (Figure 4.21), indicating that less than half of the flow of sales tax revenue is explained solely by where people live and the income at their disposal. Therefore, while urban counties with higher per capita income can indeed collect more sales tax revenue and thus export the cost of their services to neighboring jurisdictions, income and urbanization explains only a portion of the pattern.

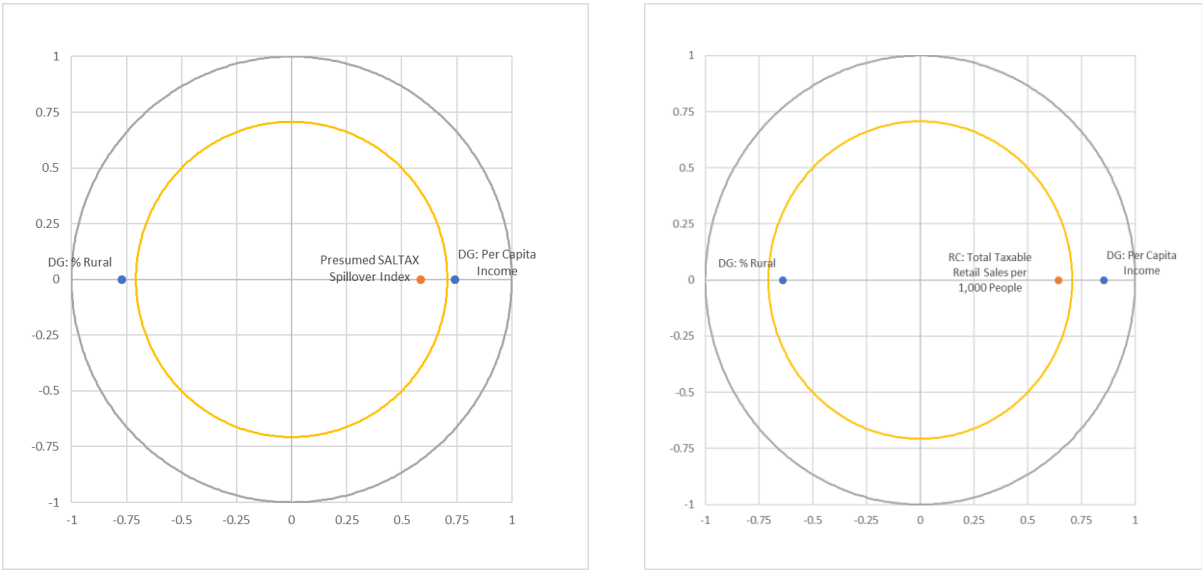


Figure 4.21. Correlation Circles for Figure 4.18

4.5 Probing Whether Crime Informs Local Tax Policy

Two special purpose local option sales taxes are observed in this study. The first allows any county to impose, without vote but subject to repeal by referendum, a 0.1% SPLOST earmarked to fund 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. Once collected, 10% of the tax remains in the county coffers and 90% is shared among the county and the cities within the county ratably based on population. The second allows counties with populations of less than one million to impose, subject to a majority approval of county voters, a 0.1% SPLOST earmarked to fund "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 in the county coffers and is not shared with the cities within the county. In state-issued literature, the special purpose location option sales tax under RCW 82.14.340 is referred to as the Criminal Justice SPLOST, while the one under RCW 82.14.350 is referred to as the Juvenile Facilities (or detention) SPLOST.

The ancillary research question is whether there is a biserial correlation between a county's decision to impose either SPLOST and the respective crime data outlined in Section 3.3.1. If a biserial correlation exists, crime data can be fitted to the Kernel model as indicative of a county's likelihood to impose one of the two SPLOSTs. In this respect, correlation is first measured between all CJ variables and a binary variable that indicates whether the county has adopted the Criminal Justice SPLOST. Correlation is then observed between all JD variables and a binary variable that indicates whether the county has adopted the Juvenile Facilities SPLOST (Figure 4.22).

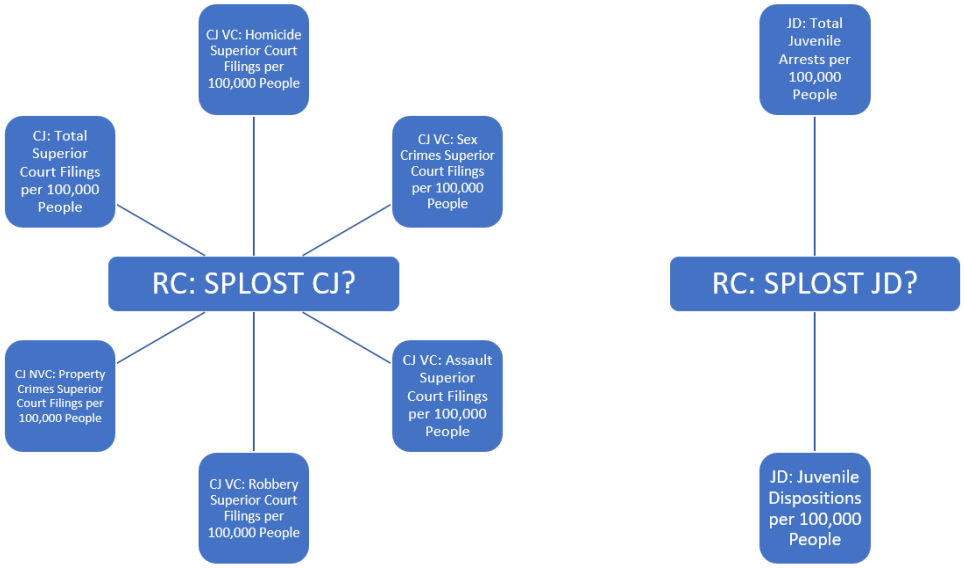


Figure 4.22. SPLOST and Crime, Radial Clusters

As of April 1, 2020, no Washington county imposes the Juvenile Facilities SPLOST without also imposing the Criminal Justice SPLOST, although state law does not require that one be a condition to the other. Only four counties—Asotin, Garfield, Klickitat, and Wahkiakum—do not impose either SPLOST. All other counties either impose only the Criminal Justice SPLOST. The Criminal Justice SPLOST is therefore far more common across the state than the Juvenile Facilities SPLOST (Figure 4.23).

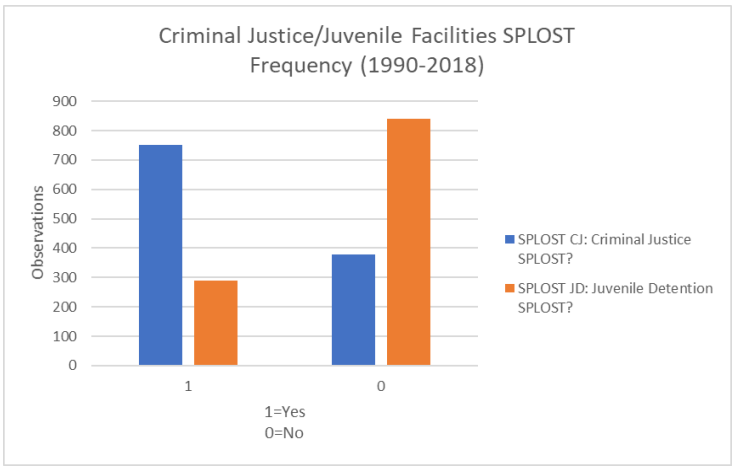


Figure 4.23. CJ and JD SPLOST, Frequency of Adoption

At a 95% confidence interval there is no statistical significance, or nearly zero relationship, between a county's decision to impose the Criminal Justice SPLOST and any of the crime observations in the study. Even the weakest statistically significant association is negative,

indicating that, to the extent a minuscule association exists, it is inversely proportional (i.e., a county is more prone to impose the Criminal Justice SPLOST where crime is lower) (Table 4.6).

Table 4.6. Correlation Matrix: CJ SPLOST/CJ Measures

Variables	SPLOST CJ: Criminal Justice SPLOST? p-value	SPLOST CJ: Criminal Justice SPLOST? Correlation
CJ VC: Homicide Superior Court Filings per 100,000 People	**< 0.0001**	**-0.249**
CJ VC: Sex Crimes Superior Court Filings per 100,000 People	**< 0.0001**	**-0.243**
CJ VC: Assault Superior Court Filings per 100,000 People	0.783	-0.005
CJ VC: Robbery Superior Court Filings per 100,000 People	0.260	0.032
CJ NVC: Property Crimes Superior Court Filings per 100,000 …	**< 0.0001**	**-0.119**
CJ: Total Superior Court Filings per 100,000 People	0.130	-0.043

The same holds true with respect to a county's propensity to impose the Juvenile Facilities SPLOST and any of the juvenile indicators in the study. Even the weakest statistically significant association is again negative, indicating that, to the extent a minuscule association exists, it is inversely proportional (i.e., a county is more prone to impose the Juvenile Facilities SPLOST where juvenile crime is lower) (Table 4.7).

Table 4.7. Correlation Matrix: JD SPLOST/JD Measures

Variables	SPLOST JD: Juvenile Detention SPLOST? p-value	SPLOST JD: Juvenile Detention SPLOST? Correlation
JD: Total Juvenile Arrests per 100,000 People	0.847	0.002
JD: Juvenile Dispositions per 100,000 People	**< 0.0001**	**-0.117**

4.5.1 *Making Sense of a County's Decision to Impose a SPLOST*

As discussed above, a county's decision to impose either the Criminal Justice or Juvenile Facilities SPLOST does not seem to be informed by crime data. What then informs this decision? A correlation matrix among all other variables in this study indicates that weak or moderate statistical associations exist only between the adoption of either SPLOST and measures of a

county's ability to raise sales tax revenue, such as per capita income, median household income, taxable retail sales, sales tax spillover, and degree of reliance on the sales tax (Table 4.8).

Table 4.8. Correlation Matrix: SPLOST/All Measures

	SPLOST CJ: Criminal Justice SPLOST?		SPLOST JD: Juvenile Detention SPLOST?	
Variables	p-value	correlation	p-value	correlation
FD: % of Total Births to Single Teenage Mothers (15-19)	< 0.0001	-0.198	< 0.0001	-0.256
FD: % of Total Births to Single Mothers	0.024	0.066	0.000	-0.107
FD: Children in Foster Care Placement per 1,000 People	< 0.0001	-0.233	< 0.0001	-0.161
FD: Divorces per 1,000 People	< 0.0001	-0.209	0.001	-0.093
SD: Population Density (PPL/Sq mi)	< 0.0001	0.218	< 0.0001	0.193
SD: % Binge Drinking	0.086	-0.049	0.263	0.031
SD: Average Reported Poor Mental Health Days	0.001	-0.104	< 0.0001	-0.153
SD: Income Inequality Ratio	0.597	0.013	0.002	0.096
SD: Residential Segregation Index - Black/White	0.405	-0.023	< 0.0001	-0.256
SD: Residential Segregation Index - non-white/White	< 0.0001	0.122	< 0.0001	-0.124
SD: High School Graduation Rate	0.725	0.007	0.006	0.079
SD: % of Population with Some College Education	0.001	-0.098	0.001	0.097
SD: % of Population with College Degree	< 0.0001	0.197	**< 0.0001**	**0.300**
ARD: % Unemployed	< 0.0001	-0.127	< 0.0001	-0.248
ARD: % Total Adults without Health Insurance	0.010	0.073	0.000	-0.111
ARD: % Children without Health Insurance	0.123	-0.044	< 0.0001	-0.145
ARD: % of Total Population in Poverty	0.326	-0.027	< 0.0001	-0.124
ARD: % Children under 18 in Poverty	< 0.0001	-0.113	< 0.0001	-0.278
ARD: % Children Participating in Basic Food Program	0.000	-0.109	< 0.0001	-0.209
ARD: % Homeowners	< 0.0001	-0.164	< 0.0001	-0.156
ARD: % Severe Housing Problems	< 0.0001	0.198	< 0.0001	0.189
DG: Per Capita Income	**< 0.0001**	**0.381**	**< 0.0001**	**0.298**
DG: Median Household Income	**< 0.0001**	**0.453**	**< 0.0001**	**0.381**
DG: % less than 18 years of age	0.010	-0.076	< 0.0001	-0.160
DG: % Female	< 0.0001	-0.159	0.038	-0.061
DG: % Not Proficient in English	< 0.0001	0.160	0.421	-0.021
DG: % Rural	< 0.0001	-0.206	< 0.0001	-0.214
DG: Relevant Previous Presidential Election Turnout	0.103	0.047	0.018	-0.070
RC: Total Taxable Retail Sales per 1,000 People	**< 0.0001**	**0.392**	**< 0.0001**	**0.302**
Presumed SALTAX Spillover Index	**< 0.0001**	**0.295**	**< 0.0001**	**0.242**
RC: Total Tax Revenue per 1,000 People	< 0.0001	-0.141	0.387	-0.023
RC: General Fund Sales and Use Tax Revenue (SALTAX)	**< 0.0001**	**0.301**	**< 0.0001**	**0.264**
RC: Degree of Reliance on Sales Tax	**< 0.0001**	**0.529**	**< 0.0001**	**0.369**

The Criminal Justice and Juvenile Facilities SPLOST are meant to provide earmarked funds for critical safety-related services. However, data shows that the decision by Washington counties

to impose either SPLOST is much more informed by economic characteristics than crime or social correlates of crime. In fact, the correlation matrix suggests that these SPLOSTs are imposed simply because a county can—it has the population, the income, and the economic activity necessary to collect these taxes—and not because there is an identifiable need for the earmarked funds.

4.6 Exploring Political Affiliation and County Social Structure

Political affiliation is often part of statistical models predicting 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 to property taxes (Jung 2001; Zhao & Jung 2008), especially when the sales tax is imposed in exchange for property tax relief (Sanders & Lee 2009; Jung 2001; Zhao & Jung 2008; Luna et al. 2007).

If a statistical association exists between a county's political affiliation and taxable retail sales or a county's propensity to impose either SPLOSTs, the political affiliation can also be fitted to the Kernel model. Data pertaining to each county's presidential election turnout over the 29-year period of this study was tabulated as binary, where 1 indicates that the county's majority vote in the immediately preceding presidential election was for the Republican candidate and 0 for the Democratic candidate (Figure 4.24).

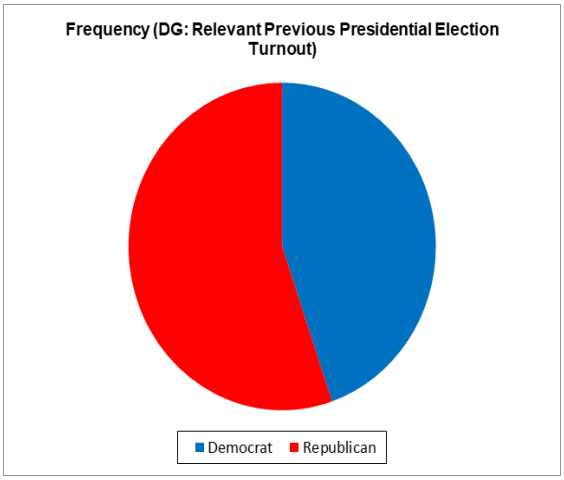


Figure 4.24. Presidential Election Turnout

At a confidence interval of 95% the biserial correlation shows that, while political affiliation is statistically significant with many variables observed in this study, it is not associated, insofar as Washington counties are concerned, with any measure related to sales tax revenue (Table 4.9).

Table 4.9. Correlation Matrix: Political Affiliation/All Measures

	Presidential Election Turnout	
Variables	p-value	correlation
CJ VC: Homicide Superior Court Filings per 100,000 People	**< 0.0001**	**0.143**
CJ VC: Sex Crimes Superior Court Filings per 100,000 People	**< 0.0001**	**0.144**
CJ VC: Assault Superior Court Filings per 100,000 People	**< 0.0001**	**0.192**
CJ VC: Robbery Superior Court Filings per 100,000 People	0.293	0.029
CJ NVC: Property Crimes Superior Court Filings per 100,000 People	**< 0.0001**	**0.134**
CJ: Total Superior Court Filings per 100,000 People	**< 0.0001**	**0.204**
JD: Total Juvenile Arrests per 100,000 People	**< 0.0001**	**0.309**
JD: Juvenile Dispositions per 100,000 People	**< 0.0001**	**0.243**
FD: % of Total Births to Single Teenage Mothers (15-19)	**< 0.0001**	**0.174**
FD: % of Total Births to Single Mothers	**< 0.0001**	**0.239**
FD: Children in Foster Care Placement per 1,000 People	0.569	0.014
FD: Divorces per 1,000 People	**< 0.0001**	**-0.22**
SD: Population Density (PPL/Sq mi)	**< 0.0001**	**-0.389**
SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)	**< 0.0001**	**-0.321**
SD: Average Reported Poor Mental Health Days	**< 0.0001**	**-0.242**
SD: Income Inequality Ratio (80th Percentile Income/20th Percentile)	**0.038**	**-0.061**
SD: Residential Segregation Index - Black/White	**0.026**	**0.065**
SD: Residential Segregation Index - non-white/White	0.062	0.054
SD: High School Graduation Rate	**0.012**	**0.074**
SD: % of Population with Some College Education	**0.001**	**-0.104**
SD: % of Population with College Degree	**< 0.0001**	**-0.345**
ARD: % Unemployed	0.137	0.042
ARD: % Total Adults without Health Insurance	**< 0.0001**	**0.26**
ARD: % Children without Health Insurance	**< 0.0001**	**0.141**
ARD: % of Total Population in Poverty	**< 0.0001**	**0.348**
ARD: % Children under 18 in Poverty	**< 0.0001**	**0.32**
ARD: % Children Participating in Basic Food Program	**< 0.0001**	**0.239**
ARD: % Homeowners	0.874	0
ARD: % Severe Housing Problems	**< 0.0001**	**-0.179**
DG: Per Capita Income	**< 0.0001**	**-0.151**
DG: Median Household Income	**< 0.0001**	**-0.166**
DG: % less than 18 years of age	**< 0.0001**	**0.234**
DG: % Female	**< 0.0001**	**-0.172**
DG: % Not Proficient in English	**< 0.0001**	**0.295**
DG: % Rural	**< 0.0001**	**0.119**
RC: Total Taxable Retail Sales per 1,000 People	**0.012**	**-0.074**
Presumed SALTAX Spillover Index	**< 0.0001**	**-0.17**
RC: Total Tax Revenue per 1,000 People	**< 0.0001**	**-0.17**
RC: General Fund Sales and Use Tax Revenue (SALTAX) per 1,000	**0.004**	**-0.083**
RC: Degree of Reliance on Sales Tax	**0.013**	**0.072**
SPLOST CJ: Criminal Justice SPLOST?	0.124	0.047
SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000	0.547	-0.015
SPLOST JD: Juvenile Detention SPLOST?	**0.016**	**-0.07**
SPLOST JD: RCW 82.14.350 Revenue (Juvenile Detention) per 1,000	**0.036**	**-0.06**

In general terms, Republican counties appear to prosecute more crimes, as evidenced by a positive association 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 Democratic 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 far more children, including more births to single mothers, but divorce less. While high school graduation rates are similar across the board regardless of political affiliation, Republican counties have starkly less people with college degrees and far more adults and children in poverty and without health insurance. At last, Republican counties in Washington are more rural, male-dominant, and are home to a greater number of 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. There is, however, no statistical significance between revenue composition and party affiliation. In other words, the tax portfolio of Washington counties is not statistically associated with how a county population votes in presidential elections.

4.7 Fitting the Kernel Regression Model

The previous sections showed that there is a clear statistical relationship between taxable retail sales and where people live, their income, and a county's tax spillover and degree of reliance on the sales tax. On the other hand, there is no correlation between crime or political affiliation and a county's propensity to impose the Criminal Justice or Juvenile Facilities SPLOST. What other social variables can contribute to better explain the flow of sales tax revenue? Figure 4.25 shows a map of correlation and coefficients of determination among all SD, ARD, and DG variables in this study against taxable retail sales.

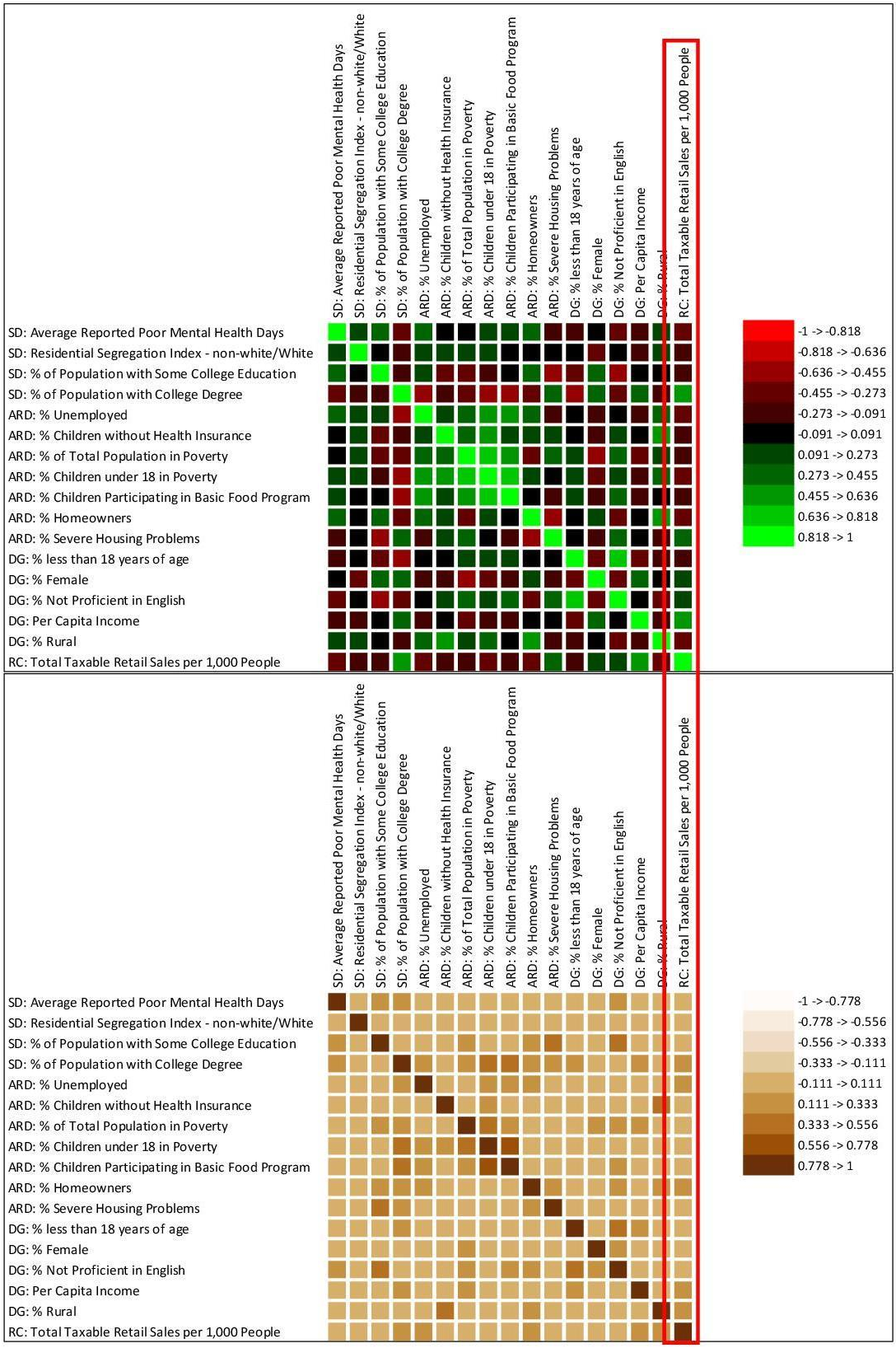


Figure 4.25. Taxable Retail Sales, Correlation and r^2 Maps

At a confidence interval of 95%, the variables shown in Table 4.10 are also statistically significant to taxable retail sales. The association is positive only with respect to the percentage of the population with college degrees, the percentage of female population, and the percentage of people not proficient in English. The association is otherwise negative with respect to all other statistically significant variables.

Table 4.10. Correlation Matrix: Taxable Retail Sales/All Measures

Variable labels	Correlation coefficient	p-values
ARD: % Children Participating in Basic Food Program	-0.1069	0.000
ARD: % Children under 18 in Poverty	-0.28017	<0.0001
ARD: % Children without Health Insurance	-0.15593	<0.0001
ARD: % Homeowners	-0.34849	<0.0001
ARD: % of Total Population in Poverty	-0.23326	<0.0001
ARD: % Severe Housing Problems	0.331828	<0.0001
ARD: % Unemployed	-0.35565	<0.0001
DG: % Female	0.210477	<0.0001
DG: % Not Proficient in English	0.167178	<0.0001
SD: % of Population with College Degree	0.467078	<0.0001
SD: Average Reported Poor Mental Health Days	-0.27466	<0.0001
SD: Residential Segregation Index - non-white/White	-0.21523	<0.0001

The variables in Table 4.10 were fitted to a Kernel regression model in addition to per capita income, the percentage of the population living in rural areas, and a county's tax spillover and degree of reliance on the sales tax. The explanatory power of the resulting Kernel model is extraordinarily high, 0.935, indicating that the independent variables are able to explain approximately 93.5% of the distribution of taxable retail sales (Figure 4.26).

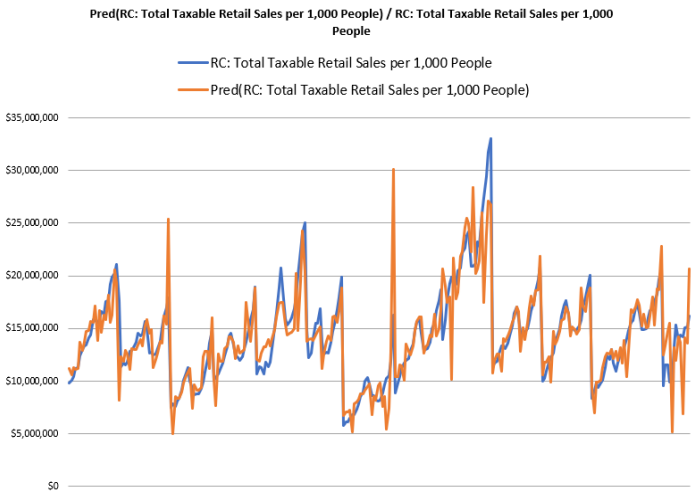


Figure 4.26. Kernel Regression Model

The next step is to validate whether the Kernel model is just as explanatory of SPLOST revenue as it is of other revenue measures in the study. If SPLOST revenue bears a strong positive statistical association to the other revenue measures (taxable retail sales, sales tax revenue, and spillover index), the Kernel model above should be equally well fitted at forecasting of SPLOST revenue.

The correlation matrix confirms that the following five revenue measures are indeed all statistically significant to each other with a strong positive association (Table 4.11 and Figure 4.27).

Table 4.11. Correlation Matrix: SPLOST/Other Revenue Measures

p-values	RC: Total Taxable Retail Sales per 1,000 People	Presumed SALTAX Spillover Index	RC: General Fund Sales and Use Tax Revenue (SALTAX) per 1,000 People
SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000 People	**<0.0001**	**<0.0001**	**<0.0001**
SPLOST JD: RCW 82.14.350 Revenue (Juvenile Detention) per 1,000 People	**<0.0001**	**<0.0001**	**<0.0001**

Correlation matrix	RC: Total Taxable Retail Sales per 1,000 People	Presumed SALTAX Spillover Index	RC: General Fund Sales and Use Tax Revenue (SALTAX) per 1,000 People
SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000 People	**0.720**	**0.658**	**0.946**
SPLOST JD: RCW 82.14.350 Revenue (Juvenile Detention) per 1,000 People	**0.964**	**0.794**	**0.686**

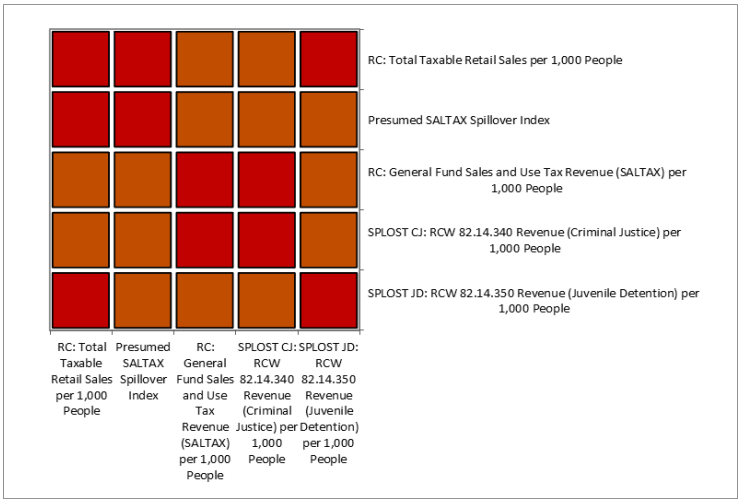


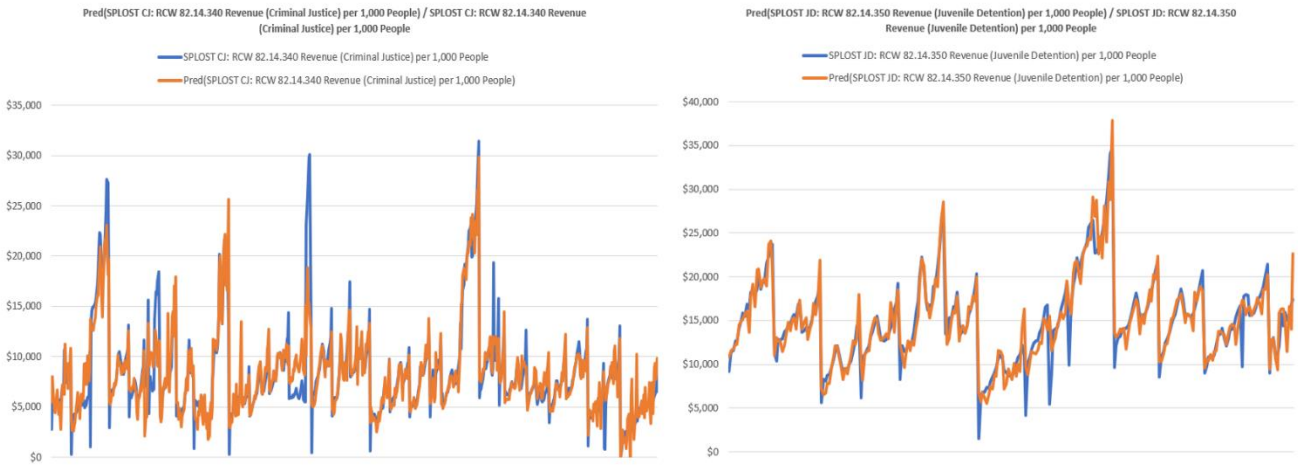
Figure 4.27. Revenue Measures, Correlation Map

Having confirmed the strong positive association between SPLOST revenue and other revenue measures, the expectation is that the previous Kernel model is also able to explain most of the flow of SPLOST revenue. In fact, when the same Kernel model is fitted to the two SPLOST revenue measures, the model r^2 values are 0.804 with respect to the Criminal Justice SPLOST and 0.868 with respect to the Juvenile Facilities SPLOST (Table 4.12), indicating that the variables making up the model are able to explain between 80% and 87% of the distribution of SPLOST revenue (Figure 4.28).

Table 4.12. Kernel Model Goodness of Fit (SPLOSTs)

	SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000 People	SPLOST JD: RCW 82.14.350 Revenue (Juvenile Detention) per 1,000 People
r^2	0.804	0.868

Figure 4.28. CJ and JD SPLOST, Kernel Regression Model



Chapter 5. AN ARIMAX MODEL TO FORECAST CRIME

5.1 THE ARIMAX MODEL

The second research question is whether there is enough explanatory information in the data collected to fit a statistical model predictive of the dispersion of adult crime and juvenile detention. This question is relevant to understand whether crime is predictable and, if it is, whether it can better inform local tax policy.

The availability of a 29-lag time series across 46 variables lends itself to a complex and potentially powerful forecasting model. It is important to remember, however, that modeling a time series analysis is a stochastic process: while statistical methods can detect patterns useful in forecasting, no model can produce exact predictions.

The model used to answer this question is the ARIMAX model. ARIMAX is a combination of autoregressive (AR) integrated (I) moving average (MA) statistical procedures with one or more explanatory variables (X). An ARIMAX model can combine autoregression and moving average of a variable's own trend along with the cointegration of multiple explanatory variables. If the ARIMAX model is well fitted, its forecasting power is far superior to regression, autoregression, or moving average, as ARIMAX brings all three elements together.

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.

First, the time series must be 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 called differencing, which consists in computing the difference between consecutive observations. After all, the predictive value of the model is not in the absolute value of the observations but in their degree of change. The degree *d* in the I element of the ARIMA model indicates the level of differencing needed to render the time series stationary. An ARIMA model with I(0) means that the data is already stationary.

$$\Delta y_t = y_t - (y_{t-d})$$

where

y_t = non-stationary dependent variable time series

d = degree of differencing

Δy_t = stationary dependent variable time series

Second, the degree of dependency *p* between an observation and its lagged observations is known as autoregression and can be expressed as AR(*p*); it represents the lingering effects of preceding scores on future scores. An AR(0) would indicate that time observations are entirely random and not dependent on each other. In statistical terms, observations with no pattern of correlation are often referred to as white noise and the resulting forecast is called a random walk.

The degree of autoregression is determined by contrasting AutoCorrelation Function (ACF) plots with Partial AutoCorrelation Function (PACF) plots. ACF plots consider a time series as a block of undivided data and provide the correlation between an observation and its lagged values considering trend and seasonality. PACF plots, on the other hand, attempt to find correlation one step at a time by factoring a residual value into the next lag and continuing the process until residuals decrease to a near zero.

In a purely autoregressive (AR) model, the point at which the PACF plot tapers off to zero can be viewed as the point in which the AR model has learned the autoregressive predictive value of past lags.

$$y_t = (\varphi_p y_{t-p}) + \varepsilon_t$$

where

y_t = dependent variable time series

φ = autoregression coefficient

p = degree of autoregression

ε_t = white noise error

Third, the degree of dependency q between an observation and the residuals from its lagged observations is known as moving average and can be expressed as MA(q). An MA(2) would indicate that residual values from two prior 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.

Just like the AR term, the order of the moving average is also determined by contrasting ACF and PACF plots. In a purely moving average (MA) model, the point at which the ACF plot tapers off to zero can be viewed as the point in which the MA model has learned the predictive value of the residuals.

$$y_t = (\theta_q \varepsilon_{t-q})$$

where

y_t = dependent variable time series

θ = moving average coefficient

q = degree of moving average

ε_t = white noise error

In ARIMA models with both AR and MA terms, both ACF and PACF plots will taper off to zero and the respective terms cannot be as easily determined by looking at the plots. In this instance, 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, the Schwarz's Bayesian Criterion (SBC) was used as the measure of prediction error to select the best AR and MA terms (Schwarz 1978). SBC scores were calculated on each iteration and the terms yielding the lowest SBC score were selected as the best fit.

Last, the explanatory variables are added to the model and incorporated in the observed variable forecast to the extent of cointegration in the multivariate time series.

$$y_t = (\beta x_{it})$$

where

y_t = dependent variable time series

X_{it} = covariate(s) x_i time series

β = covariate coefficient

Placing together the pieces that make up the ARIMAX model, the model can be written as:

ARIMAX (p, d, q)

$$\Delta y_t = (\varphi_p \Delta y_{t-p}) + (\theta_q \varepsilon_{t-q}) + (\beta x_{it}) + \varepsilon_t$$

5.2 Rendering the Data Stationary

A stationary time series is a series whose properties do not vary with time. White noise is an example of a stationary time series, where the distribution of y_t is independent of t. The reason why the ARIMAX model rests on stationary data is because it learns from what makes the data non-stationary. If a non-stationary time series can be rendered stationary in observing the

difference between each value at *t* time point, the model can learn from the degrees of differencing. If the time series is already stationary, the degree *d* in the I element of the ARIMAX model would take a value of 0, indicating that the model is an ARMAX model, where the differencing does not contribute to the model.

To test the time series for stationarity, a random sample of four counties (Chelan, Kitsap, Spokane, Yakima) was selected and each adult crime and juvenile detention measure was tested under the Dickey and Fuller (1979) stationarity test.

Table 5.13. Stationarity Test: Select Counties

Variables	Counties
CJ VC: Homicide Superior Court Filings per 100,000 People	Chelan
CJ VC: Sex Crimes Superior Court Filings per 100,000 People	Kitsap
CJ VC: Assault Superior Court Filings per 100,000 People	Spokane
CJ VC: Robbery Superior Court Filings per 100,000 People	Yakima
CJ NVC: Property Crimes Superior Court Filings per 100,000 People	
CJ: Total Superior Court Filings per 100,000 People	
JD: Total Juvenile Arrests per 100,000 People	
JD: Juvenile Dispositions per 100,000 People	

In each instance, all variables and all four counties, the p-value of the Dickey and Fuller stationarity test was above 0.05, which means that the null hypothesis could not be rejected at a confidence interval of 95% until 1 degree of differencing was added to render the data stationary (Figure 5.29).

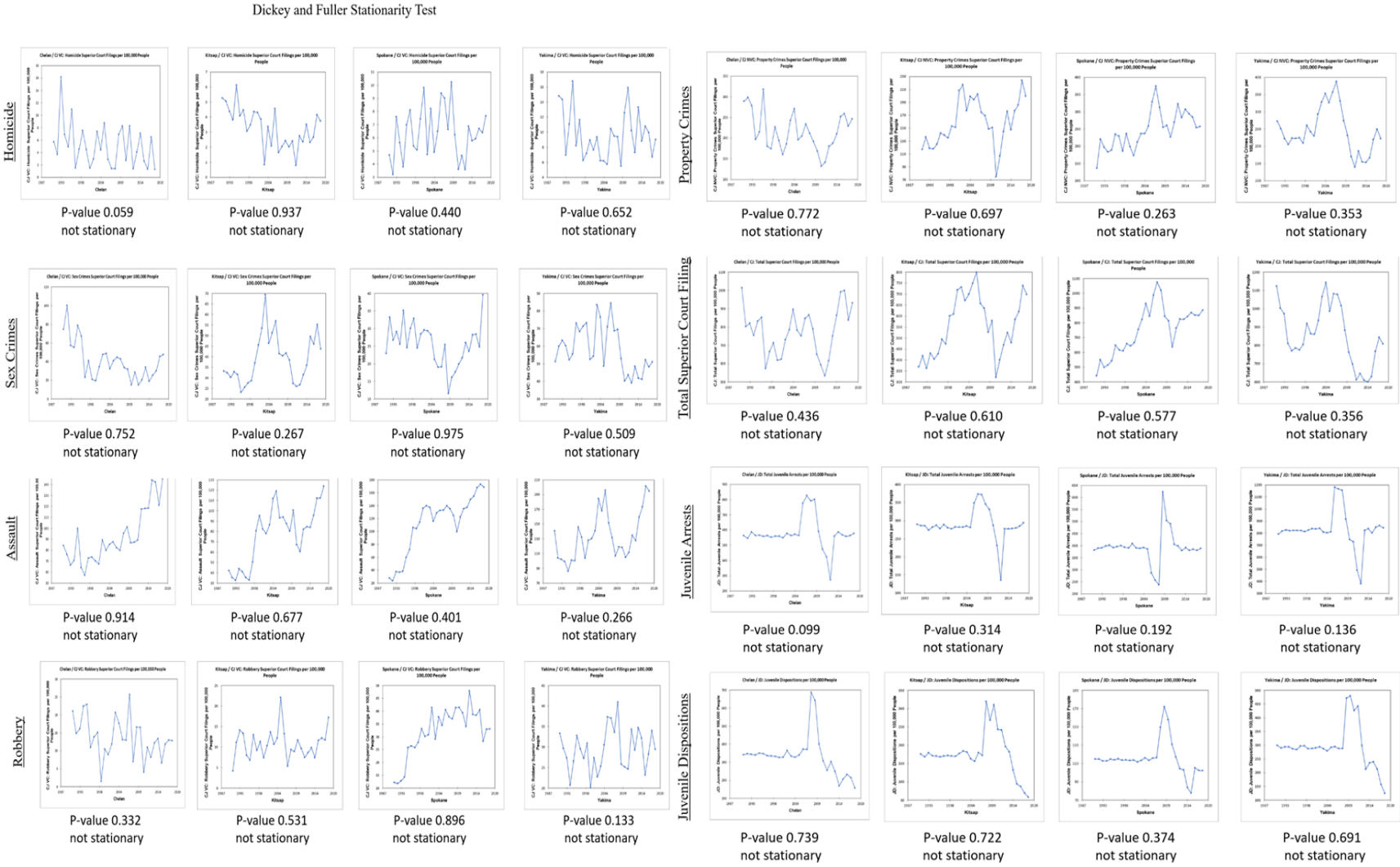


Figure 5.29. Crime Measures, Time Series Stationarity Tests

5.3 Finding the Degree of Autoregression and Moving Average

The literature consistently indicates that crime is spatially autocorrelated (Huebner and 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 refers to a future observation being predictable based on past observations, implying that a statistical relationship exists between past lags and future lags.

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

In this study, a sample ARIMAX model was run for each of four randomly selected counties (King, Jefferson, Lewis, Whatcom) on multiple AR and MA terms to verify whether the autocorrelation terms in the time series is 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 5.14). The result was evident that no AR and MA term would fit every county for every observed measure. Instead the ARIMAX model must be fitted on a county-by-county level as each county's crime patterns follow different terms of autocorrelation.

Table 5.14. 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)
CJ VC: Homicide Superior Court Filings per 100,000 People	1	1	1	1	1	1	1	1
CJ VC: Sex Crimes Superior Court Filings per 100,000 People	1	1	1	1	1	1	1	1
CJ VC: Assault Superior Court Filings per 100,000 People	1	1	1	2	1	1	1	1
CJ VC: Robbery Superior Court Filings per 100,000 People	1	3	1	2	1	1	1	1
CJ NVC: Property Crimes Superior Court Filings per 100,000 People	1	3	1	2	1	1	1	1
CJ: Total Superior Court Filings per 100,000 People	1	3	1	2	1	1	1	1
JD: Total Juvenile Arrests per 100,000 People	1	4	1	4	1	1	1	1
JD: Juvenile Dispositions per 100,000 People	1	4	1	4	1	1	2	2

5.4 IDENTIFYING AND INCORPORATING THE EXPLANATORY VARIABLES

This study observes two SPLOST measures targeting different programmatic objectives. On the one hand, the Juvenile Facilities SPLOST is earmarked for "juvenile detention facilities and jails." RCW 82.14.350. On the other hand, the Criminal Justice SPLOST is more broadly targeted to "activities that substantially assist the criminal justice system." RCW 82.14.340. Although in Section 4.5 the study found no statistical significance, or nearly zero relationship, between a county's decision to impose either SPLOST and the corresponding crime measures, this section explores the connection between SPLOST and crime on a deeper level by looking at the underlying social factors that are statistically significant to both sales tax revenue and crime.

Based on consistent findings in criminological research, the expectation is that many of the same social variables used in the SPLOST Kernel model also offer explanatory value as to the distribution of adult crimes and juvenile detention across Washington counties. Criminological research in fact suggests that those same social variables used in the Kernel model belong to one of four key paradigms of the strongest and most stable correlates of crime: indicators of social disorganization (SD), family disruption (FD), absolute or relative deprivation (ARD), and demographics (DG) (Nivette 2011; Pratt and Cullen 2005) (Figure 5.30).

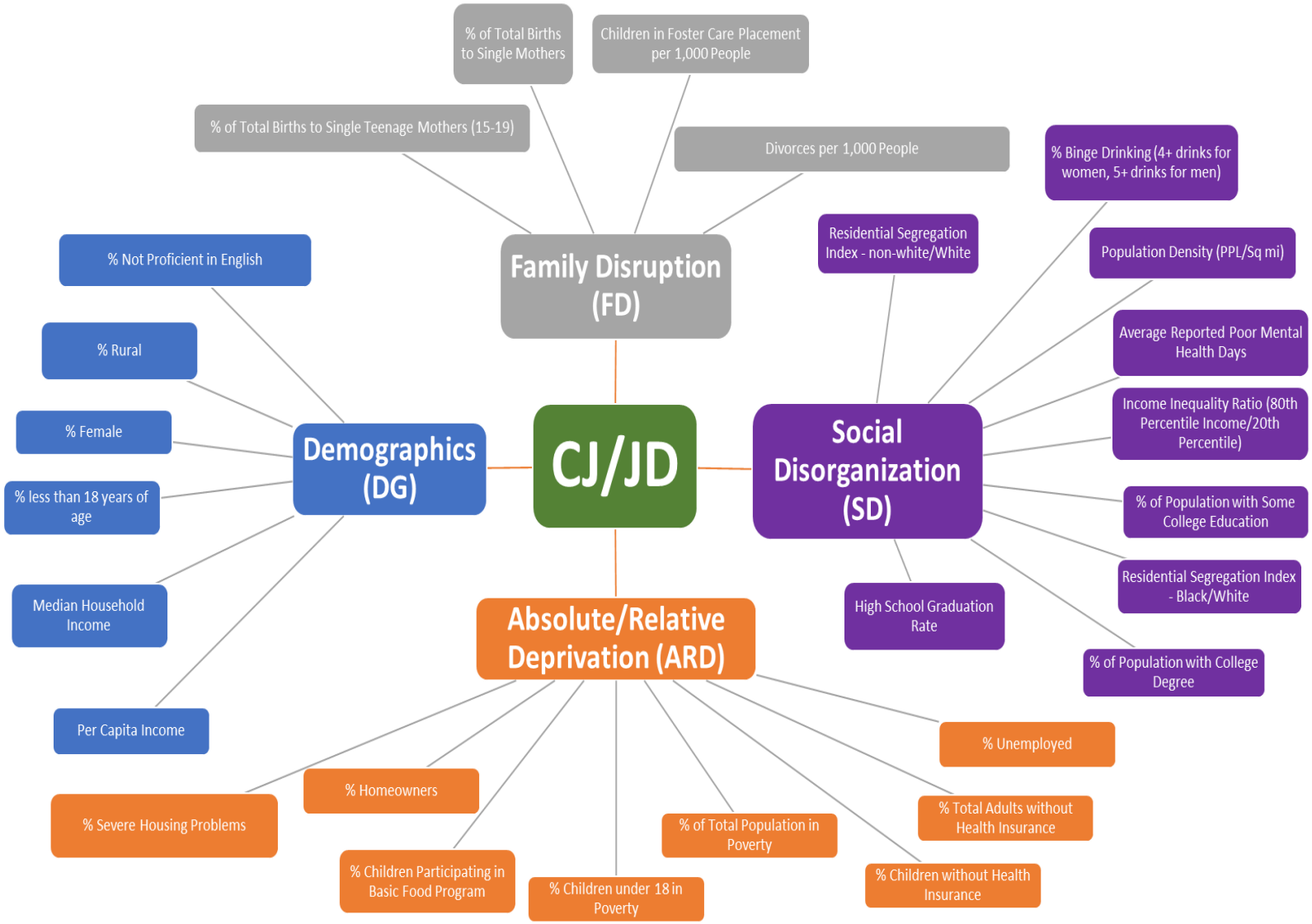


Figure 5.30. Crime and Social Variables, Radial Cluster

A correlation matrix was employed to explore the bidirectional statistical relationship between each observed CJ measure and each social variable fitting one of the four paradigms of crime (Figure 5.31).

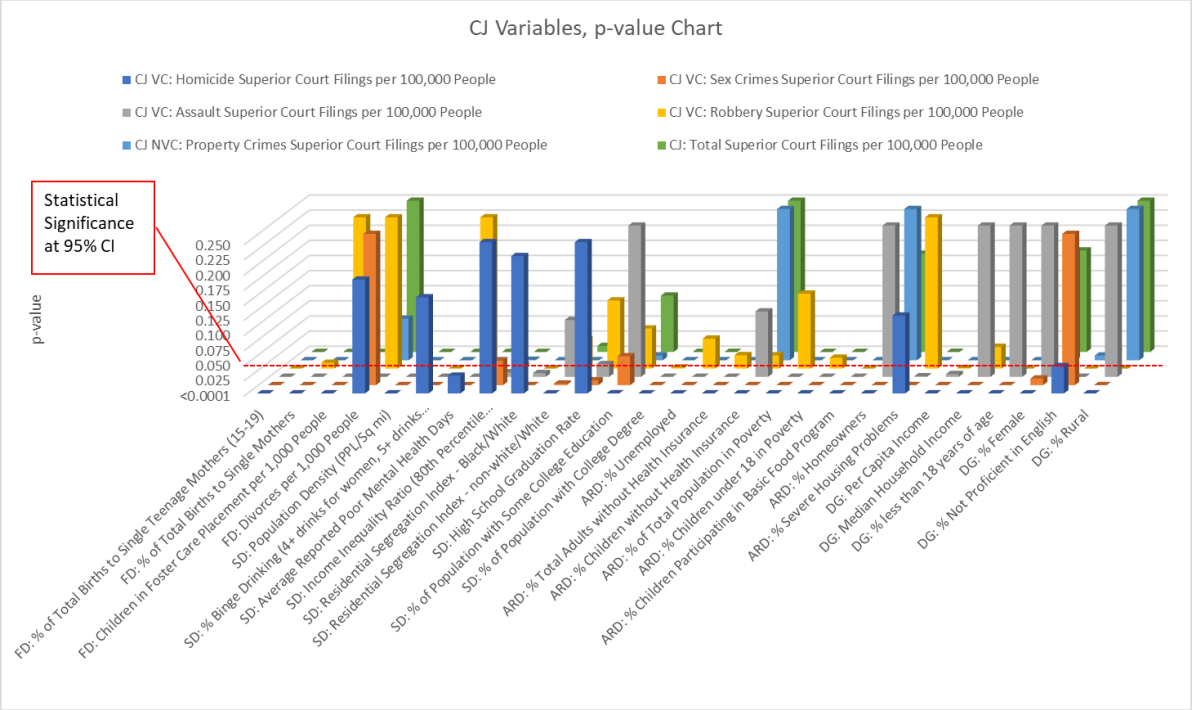


Figure 5.31. CJ Measures, p-value Histogram

While some variables (e.g., population density, percentage population with college degrees, or income per capita) are statistically significant with respect to all observed measures of adult crime, other variables are statistically significant only for some specific measures. For example, income inequality is statistically significant with respect to all observed measures other than homicides. Similarly, median household income is statistically significant with respect to all observed measures other than assault. Another variable, divorce rate, is statistically significant only with respect to assault. In general terms, indicators of family disruption and absolute or relative deprivation prove to be more valuable to a predictive model (Table 5.15).

Table 5.15. Explanatory Variables Statistically Significant to CJ Measures

Variable labels		Always Signigicant (6 measures)	Signigicant on 5+ measures	Signigicant on 4+ measures	Signigicant on 4+ measures	Signigicant on 3+ measures	Signigicant on 2+ measures	Signigicant on 1+ measures
FD: % of Total Births to Single Teenage Mothers (15-19)	6	YES	YES	YES	YES	YES	YES	YES
FD: % of Total Births to Single Mothers	6	YES	YES	YES	YES	YES	YES	YES
FD: Children in Foster Care Placement per 1,000 People	5		YES	YES	YES	YES	YES	YES
FD: Divorces per 1,000 People	1							YES
SD: Population Density (PPL/Sq mi)	6	YES	YES	YES	YES	YES	YES	YES
SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)	5		YES	YES	YES	YES	YES	YES
SD: Average Reported Poor Mental Health Days	5		YES	YES	YES	YES	YES	YES
SD: Income Inequality Ratio (80th Percentile Income/20th Percentile)	5		YES	YES	YES	YES	YES	YES
SD: Residential Segregation Index - Black/White	5		YES	YES	YES	YES	YES	YES
SD: Residential Segregation Index - non-white/White	5		YES	YES	YES	YES	YES	YES
SD: High School Graduation Rate	4			YES	YES	YES	YES	YES
SD: % of Population with Some College Education	3					YES	YES	YES
SD: % of Population with College Degree	6	YES	YES	YES	YES	YES	YES	YES
ARD: % Unemployed	6	YES	YES	YES	YES	YES	YES	YES
ARD: % Total Adults without Health Insurance	6	YES	YES	YES	YES	YES	YES	YES
ARD: % Children without Health Insurance	3					YES	YES	YES
ARD: % of Total Population in Poverty	5		YES	YES	YES	YES	YES	YES
ARD: % Children under 18 in Poverty	6	YES	YES	YES	YES	YES	YES	YES
ARD: % Children Participating in Basic Food Program	6	YES	YES	YES	YES	YES	YES	YES
ARD: % Homeowners	3					YES	YES	YES
ARD: % Severe Housing Problems	4			YES	YES	YES	YES	YES
DG: Per Capita Income	6	YES	YES	YES	YES	YES	YES	YES
DG: Median Household Income	5		YES	YES	YES	YES	YES	YES
DG: % less than 18 years of age	5		YES	YES	YES	YES	YES	YES
DG: % Female	3					YES	YES	YES
DG: % Not Proficient in English	5		YES	YES	YES	YES	YES	YES
DG: % Rural	3					YES	YES	YES

The same process was repeated to explore the bidirectional statistical relationship between each observed JD measure and each social variable fitting one of the four paradigms of crime (Figure 5.32).

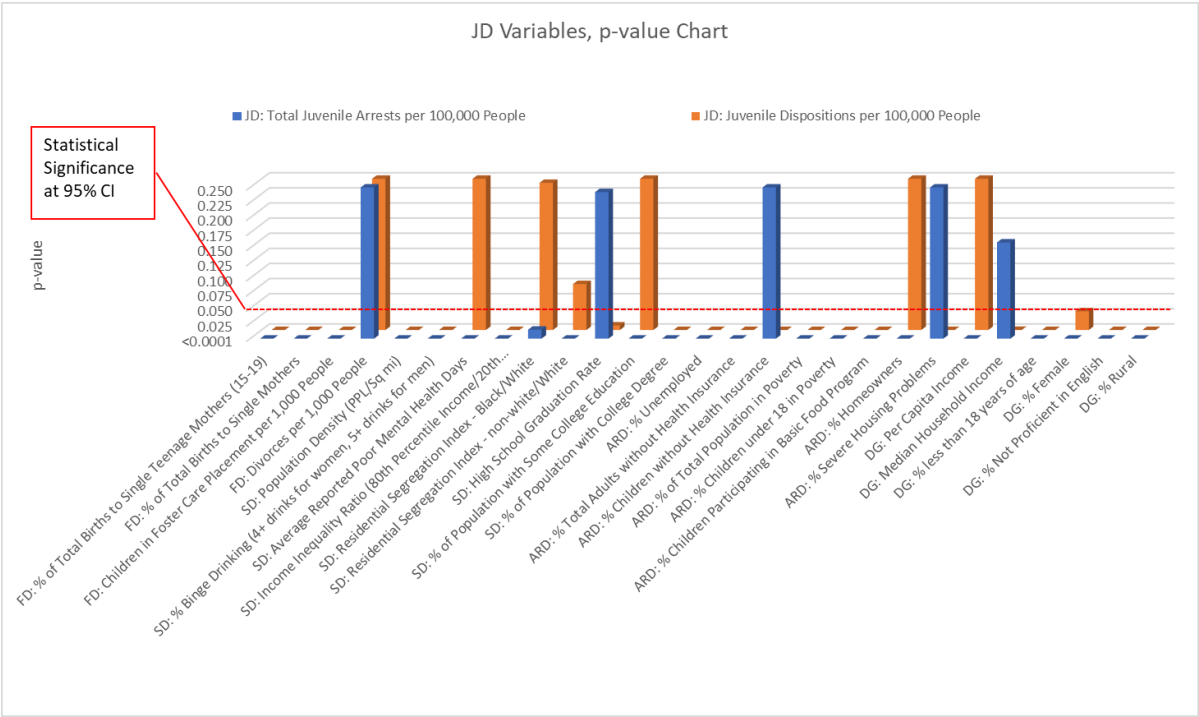


Figure 5.32. JD Measures, p-value Histogram

Just as it was the case for measures of adult crime, indicators of family disruption and absolute or relative deprivation are again particularly valuable to a model explaining juvenile detention. However, while demographics indicators were not always statistically significant with respect to measures of adult crime, they are all statistically significant with respect to measures of juvenile detention. Divorce rate was once again not correlated, indicating that, insofar as Washington counties are concerned, divorce does not offer explanatory power with respect to incidences of adult crime or juvenile detention (Table 5.16).

Table 5.16. Explanatory Variables Statistically Significant to JD Measures

Variable labels	Significant to both JD Measures?
FD: % of Total Births to Single Teenage Mothers (15-19)	YES
FD: % of Total Births to Single Mothers	YES
FD: Children in Foster Care Placement per 1,000 People	YES
FD: Divorces per 1,000 People	
SD: Population Density (PPL/Sq mi)	YES
SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)	YES
SD: Average Reported Poor Mental Health Days	
SD: Income Inequality Ratio (80th Percentile Income/20th Percentile)	YES
SD: Residential Segregation Index - Black/White	
SD: Residential Segregation Index - non-white/White	
SD: High School Graduation Rate	
SD: % of Population with Some College Education	
SD: % of Population with College Degree	YES
ARD: % Unemployed	YES
ARD: % Total Adults without Health Insurance	YES
ARD: % Children without Health Insurance	
ARD: % of Total Population in Poverty	YES
ARD: % Children under 18 in Poverty	YES
ARD: % Children Participating in Basic Food Program	YES
ARD: % Homeowners	
ARD: % Severe Housing Problems	
DG: Per Capita Income	
DG: Median Household Income	
DG: % less than 18 years of age	YES
DG: % Female	YES
DG: % Not Proficient in English	YES
DG: % Rural	YES

There are overlaps of social variables that serve as statistically significant indicators of both adult crime and juvenile detention. Most variables are in fact predictive of either both measures or neither, with some notable exceptions. In general terms, the degree of rurality and gender

distribution, for example, is statistically significant to juvenile detention but not to adult crime. To the contrary, income, housing, and segregation are statistically significant to adult crime but not to juvenile detention (Table 5.17).

Table 5.17. Matrix of Explanatory Variables Significant to CJ and JD Measures

Variable labels	Signigicant to 4+ CJ Measures?	Significant to both JD Measures?
FD: % of Total Births to Single Teenage Mothers (15-19)	YES	YES
FD: % of Total Births to Single Mothers	YES	YES
FD: Children in Foster Care Placement per 1,000 People	YES	YES
FD: Divorces per 1,000 People		
SD: Population Density (PPL/Sq mi)	YES	YES
SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)	YES	YES
SD: Average Reported Poor Mental Health Days	YES	
SD: Income Inequality Ratio (80th Percentile Income/20th Percentile)	YES	YES
SD: Residential Segregation Index - Black/White	YES	
SD: Residential Segregation Index - non-white/White	YES	
SD: High School Graduation Rate	YES	
SD: % of Population with Some College Education		
SD: % of Population with College Degree	YES	YES
ARD: % Unemployed	YES	YES
ARD: % Total Adults without Health Insurance	YES	YES
ARD: % Children without Health Insurance		
ARD: % of Total Population in Poverty	YES	YES
ARD: % Children under 18 in Poverty	YES	YES
ARD: % Children Participating in Basic Food Program	YES	YES
ARD: % Homeowners		
ARD: % Severe Housing Problems	YES	
DG: Per Capita Income	YES	
DG: Median Household Income	YES	
DG: % less than 18 years of age	YES	YES
DG: % Female		YES
DG: % Not Proficient in English	YES	YES
DG: % Rural		YES

In addition to the explanatory variables in Table 5.17, criminological research points out another critical element of crime prediction: crime is intercorrelated. Intercorrelation refers to the fact that incidences of crime are accompanied by other crimes and therefore a predictive model must account for crime as an explanatory factor of crime itself. Hence, the expectation is that all observed CJ and JD measures are statistically significant to each other with strong multidirectional positive association. If that is the case, then each observed CJ and JD measure will also serve as an explanatory variable x in the ARIMAX model for y.

The expectation of a strong multidirectional positive association is confirmed by high correlation and always positive coefficients of determination among all the CJ and JD measures (Figure 5.33).

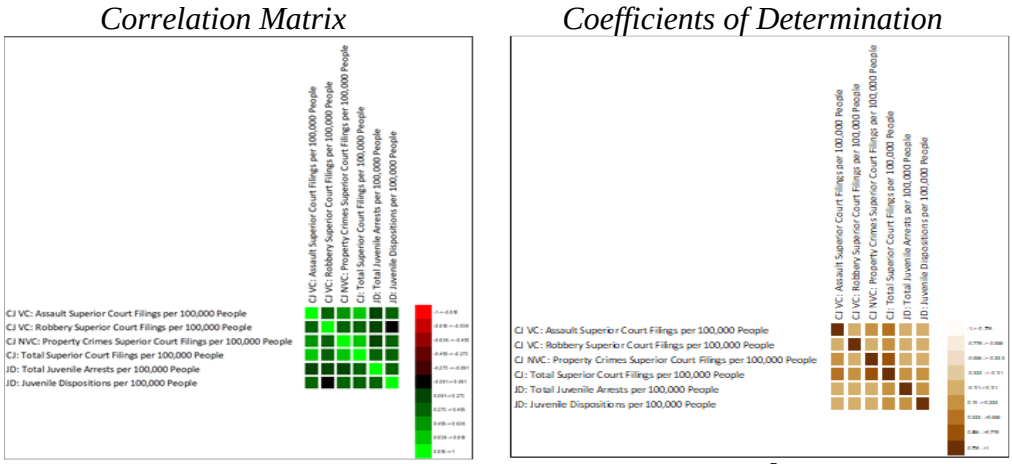


Figure 5.33. Crime Measures, Correlation and r^2 Maps

The degree of nonviolent property crimes is overall the most consistently positive indicator of all other measures in the study, suggesting that all other observed crimes may either stem from, or culminate in, a nonviolent property crime (Figure 5.34). This reflection is relevant insofar as the incidence of nonviolent property crimes may serve as the best indicator of crime dispersion across Washington counties.

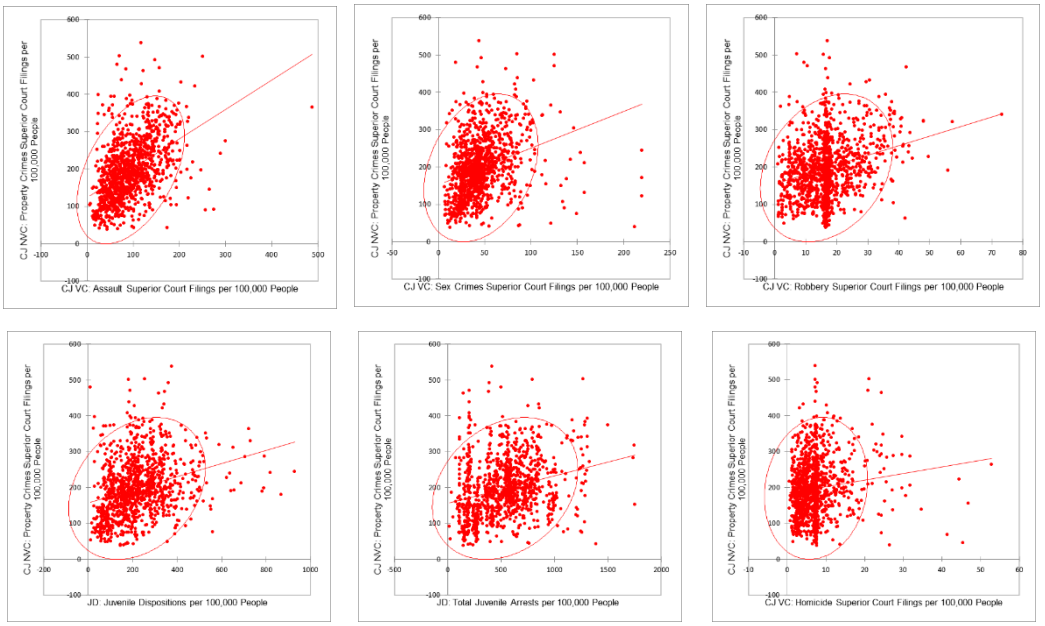


Figure 5.34. Crime Measures, Correlation Scatterplots

5.5 FITTING THE ARIMAX MODEL

Fitting an ARIMAX model requires some trial and error. The quality of the ARIMAX model is ultimately judged by the degree of autocorrelation of the residuals and whether the model forecast can taper off the residuals close to zero. If the residual values are not dependent on each other, the model has captured all the information available and produced unbiased results. The previous descriptive statistics have shown that it is not possible to fit the same ARIMAX model to each Washington county as each county's crime patterns follow different terms of autocorrelation. To verify the predictive validity of the ARIMAX model, the model was fitted separately to a selection of 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, *1*, q_c)

Where

1=degree of differencing to render the time series stationary

X=explanatory variables[56]

p_c=county specific AR term

q_c=county specific MA term

5.5.1 *Homicide ARIMAX*

This study observed a 29-year history of criminal superior court filings where the primary charge involved murder, manslaughter, excusable homicide, or justifiable homicide (*CJ VC: Homicide*). Observing the degree of autocorrelation of *CJ VC: Homicide* separately for Benton, Douglas, Pierce, and Stevens county, an ARIMAX model was fitted to each county based on

[56] See Table 5.17. Matrix of Explanatory Variables Significant to CJ and JD Measures.

consistent differencing term and explanatory variables but county-specific AR and MA terms. To test the quality of each ARIMAX model, the study observed (a) the degree of autocorrelation of the residuals, (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 repetition in the explanatory variables for the next 29 years (Figure 5.35, Figure 5.36, Figure 5.37, and Figure 5.38).

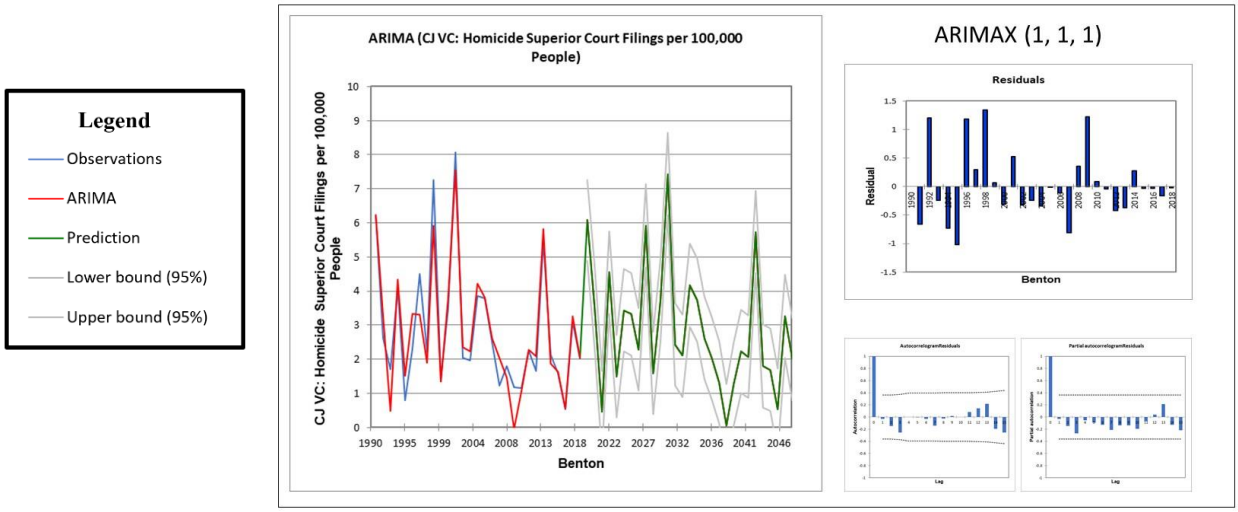


Figure 5.35. Benton, Homicide ARIMAX Visualization

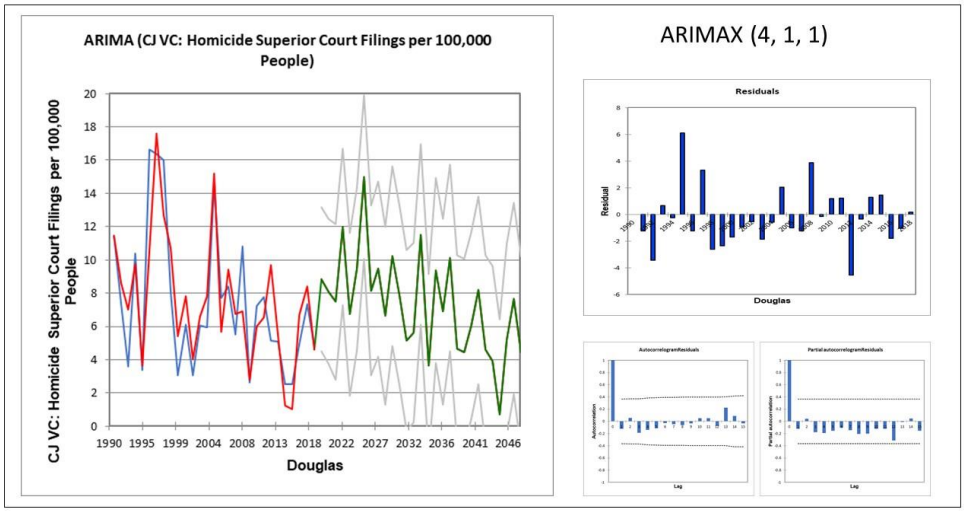


Figure 5.36. Douglas, Homicide ARIMAX Visualization

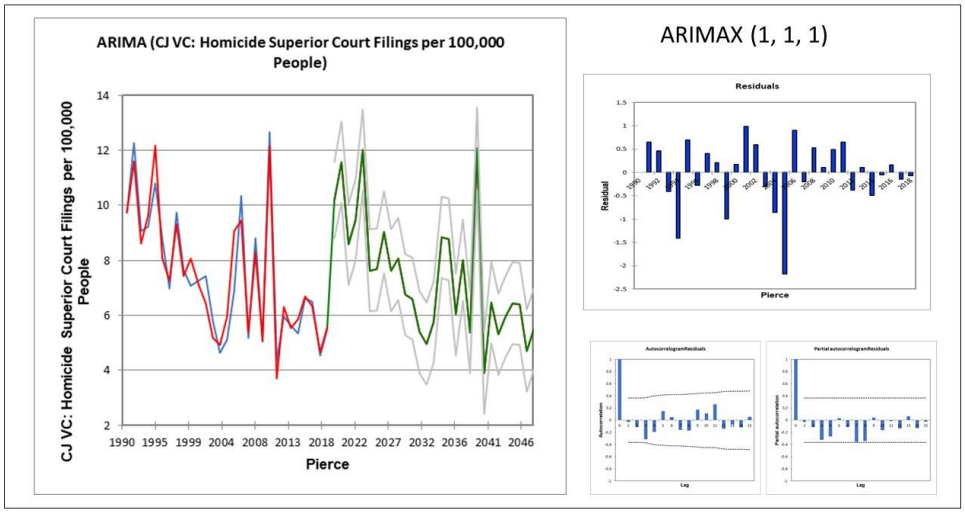


Figure 5.37. Pierce, Homicide ARIMAX Visualization

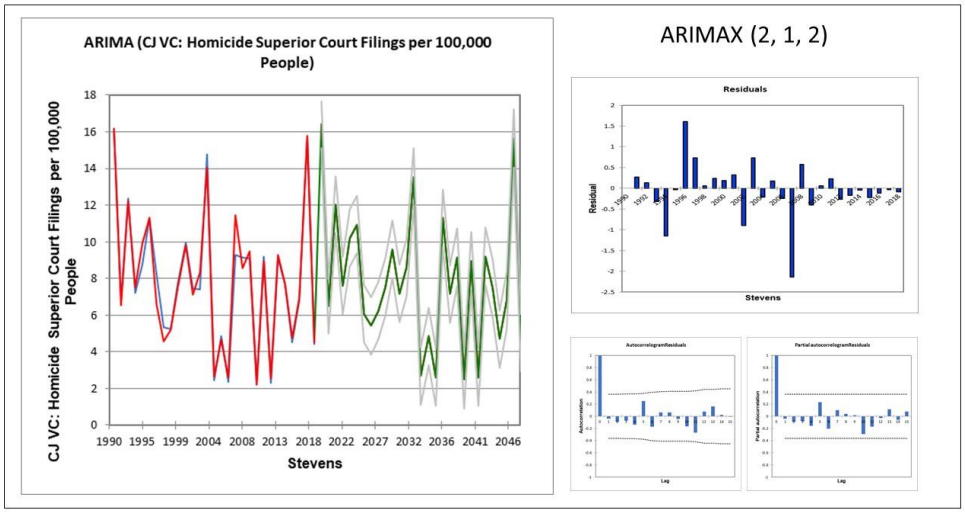


Figure 5.38. Stevens, Homicide ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series, which indicates a good forecasting quality in the model. Similarly, there is no degree of autocorrelation in the residuals as all residuals (but the first lag) fall inside the 95% confidence bounds indicating the residuals appear to be random. This is another good indicator of quality in the model, as the model is forecasting values based on the AR terms, MA terms, and explanatory variables rather than by

leveraging the autocorrelation in the residuals. At last, assuming an identical repetition in the explanatory variables for the next 29 years, the width of upper and lower bound forecasts at a 95% confidence interval is narrow for Benton, Pierce, and Stevens County but not for Douglas county.

Given the generally low count of homicide charges, swings and volatility in values are normal and forecasting is less reliable, which is why the ARIMAX is likely not particularly useful for explaining incidences of homicide despite the seemingly good fit of the model.

5.5.2 *Sex Crimes ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of criminal superior court filings where the primary charge involved sexual exploitation of a minor, incest, rape, statutory rape, or indecent liberties (*CJ VC: Sex Crimes*) (Figure 5.39, Figure 5.40, Figure 5.41, and Figure 5.42).

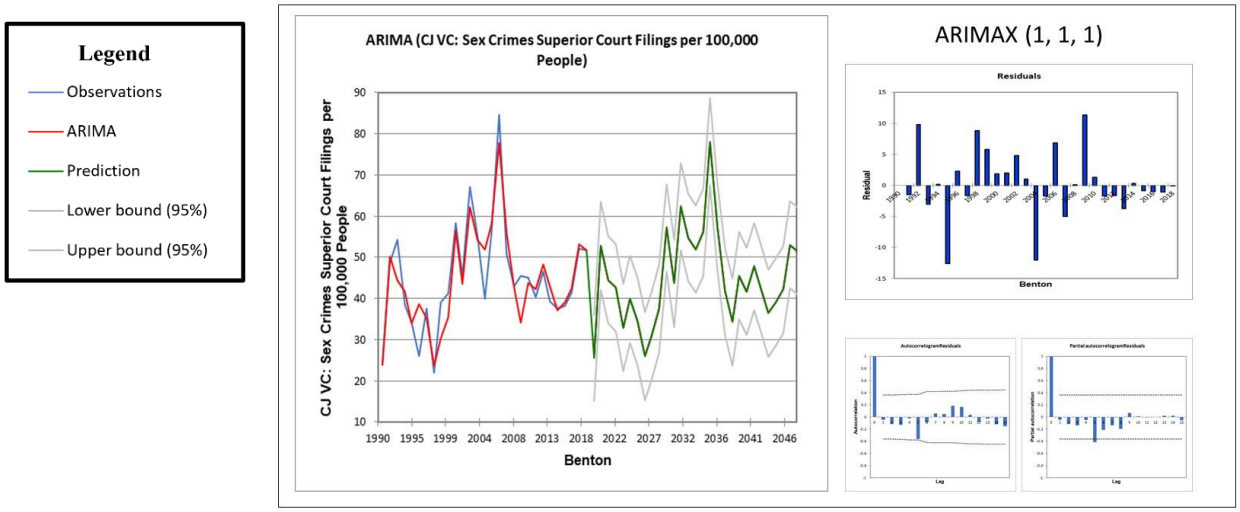


Figure 5.39. Benton, Sex Crimes ARIMAX Visualization

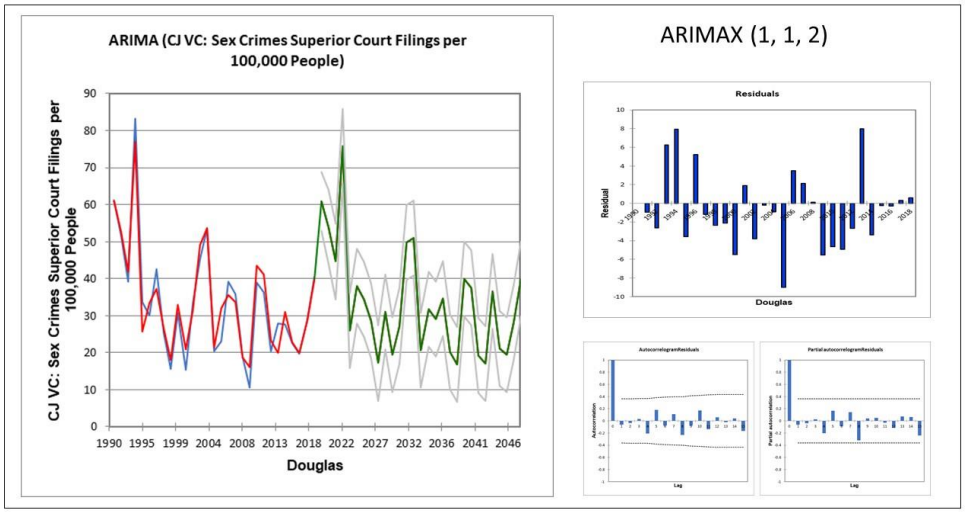


Figure 5.40. Douglas, Sex Crimes ARIMAX Visualization

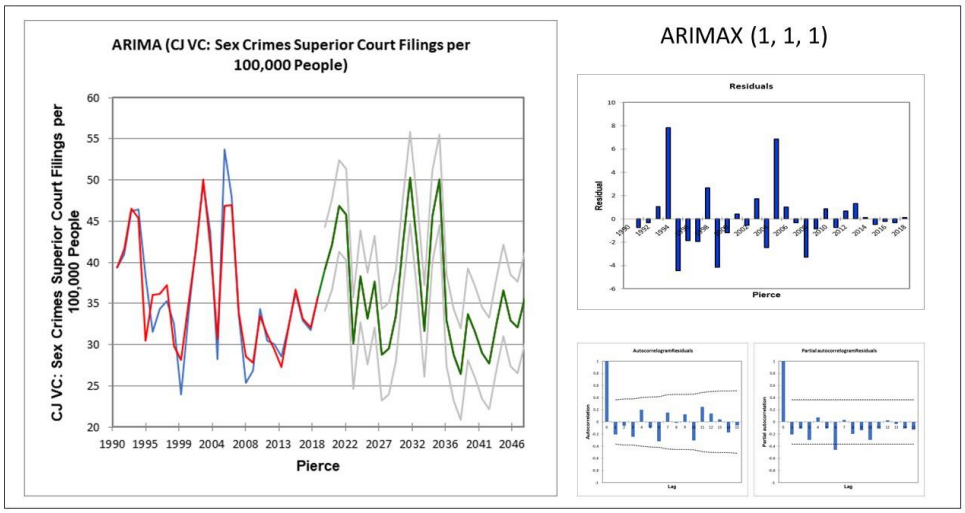


Figure 5.41. Pierce, Sex Crimes ARIMAX Visualization

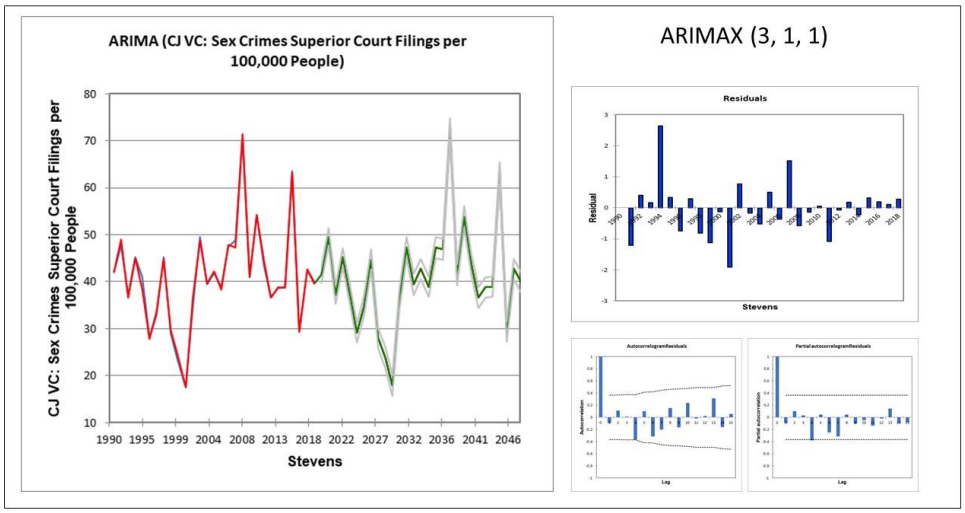


Figure 5.42. Stevens, Sex Crimes ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. The width of upper and lower bound forecasts at a 95% confidence interval indicates at large that forecasting sex crimes is more possible than forecasting homicide and particularly possible in Stevens county.

5.5.3 *Assault ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of criminal superior court filings where the primary charge involved assault or intent to cause another person physical harm, including malicious harassment and coercion (*CJ VC: Assault*) (Figure 5.43, Figure 5.44, Figure 5.45, and Figure 5.46).

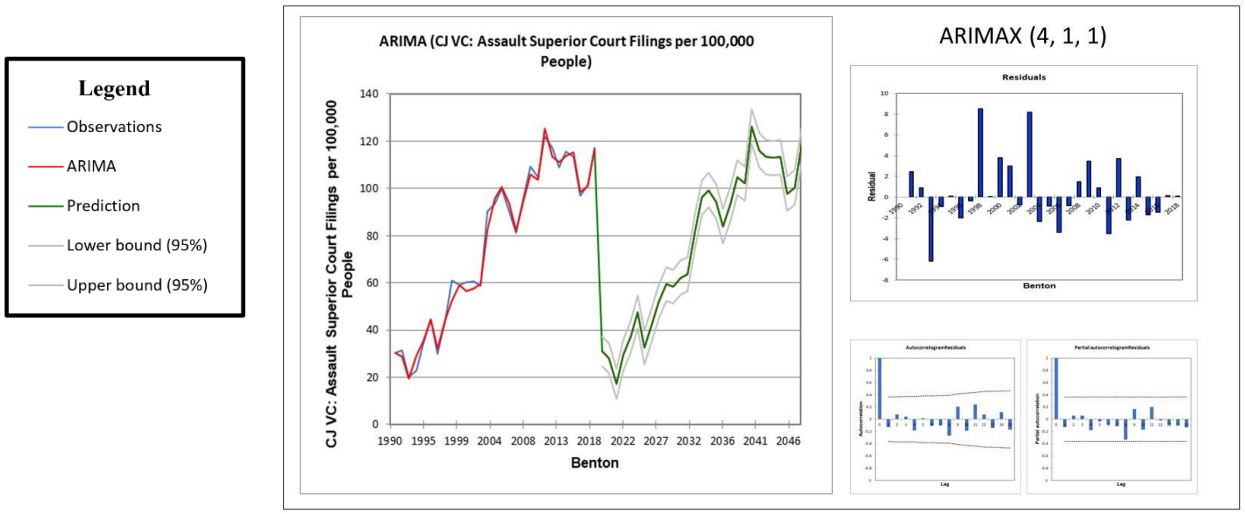


Figure 5.43. Benton, Assault ARIMAX Visualization

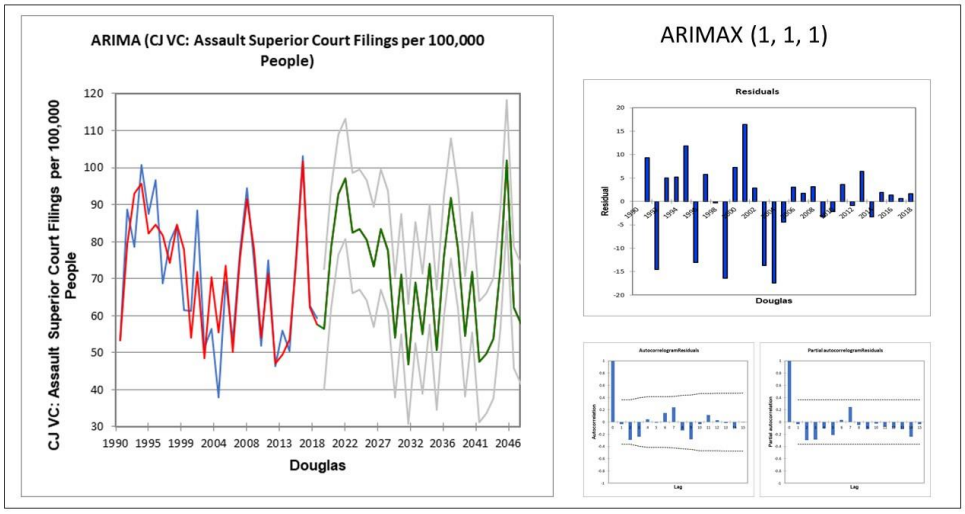


Figure 5.44. Douglas, Assault ARIMAX Visualization

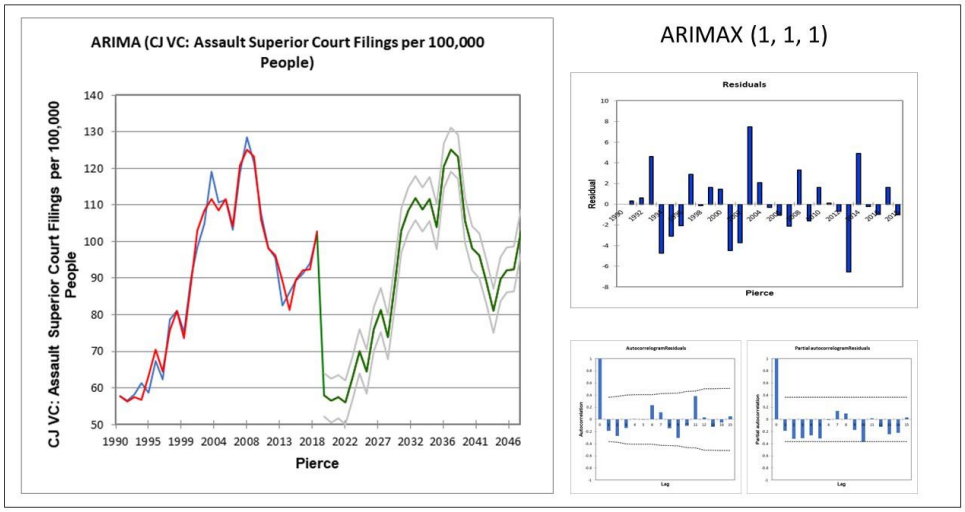


Figure 5.45. Pierce, Assault ARIMAX Visualization

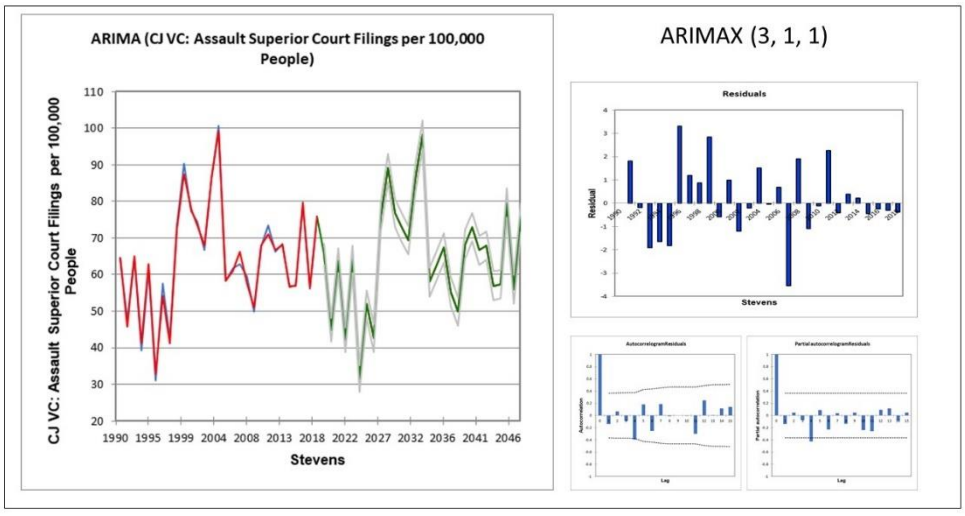


Figure 5.46. Stevens, Assault ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. The width of upper and lower bound forecasts at a 95% confidence interval indicates at large that forecasting assault is even more possible than forecasting sex crimes and particularly possible in Benton and Stevens county.

5.5.4 *Robbery ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of criminal superior court filings where the primary charge involved theft of property by the use of force, violence, or fear of injury to a person or his or her property (*CJ VC: Robbery*) (Figure 5.47, Figure 5.48, Figure 5.49, and Figure 5.50).

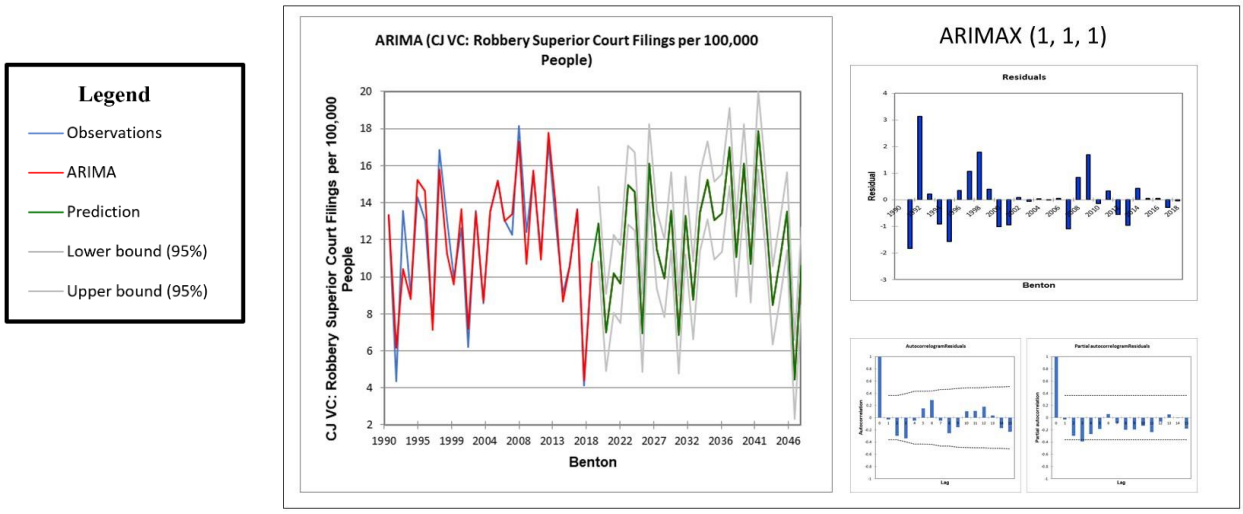


Figure 5.47. Benton, Robbery ARIMAX Visualization

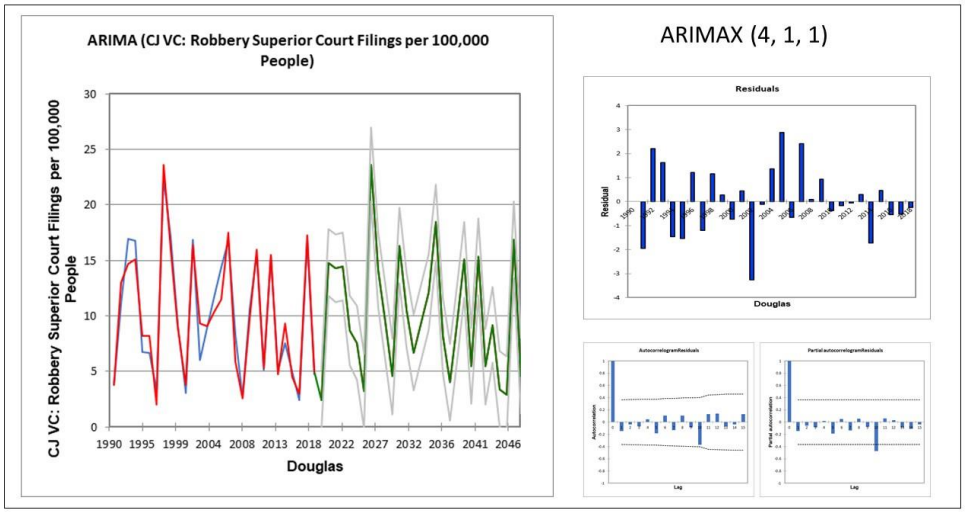


Figure 5.48. Douglas, Robbery ARIMAX Visualization

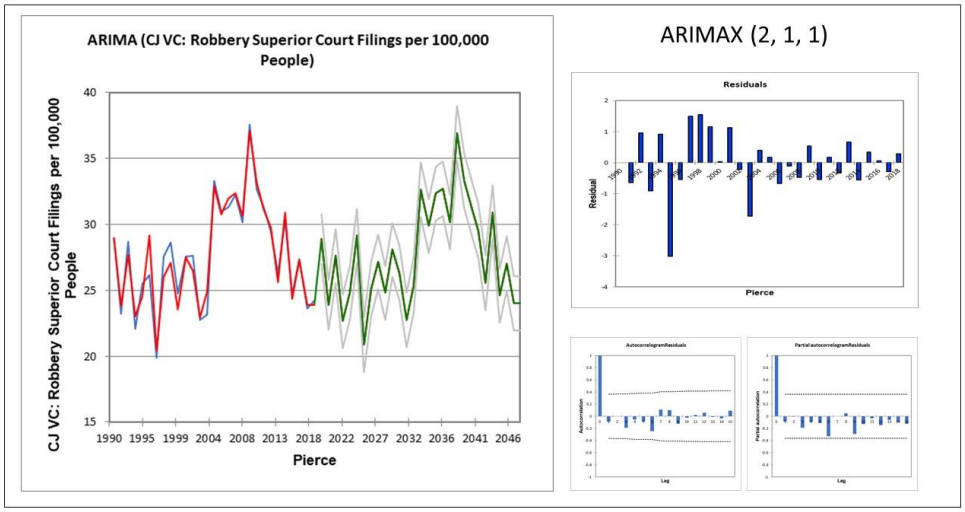


Figure 5.49. Pierce, Robbery ARIMAX Visualization

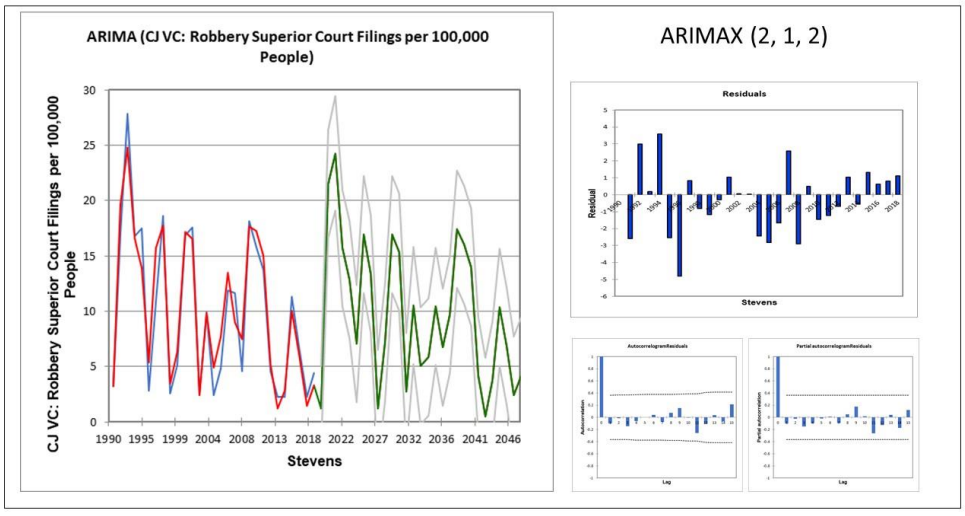


Figure 5.50. Stevens, Robbery ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. Many of the same considerations that apply to homicide seem to also apply to robbery. Given the generally low count of robbery charges, swings and volatility in values are normal and forecasting appears less feasible and reliable.

5.5.5 *Non-violent Property Crimes ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of criminal superior court filings where the primary charge involved non-violent theft of property, possession of stolen property, extortion, burglary, criminal trespass and taking a motor vehicle without permission (*CJ NVC: Property Crimes*) (Figure 5.51, Figure 5.52, Figure 5.53, and Figure 5.54).

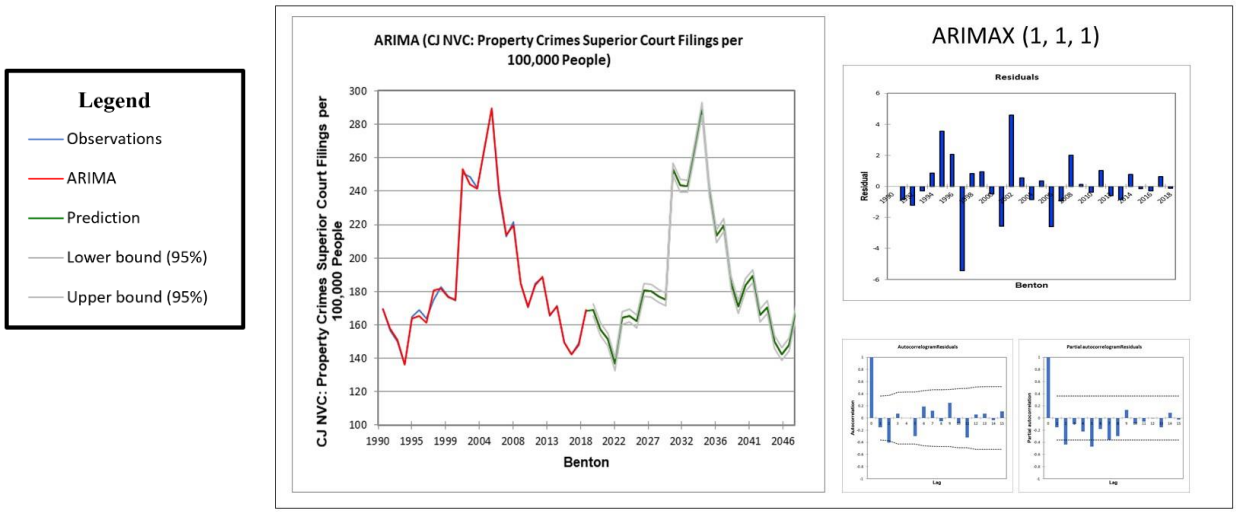


Figure 5.51. Benton, Nonviolent Property Crimes ARIMAX Visualization

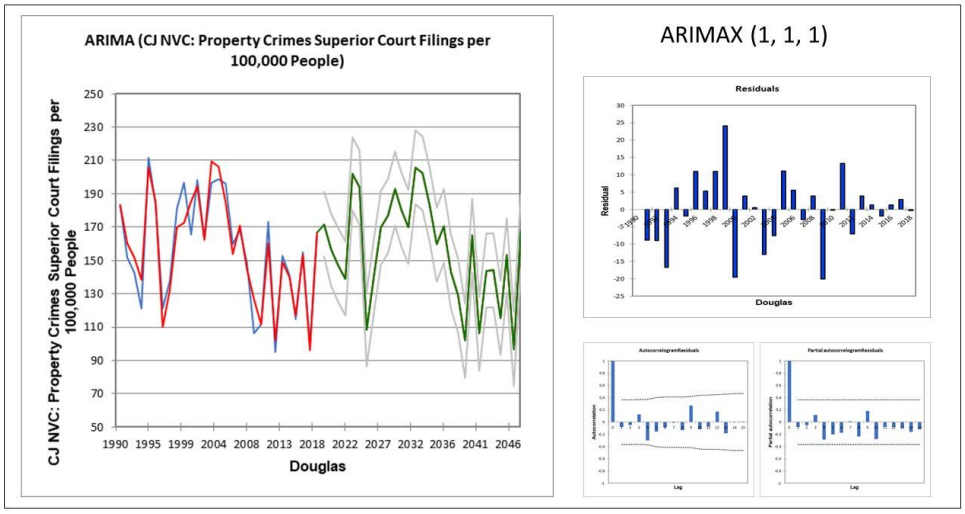


Figure 5.52. Douglas, Nonviolent Property Crimes ARIMAX Visualization

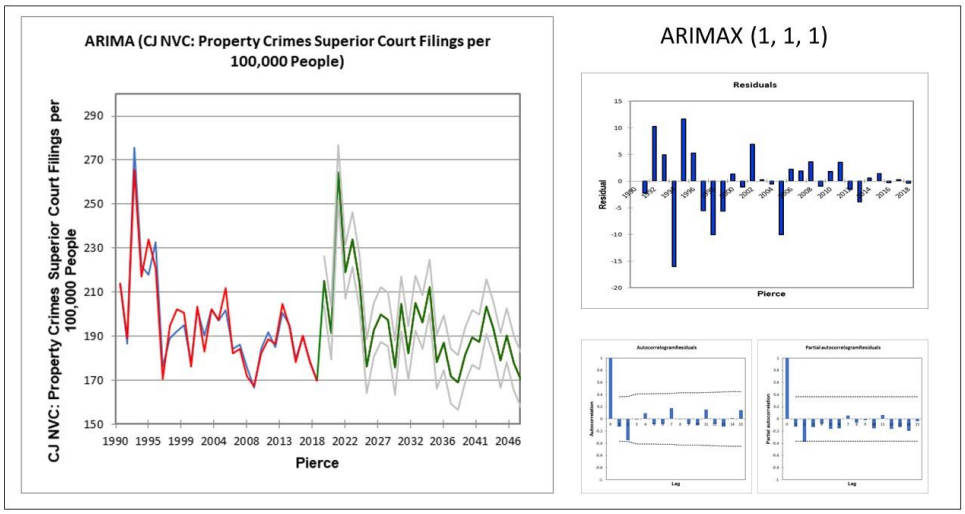


Figure 5.53. Pierce, Nonviolent Property Crimes ARIMAX Visualization

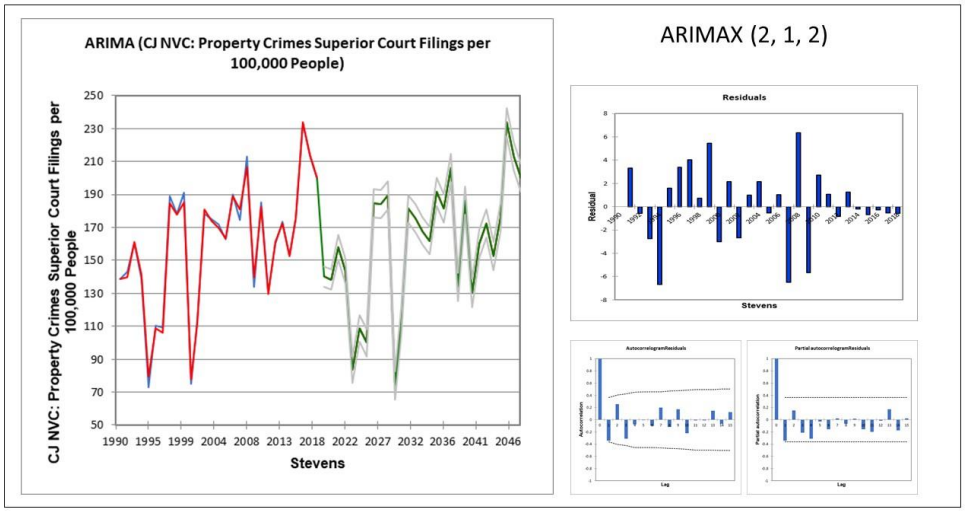


Figure 5.54. Stevens, Nonviolent Property Crimes ARIMAX Visualization

While the residuals again taper off to zero by the end of the time series and appear to be random, the width of upper and lower bound forecasts at a 95% confidence interval indicates that the ARIMAX model is very well fitted to explain non-violent property crimes. This is true for all four counties but especially for Benton and Stevens county.

5.5.6 *Total Superior Court Filings ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of all criminal superior court filings for all offenses (*CJ: Total*) (Figure 5.55, Figure 5.56, Figure 5.57, and Figure 5.58).

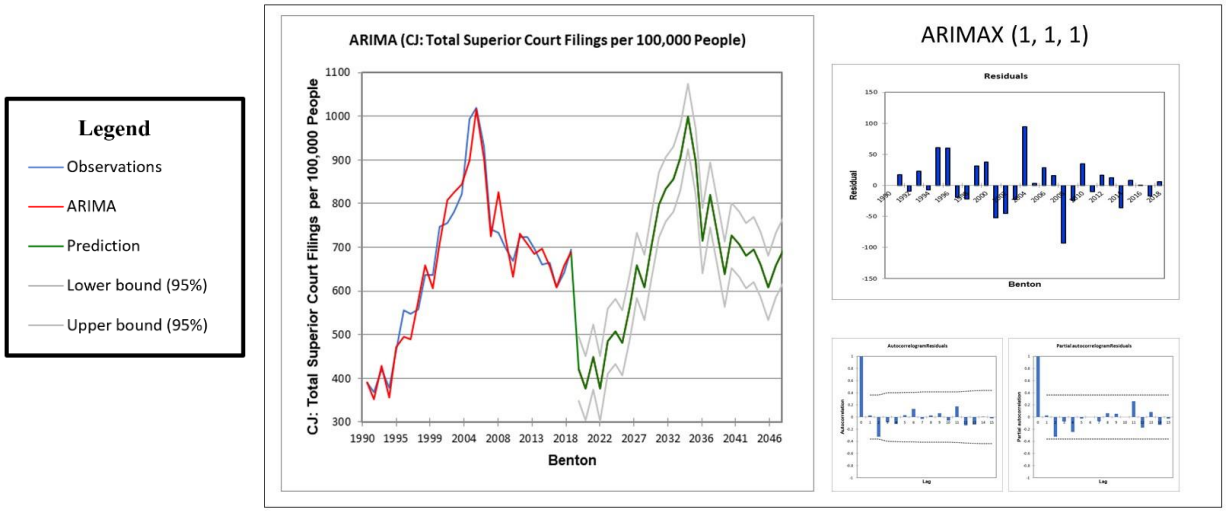


Figure 5.55. Benton, Total Adult Charges ARIMAX Visualization

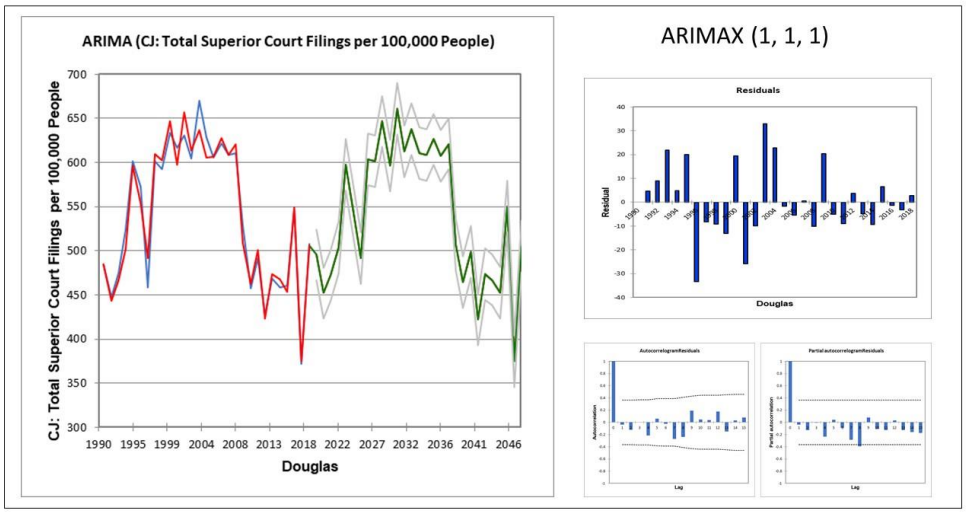


Figure 5.56. Douglas, Total Adult Charges ARIMAX Visualization

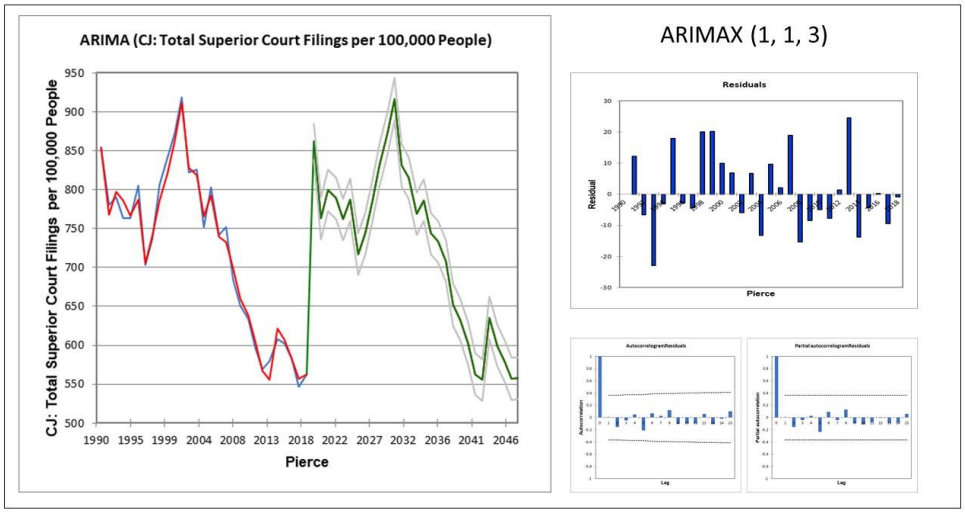


Figure 5.57. Pierce, Total Adult Charges ARIMAX Visualization

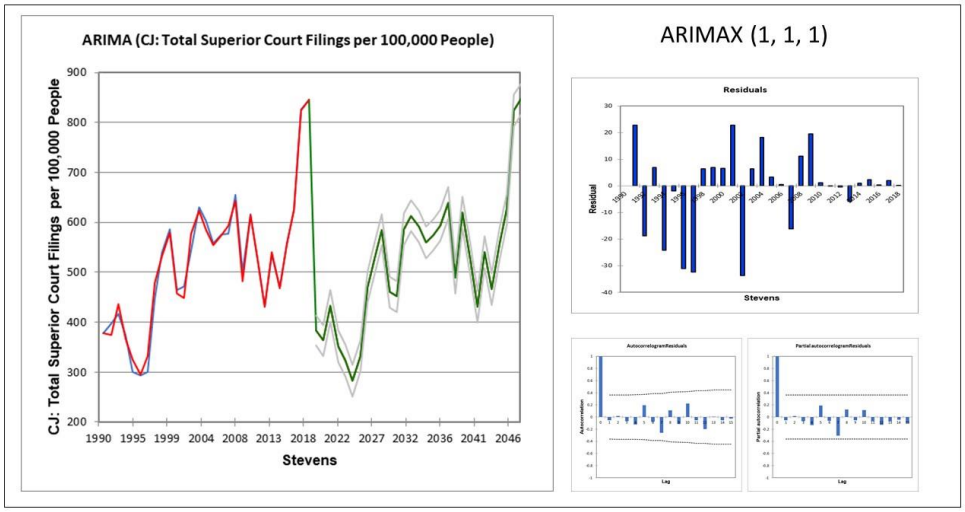


Figure 5.58. Stevens, Total Adult Charges ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. The width of upper and lower bound forecasts at a 95% confidence interval is quite narrow for all four counties indicating very good forecasting qualities with respect to all criminal superior court filings for all offenses.

5.5.7 *Juvenile Arrests ARIMAX*

The same approach was used to fit ARIMAX models to Benton, Douglas, Pierce, and Stevens county for a 29-year history of all juvenile arrests for all suspected offenses (*JD: Total Juvenile Arrests*) (Figure 5.59, Figure 5.60 , Figure 5.61, and Figure 5.62).

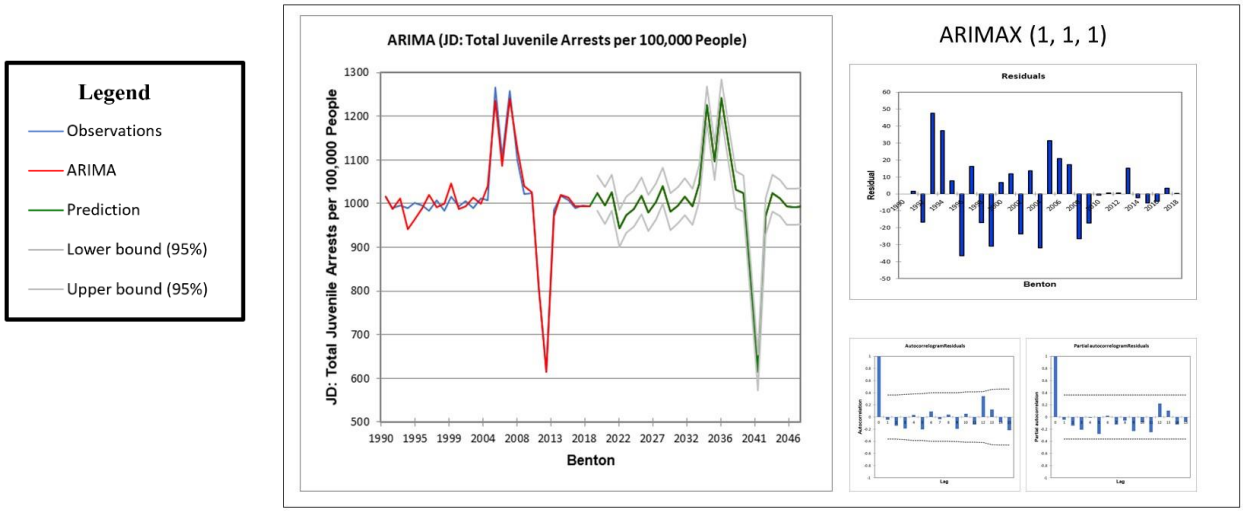


Figure 5.59. Benton, Juvenile Arrests ARIMAX Visualization

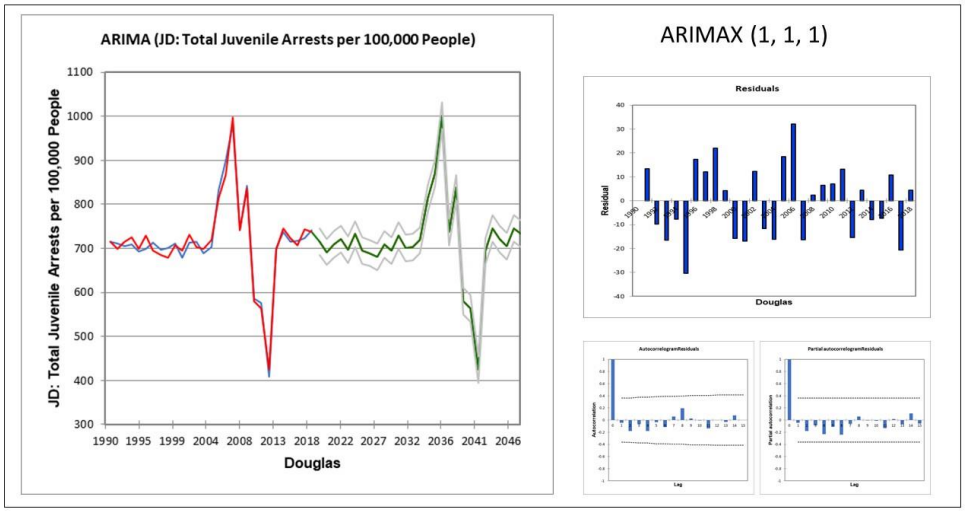


Figure 5.60. Douglas, Juvenile Arrests ARIMAX Visualization

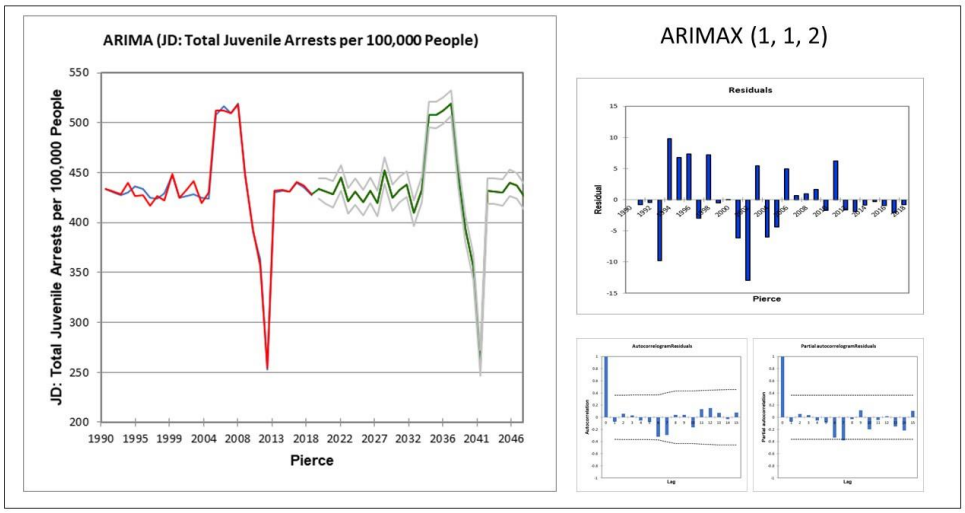


Figure 5.61. Pierce, Juvenile Arrests ARIMAX Visualization

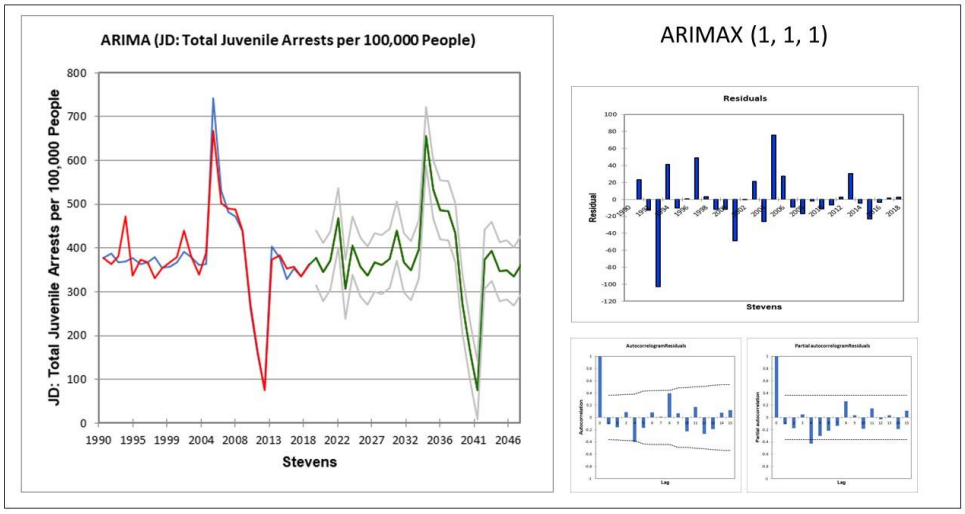


Figure 5.62. Stevens, Juvenile Arrests ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. The width of upper and lower bound forecasts at a 95% confidence interval indicates good forecasting qualities across all four counties.

5.5.8 *Total Juvenile Dispositions ARIMAX*

At last, ARIMAX models were fitted to Benton, Douglas, Pierce, and Stevens county for a 29-year history of all juvenile sentences for all offenses (*JD: Juvenile Dispositions*) (Figure 5.63, Figure 5.64, Figure 5.65, and Figure 5.66).

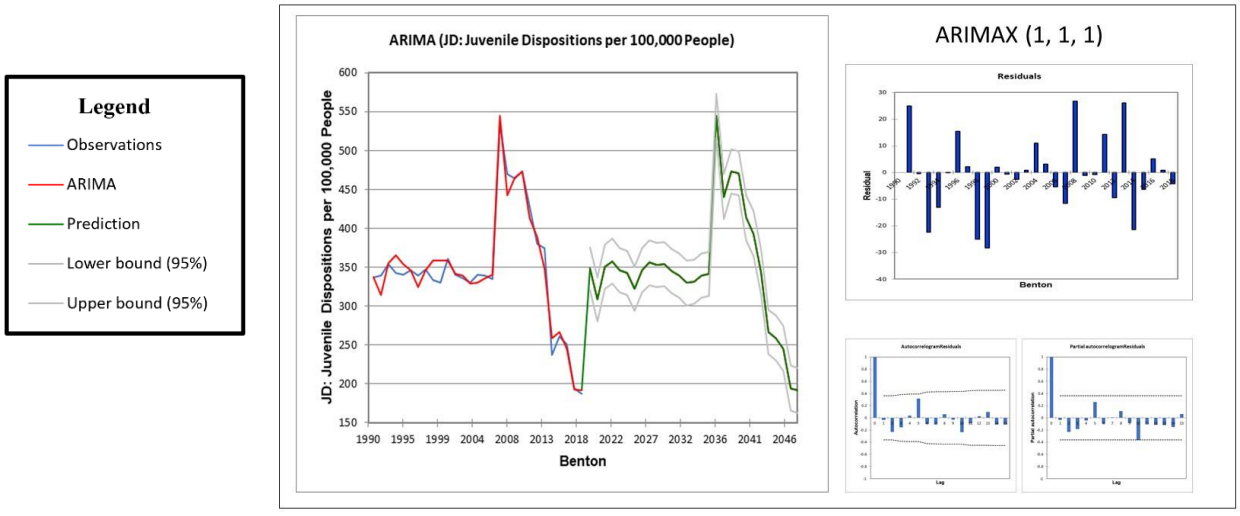


Figure 5.63. Benton, Juvenile Arrests ARIMAX Visualization

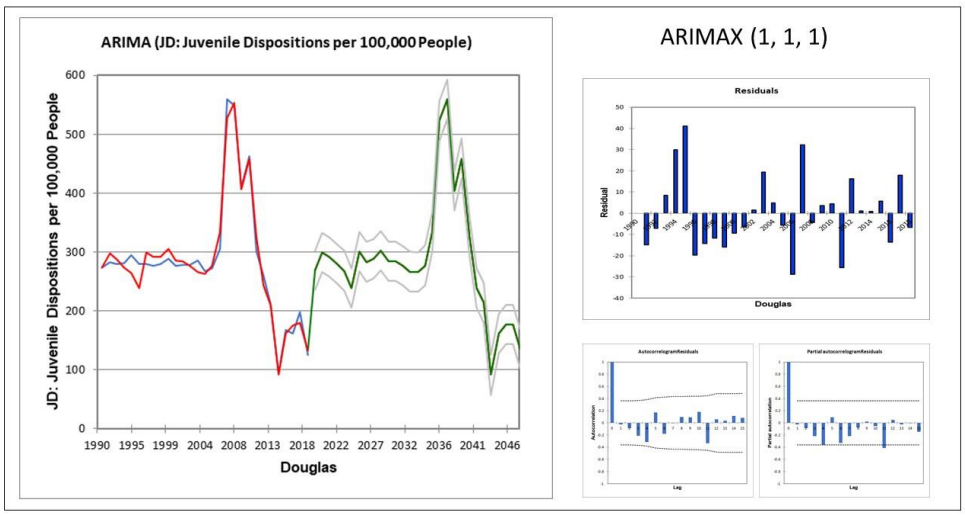


Figure 5.64. Douglas, Juvenile Dispositions ARIMAX Visualization

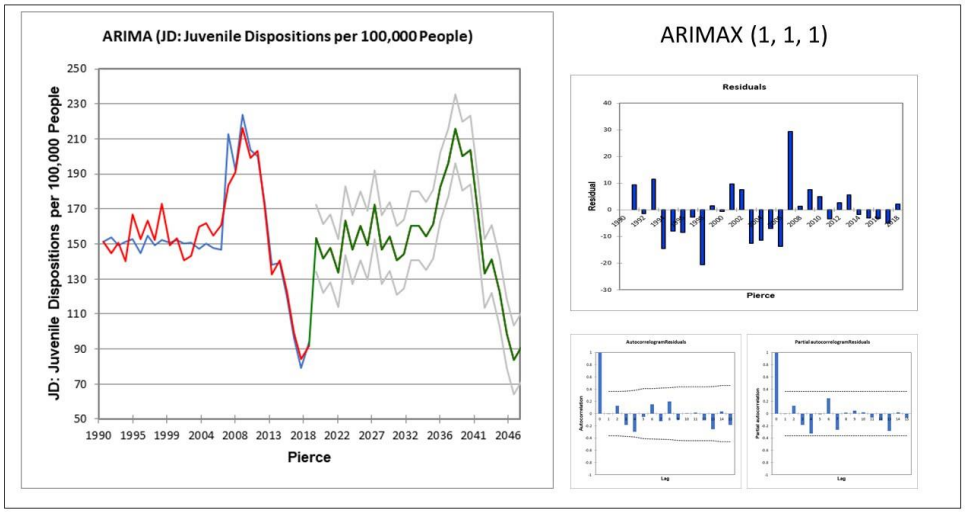


Figure 5.65. Pierce, Juvenile Dispositions ARIMAX Visualization

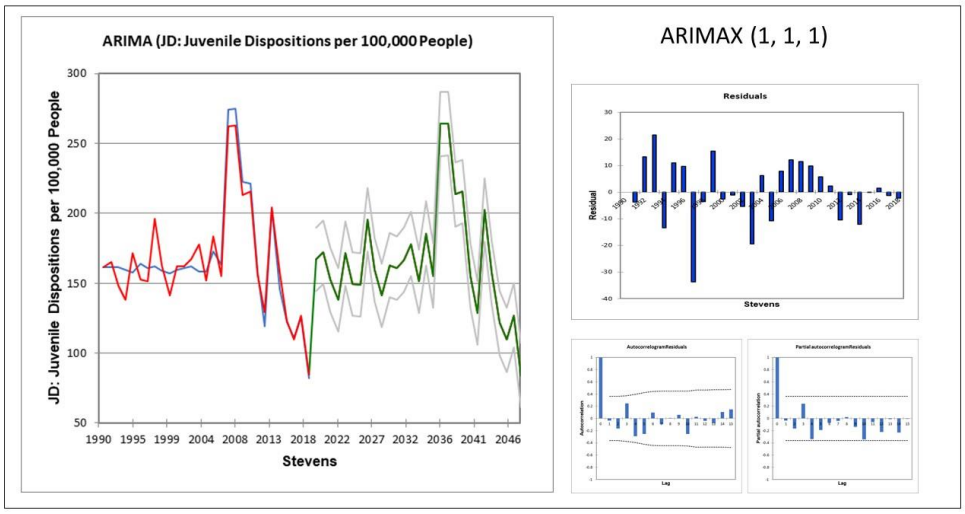


Figure 5.66. Stevens, Juvenile Dispositions ARIMAX Visualization

In each instance the residuals taper off to zero by the end of the time series and appear to be random. The width of upper and lower bound forecasts at a 95% confidence interval indicates good forecasting qualities across all four counties.

5.5.9 *Reflections on the ARIMAX Model*

In all observed instances the ARIMAX model showed a consistent goodness of fit, evidenced by residuals tapering off to zero by the end of the time series and no degree of autocorrelation between them. The model, however, was not equally effective across all observed 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 is 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 is very well fitted at anticipating the overall count of adult criminal charges without regard to type.
4. With respect to the observed juvenile measures, the model fits equally well for total juvenile arrests and total juvenile dispositions, implying a cointegration in the two observed JD time series.

Chapter 6. MOVING TOWARDS DATA-DRIVEN POLICIES

6.1 FUTURE RESEARCH

Washington Senate Bill No. 6913 (1990 2nd. Ex. Sess.), which laid the foundation for the Criminal Justice and Juvenile Facilities SPLOSTs, 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."*

From the legislative premise, two critical unwarranted assumptions emerge:

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

There is nothing in the Senate Bill indicating whether the above assumptions, which are of immense importance to the policy they premise, are based on fact, data, or science. There is in fact a dangerously tacit postulation to overall SPLOST policy in Washington: that spending tax dollars on something makes it better. In addition, the legislature appears to have relied on a naïve definition of "criminal justice" composed of three dimensions—police, courts, and jails—whereas the literature and this study's findings unequivocally show that criminal justice is embedded in a web of far more complex socioeconomic factors.

Looking ahead, future research could evaluate whether the Criminal Justice and Juvenile Facilities SPLOSTs are producing the positive impact the legislature expected by exploring causal inferences between tax dollars spent and outcomes. If, as the legislature implies, more money makes things better and problems can be solved backwards by tackling the outcome, there should

be a strong inversely proportional cointegration between the time series of SPLOST collection and crime. This question was not at the heart of this study primarily because both SPLOSTs are recent and there is not yet enough time series to draw causal inferences. A preliminary analysis, however, suggests that there is either no cointegration at all between the time series of SPLOST revenue and observed crime measures or, if there is a cointegration, it is directly proportional. The apparent lack of cointegration can be observed with respect to all those counties which implemented either the Criminal Justice or Juvenile Facilities SPLOST in the middle of the 29-year time series observed in this study. For example, Cowlitz, Grant, Pend Oreille, Walla Walla, Whitman, and Whatcom counties all adopted the Criminal Justice SPLOST between 1999 and 2004 and none of the observed crime measures decreased afterward (Figure 6.67, Figure 6.68, Figure 6.69, Figure 6.70, Figure 6.71, and Figure 6.72). The trend in Pend Oreille actually suggests a positive cointegration, which is discussed more in depth in Section 6.2.3, indicating that additional SPLOST funds may have resulted in an *increase* in adult prosecutions.

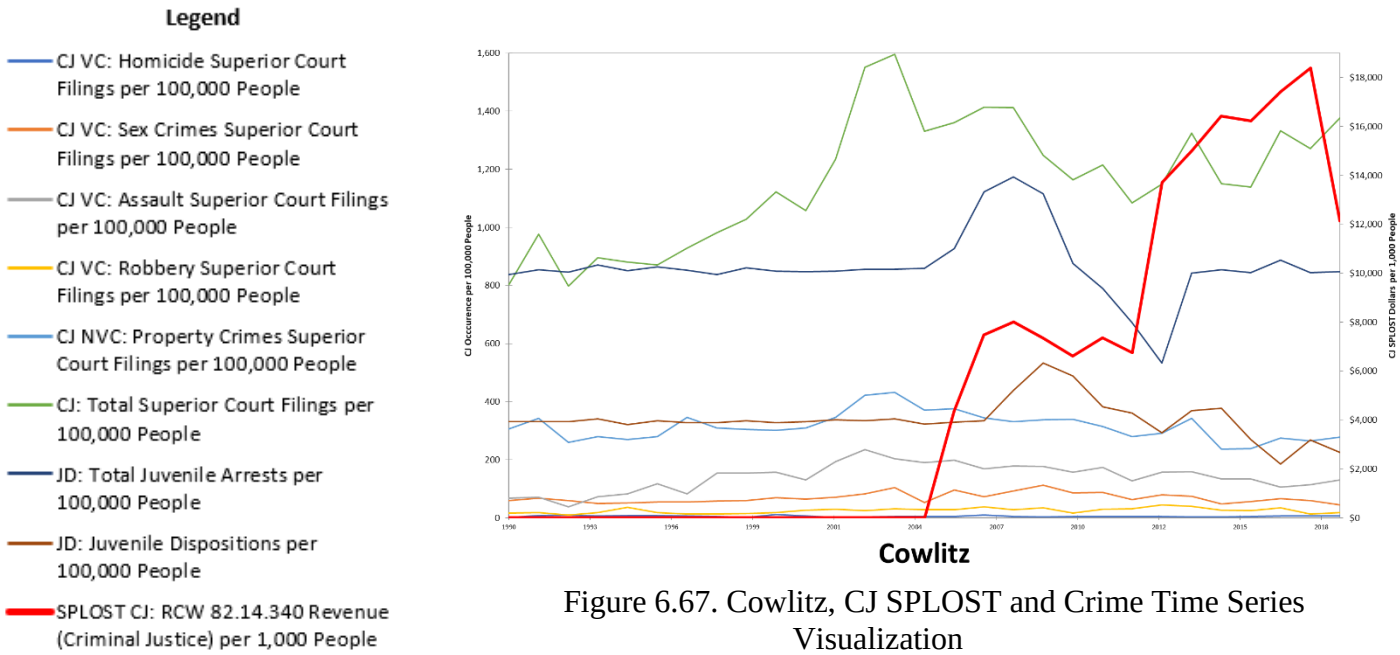


Figure 6.67. Cowlitz, CJ SPLOST and Crime Time Series Visualization

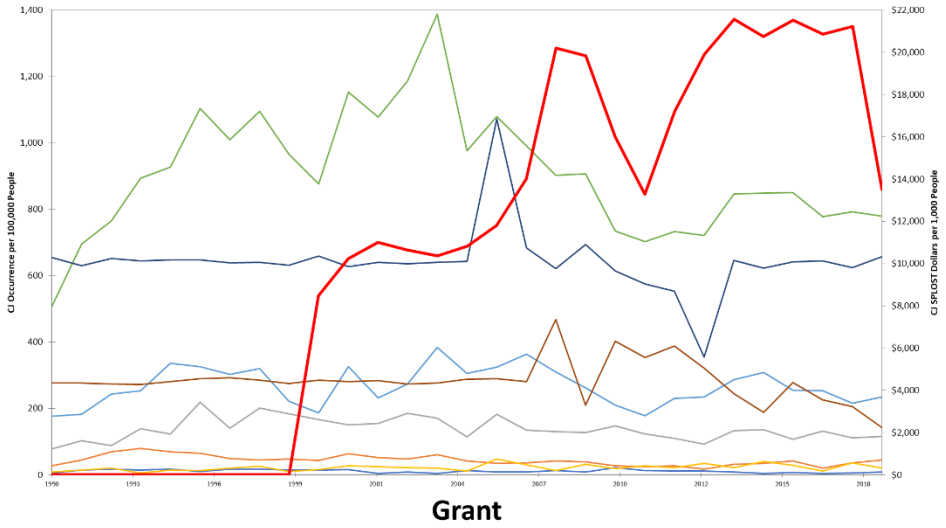


Figure 6.68. Grant, CJ SPLOST and Crime Time Series Visualization

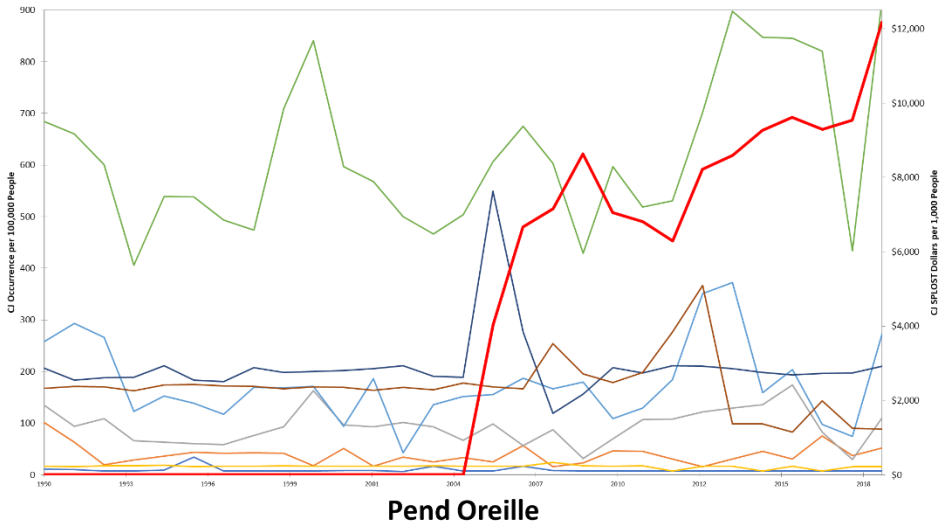


Figure 6.69. Pend Oreille, CJ SPLOST and Crime Time Series Visualization

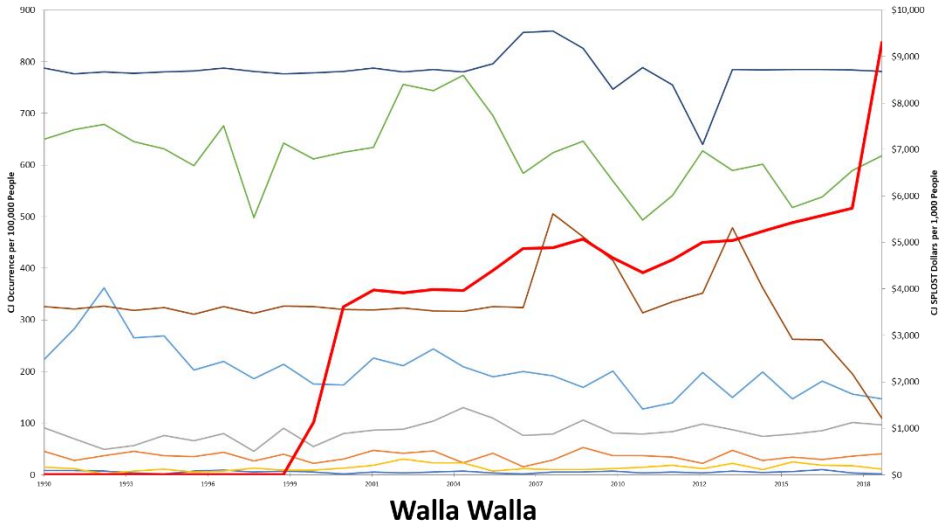


Figure 6.70. Walla Walla, CJ SPLOST and Crime Time Series Visualization

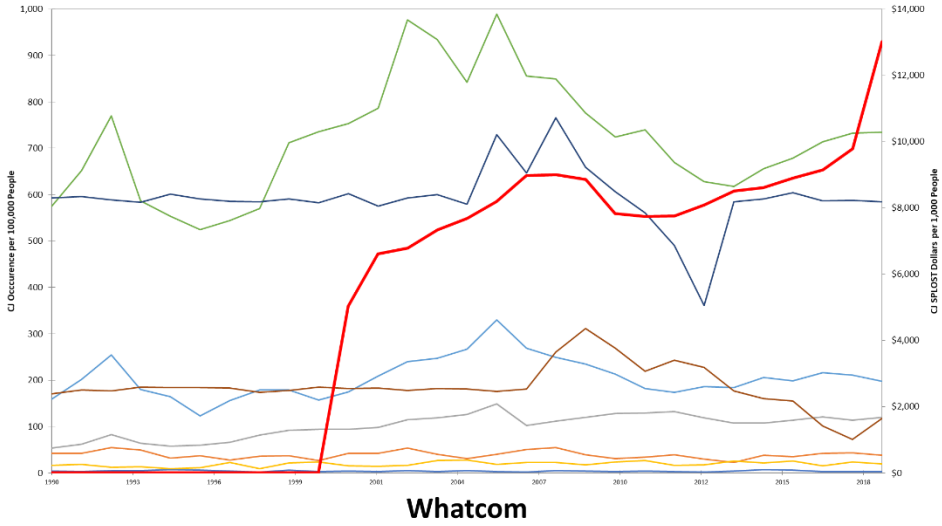


Figure 6.71. Whatcom, CJ SPLOST and Crime Time Series Visualization

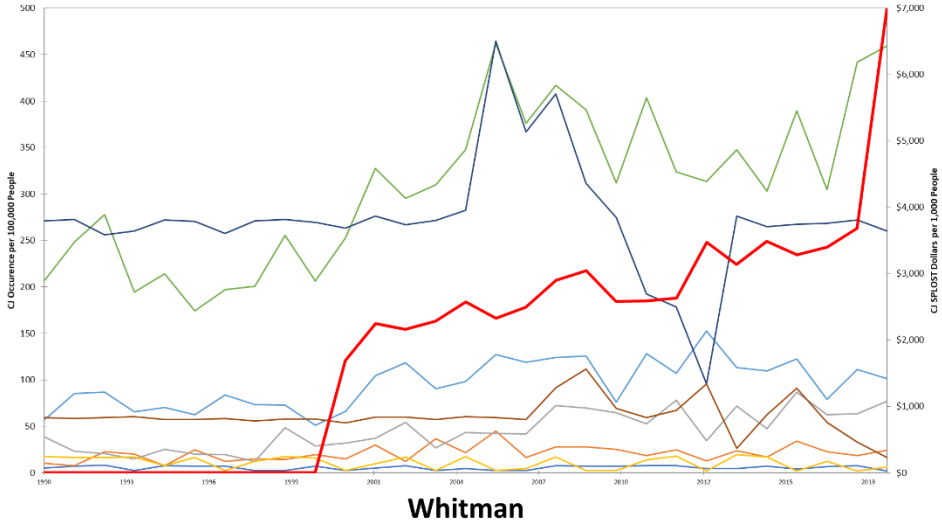


Figure 6.72. Whitman, CJ SPLOST and Crime Time Series Visualization

Similar results can be observed for three of five counties that adopted the Juvenile Facilities SPLOST between 1999 and 2006 (Island, Kitsap, and Lewis), where no observed crime measure decreased after the SPLOST was adopted (Figure 6.73, Figure 6.74, and Figure 6.75). The trend in Island even suggests a positive cointegration, which is discussed more in depth in Section 6.2.3, indicating that additional SPLOST funds may have resulted in an *increase* in juvenile arrests.

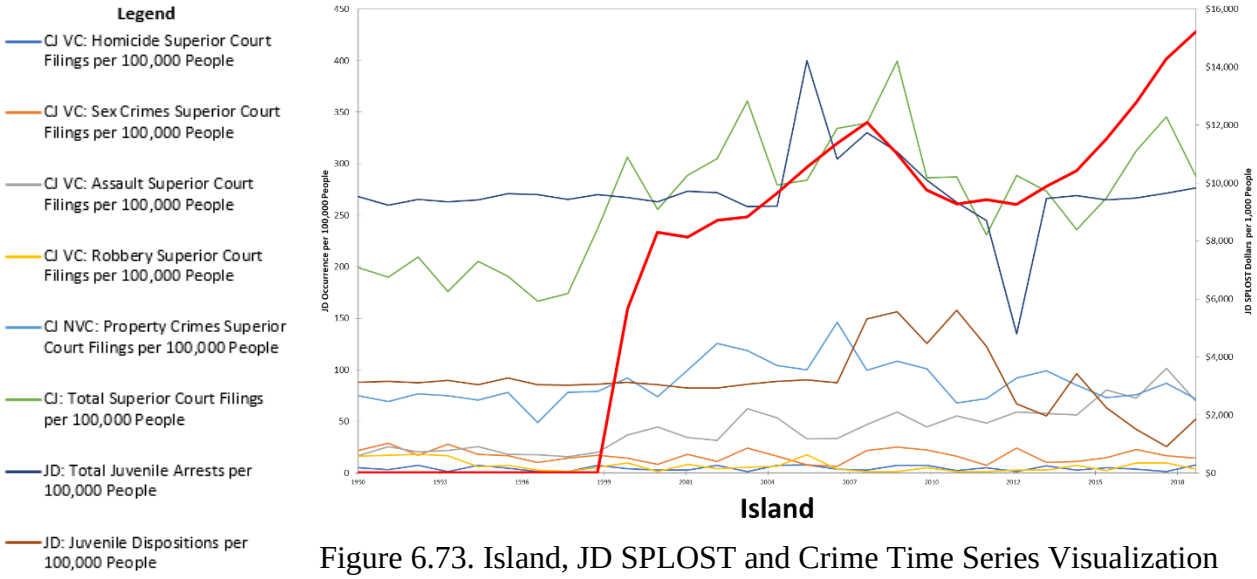


Figure 6.73. Island, JD SPLOST and Crime Time Series Visualization

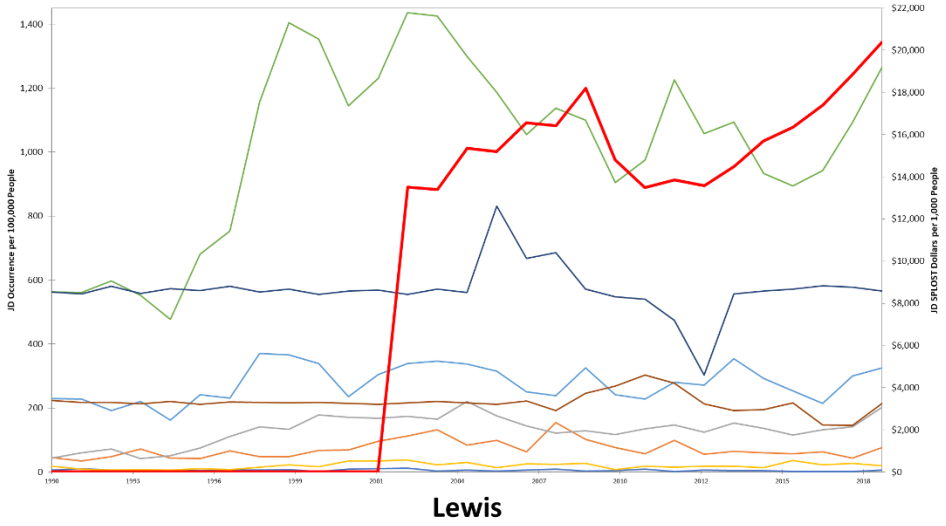


Figure 6.74. Lewis, JD SPLOST and Crime Time Series Visualization

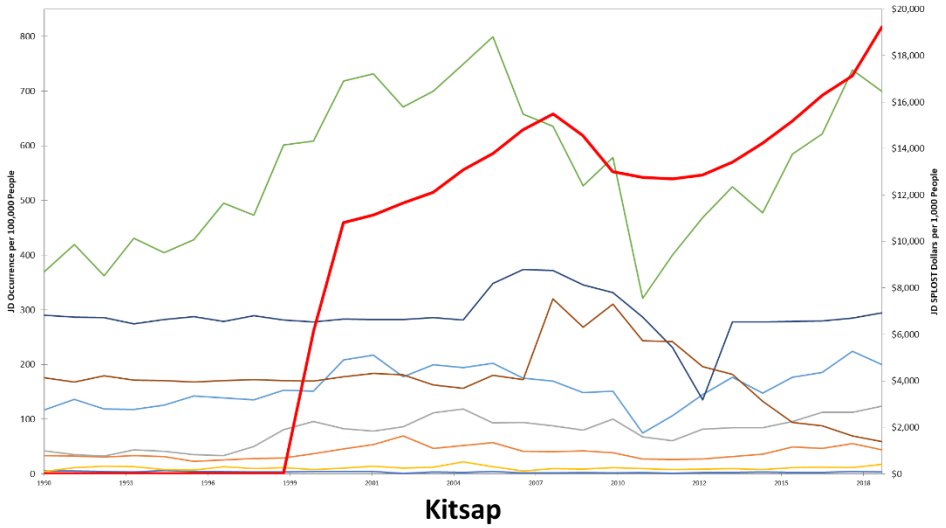


Figure 6.75. Kitsap, JD SPLOST and Crime Time Series Visualization

Only in the case of Whitman and Whatcom counties, preliminary results from a cointegration test[57] suggest a minuscule 0.03 cointegration coefficient between the Juvenile Facilities SPLOST and the total count of juvenile sentences (Figure 6.76 and Figure 6.77).

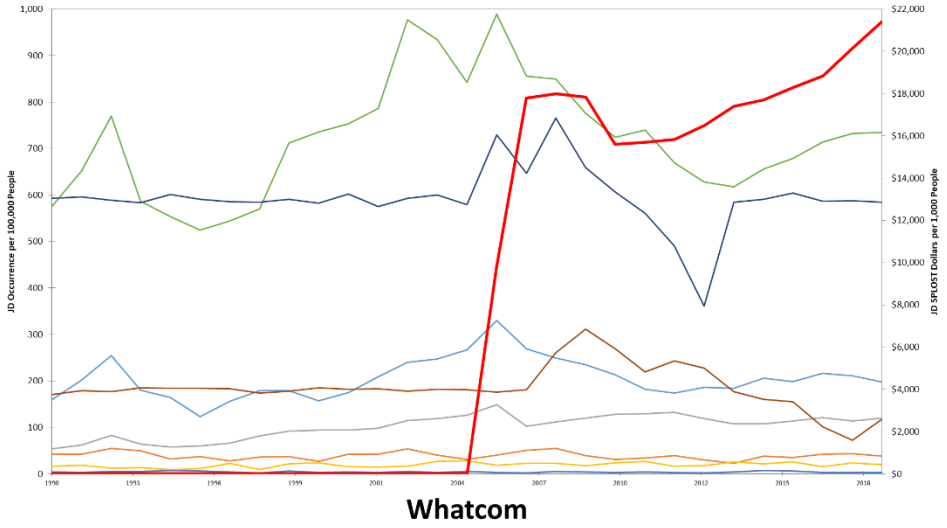


Figure 6.76. Whatcom, JD SPLOST and Crime Time Series Visualization

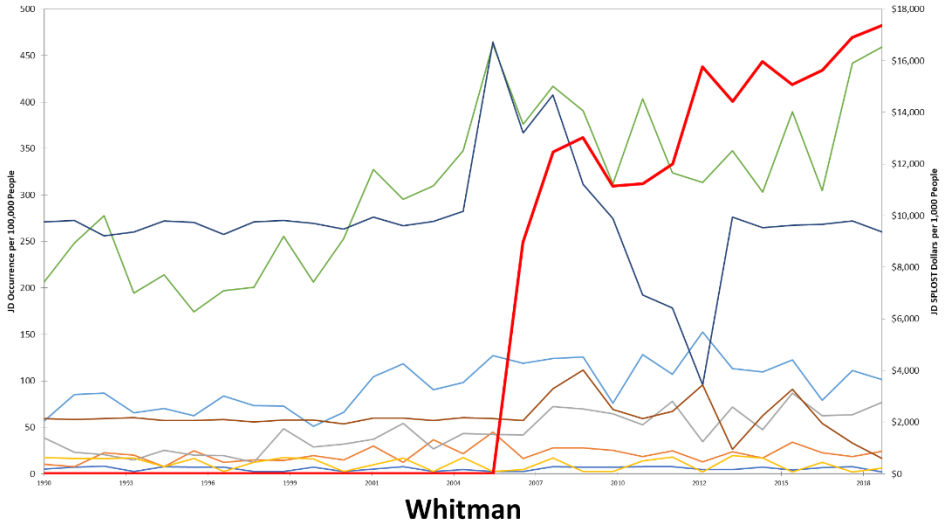


Figure 6.77. Whitman, JD SPLOST and Crime Time Series Visualization

In sum, while it is not possible to reach a conclusion without a lengthier time series, there is reason to suspect that the amount of SPLOST tax either (a) makes no difference whatsoever, or (b) results in an *increase* to prosecutions and arrests (e.g., Pend Oreille and Island), or, in a best

[57] Applying the Vector Autoregressive (VAR) model for cointegration first introduced by Engle and Granger (1987).

case scenario, (c) yields miniscule positive results on criminal justice akin to a return on investment of 3% (e.g., Whatcom and Whitman).

6.2 Legislative Recommendations

The objective of this study was not *to forecast* but to verify *whether it is possible to forecast* the flow of SPLOST revenue and the incidence of crime across Washington counties. In Section 4.7 a Kernel model was built with r^2 values of 0.876 with respect to the Criminal Justice SPLOST and 0.722 with respect to the Juvenile Facilities SPLOST, indicating that the social variables in the model are able to explain approximately between 72% and 88% of the distribution of SPLOST revenue at a confidence internal of 95%. In Section 5.5, two distinct ARIMAX models proved to be particularly well fitted at forecasting the incidence of non-violent property crimes, the overall count of adult criminal charges without regard to type, and juvenile arrests. Together, the empirical findings demonstrate that it is reasonably possible to forecast, within obvious margins of error, the flow of SPLOST revenue as well as the incidence of crime by leveraging the explanatory power of numerous observations embedded in the socioeconomic structure of Washington counties.

The statistical models simply show that forecasting is possible; the forecast itself, however, is neither feasible nor essential. Clearly, the models cannot predict future crime or SPLOST revenue because we do not know the future values of all the necessary explanatory variables the models require. However, what the models reveal is that society offers clues that can inform legislative policy, both in terms of criminal justice and tax policy. The models should serve as confirmation that legislative policy should be informed by demographics, wealth distribution, poverty, educational attainment, and unemployment, rather than politics, police staffing, jail sizes, or a desire to reduce property tax rates. In this respect, the study can offer four core legislative recommendations.

6.2.1 *Focus on Washington Youth*

Some explanatory variables observed in the study proved to be statistically significant to all three models (Table 6.18).

Table 6.18. Matrix of Explanatory Variables Significant to All Three Models

Variable labels	Kernel Model: SPLOST Forecasting	ARIMAX Model: CJ Forecasting	ARIMAX Model: JD Forecasting
FD: % of Total Births to Single Teenage Mothers (15-19)		✔	✔
FD: % of Total Births to Single Mothers		✔	✔
FD: Children in Foster Care Placement per 1,000 People		✔	✔
FD: Divorces per 1,000 People			
SD: Population Density (PPL/Sq mi)		✔	✔
SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)		✔	✔
SD: Average Reported Poor Mental Health Days	✔	✔	
SD: Income Inequality Ratio (80th Percent. Income/20th Percent.)		✔	✔
SD: Residential Segregation Index - Black/White		✔	
SD: Residential Segregation Index - non-white/White	✔	✔	
SD: High School Graduation Rate		✔	
SD: % of Population with Some College Education			
SD: % of Population with 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	✔		✔
CJ VC: Sex Crimes Superior Court Filings per 100,000 People		✔	✔
CJ VC: Assault Superior Court Filings per 100,000 People		✔	✔
CJ VC: Robbery Superior Court Filings per 100,000 People		✔	✔
CJ NVC: Property Crimes Superior Court Filings per 100,000 People		✔	✔
CJ: Total Superior Court Filings per 100,000 People		✔	✔
JD: Total Juvenile Arrests per 100,000 People		✔	✔
JD: Juvenile Dispositions per 100,000 People		✔	✔

Measures of absolute or relative deprivation were generally the most valuable explanatory variables across the study, and most specifically poverty among children and unemployment. A generalization can be made that poverty among children and unemployment are the best indicators of crime (with which they bear a positive association) and SPLOST revenue (with which they bear a negative association). After all, it is no surprise that poverty can lead to more crime and cause a county to collect less sales tax. Educational attainment and English proficiency also proved to be crucial to crime and revenue forecasts, both bearing a negative association with crime and a positive association with SPLOST revenue. While the study did not explore the causal relationship between these indicators, the broad view suggests that a population well versed in English has access to more educational and employment opportunities and consequently spends more and commits less crime.

The above conclusions lead to an additional important observation. Of the six variables statistically significant throughout the study, at least four of them can be related to how a child grows up in Washington and all four are precursors to the other two (Figure 6.78). Perhaps the most important message from this study is that investing in Washington youth is by far the best approach to prevent crime, boost the economy, and promote a solid tax revenue stream.

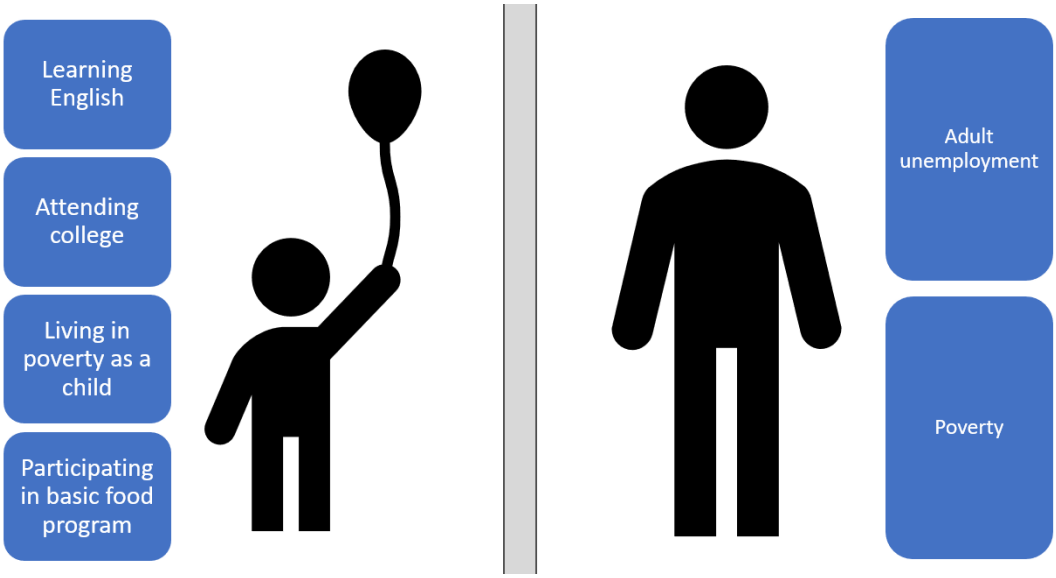


Figure 6.78. Most Important Explanatory Variables, Children and Adults

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 those tax dollars would have had a greater positive impact on criminal justice if they had been spent on three simple cost objects: to ensure that Washington kids (a) don't go hungry, (b) learn English so that they may have wider access to educational and employment opportunities, and (c) graduate from college.

6.2.2 *Establish Technical Review Panels*

This study shows that indicators of both crime and revenue lie in the socioeconomic structure of a county. Therefore, tax policy should not be informed just by output measures (such as crime) and tax revenue cannot be spent directly on the output measure without addressing the underlying social factors. For example, spending more money to increase jail sizes does not prevent or fight crime, which is the result of underlying social factors. Why then are SPLOSTs on the rise?

It is possible to identify two main reasons why SPLOSTs are on the rise. The first reason, the official one, is what is sold to voters or made part of legislative records. This reason typically fits a demagogic narrative, such as to ensure public safety, advance criminal justice, improve mental health,[58] or promote tourism.[59] The second reason, the empirically evident one, is that counties impose SPLOSTs just because they can—they have the population, the income, and the economic activity. Looking at the most recent data, in fact, shows no spatial relationship in Washington counties between adult criminal charges, juvenile arrests, and SPLOST revenue, suggesting that these three measures, which the legislature believes to be associated, may not be associated at all (Figure 6.81, Figure 6.80, and Figure 6.79).

[58] RCW 82.14.460.
[59] RCW 35.101.010 *et seq.*

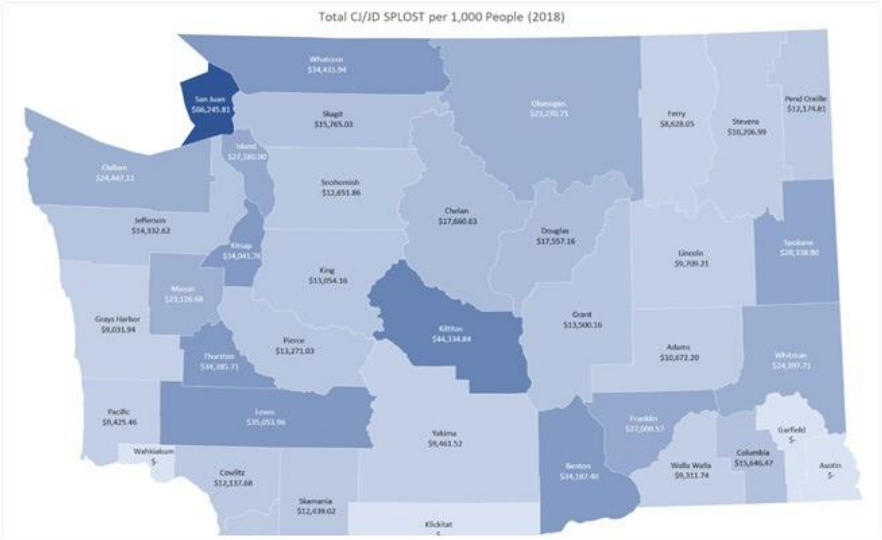


Figure 6.79. SPLOST Revenue by County (2018)

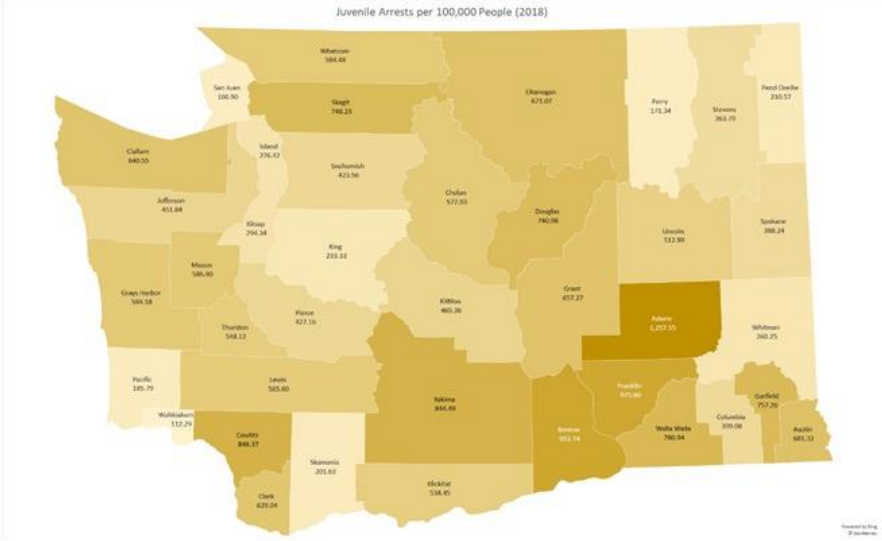


Figure 6.80. Juvenile Arrests by County (2018)

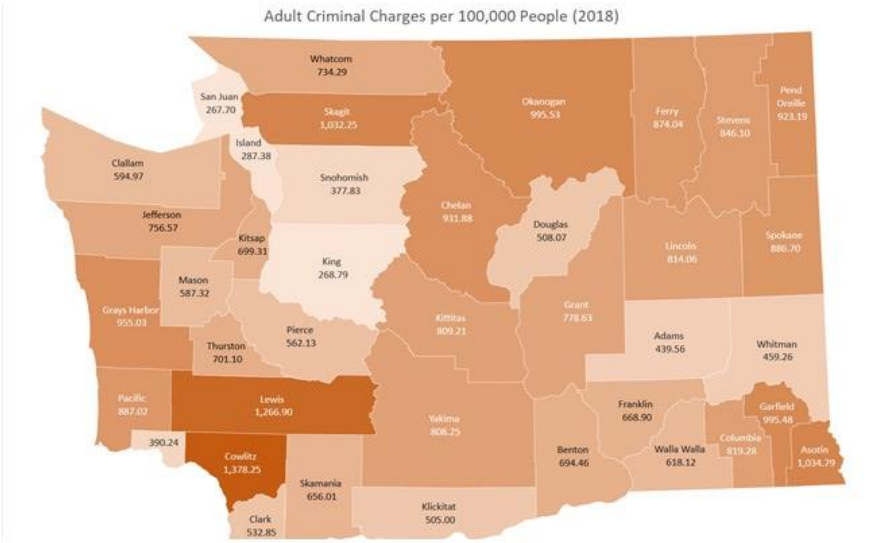


Figure 6.81. Adult Criminal Charges by County (2018)

While it may be reasonable to levy unappropriated taxes feeding into a general fund based solely on budgetary needs and ability to collect, taxes earmarked for special purposes should be informed by science and objective data. A SPLOST system that generates from unwarranted assumptions and leaves up to local governments the decision to impose the tax does not in any way prove that there is a need or use for the tax. This is true even when the tax is subject to vote because the electorate lacks the technical wherewithal to make such a determination.

John Marshall, Chief Justice of the United States from 1801 to 1835, once wrote that "[a]n unlimited power to tax involves, necessarily, a power to destroy."[60] Taxes earmarked for special purposes risk leveraging the power to tax toward destruction by exacerbating inequalities and tying critical social services to unevenly distributed funds. The recommendation is that taxes earmarked for special purposes should be subject to preliminary scrutiny and vote by an independent scientific committee of economists and technical experts who can first certify a concrete need and the expectation that the anticipated revenue will have a positive impact on root causes of the problem.

6.2.3 *Associate Proper Cost Objects*

In the state accounting system, expense accounts are not tied to specific revenue sources but to programmatic goals, rendering it impossible to trace how money is spent and what impact it may be having. For example, the Criminal Justice SPLOST can be pay for items expensed through BARS accounts 512 (superior courts and juvenile courts), 515 (legal services and indigent defense), 521 (law enforcement), 523 (detention facilities), 524 (protective inspection services), 528 (dispatch services), or 565 (domestic violence). Similarly, while the Juvenile Facilities SPLOST is earmarked towards "costs associated with financing, design, acquisition, construction,

[60] Marshall, John. (1819). Opinion in *McCulloch v. Maryland,* 17 U.S. 316, 4 L.Ed. 579 (1819).

equipping, operating, maintaining, remodeling, repairing, reequipping, and improvement of juvenile detention facilities and jails," there is no expenditure BARS account specifically designated to juvenile detention facilities and jails. Funds from the Juvenile Facilities SPLOST could be used to pay for items expensed through BARS accounts 523 (detention facilities) or 527 (juvenile services).

The expense accounts associated with the two SPLOSTs are consistent with the legislature's narrow view of what criminal justice means: police, courts, and jails. In some counties, the increase in SPLOST revenue has in fact been accompanied by a dramatic increase in arrests and prosecutions. This stark increase is most evident in Pend Oreille and Stevens county (Figure 6.82 and Figure 6.83) , but also very noticeable in Chelan, Grays Harbor, Jefferson, and Kittitas counties (Figure 6.84).

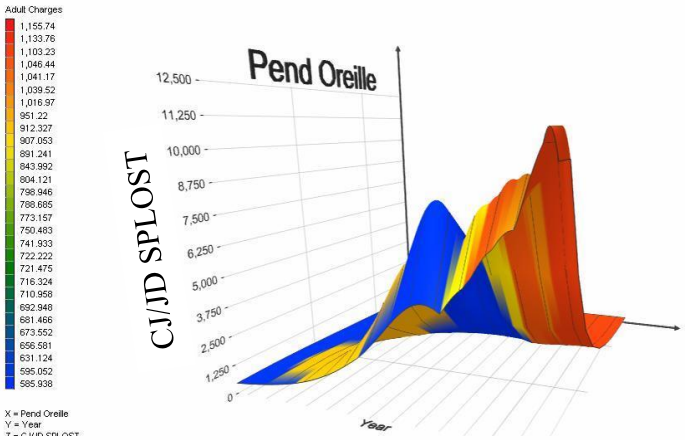


Figure 6.82. SPLOST, Arrests and Prosecutions, Pend Oreille 3D Time Series Heatmap

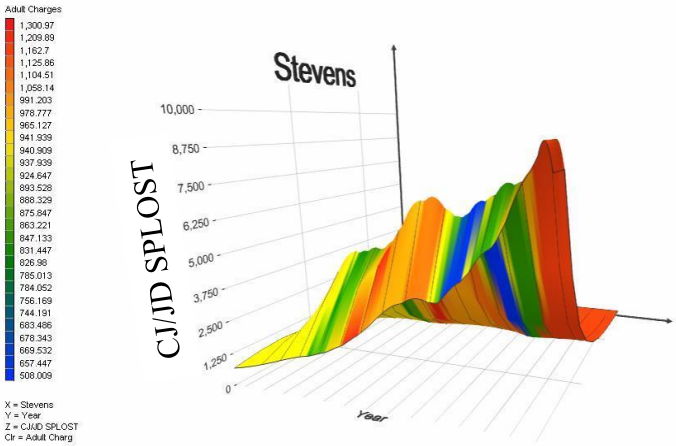


Figure 6.83. SPLOST, Arrests and Prosecutions, Stevens 3D Time Series Heatmap

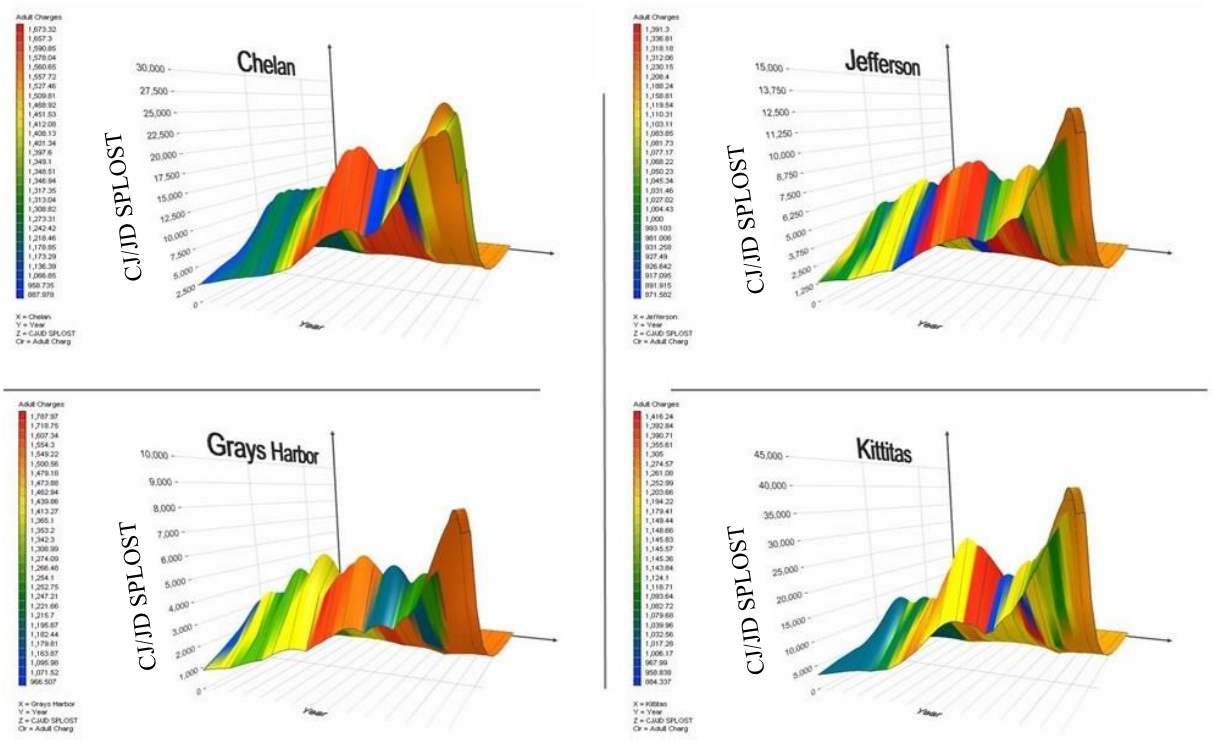


Figure 6.84. SPLOST, Arrests and Prosecutions, Other Counties 3D Time Series Heatmap

Because of the current composition of the BARS accounting system, it is unclear whether, and unlikely that, any funds from the Criminal Justice and Juvenile Facilities SPLOST is being spent on family services, food programs, youth mentoring, education tutoring, and other similar social services. The state should establish these new expense accounts in its BARS system and tie funds deposited into accounts 313.71.00 (Criminal Justice SPLOST) and 313.72.00 (Juvenile Facilities SPLOST) to these new cost objects. Only then, one day, it will be possible to truly assess whether and to what extent these SPLOSTs have had a positive impact on criminal justice.

6.2.4 *Implement Demand-based Revenue Sharing*

Studies have repetitively found that the devolution phenomenon causes local governments to compete for tax revenue, which in turn results in the uneven distribution of funds necessary to pay

for critical government services. The logical and widespread assumption is that partial revenue reallocation among horizontally equivalent jurisdictions can effectively mitigate fiscal disparity. This reallocation can take the form of tax base sharing (Cigler 1993), equalizing statewide programs (Zhao and Hou 2008), centrally managed intergovernmental aid (Downes and Pogue 1992), mandated statewide revenue sharing (McHugh and Jolley 2012), or voluntary regional coalitions (Wolman et al. 2004; Harvard Law Review 2005; Zhao 2010; Jones and McIntosh 1974). However, research has shown that the impact of these intergovernmental aid programs is questionable (Pagano and Johnston 2000; Johnston et al. 2000) because they do not alleviate the overall revenue burden on local governments and, in some cases, promote dependency.

The objective of revenue sharing and intergovernmental aid is to alleviate horizontal tax competition. In this respect, revenue is reallocated among horizontally equivalent jurisdictions: counties with counties or cities with cities. While the State of Washington embraces the general belief that revenue reallocation is effective at ameliorating fiscal disparity, it implements it vertically, rather than horizontally. Many SPLOSTs in Washington are in fact shared between the county and cities within the county, but not among counties. For example, the Criminal Justice SPLOST is a county-level sales tax, which lends itself to a traditional horizontal competition dilemma where counties compete for the same revenue base. Instead of mandating county-level revenue sharing, the state requires a vertical sharing scheme where 10% of the tax remains in the county coffers and 90% is shared among the county and the cities within the county ratably based on population. This system does not attempt, in any way, to correct for fiscal disparities among counties.

Regardless of form, all revenue sharing schemes rest on the assumption that the true problem is the uneven distribution of revenue and therefore reallocation can offer mitigating benefits. While

this may be true for unappropriated general fund taxes, it is not the case for taxes earmarked for special purposes. Unlike general fund taxes, SPLOSTs should stem from a proven data-driven need. In that respect, simply sharing revenue would not address or ameliorate the underlying need. For example, if a SPLOST is adopted to pay for drug rehabilitation programs, the revenue sharing must happen based on the demand for drug rehabilitation, not population, income, or some other measure unrelated to the demand for drug rehabilitation.

The State of Washington should reconsider its revenue sharing scheme for special purpose local option sales taxes. These taxes should be shared horizontally and based on a proven data-driven need for the programs they are meant to fund.

6.3 CONCLUSION

Since the Reagan administration, local governments have had to reinvent themselves in a constant state of fiscal uncertainty. The State of Washington follows national trends with its increasing landscape of special purpose sales taxes that signify disoriented tax policy. As the devolution phenomenon is here to stay, local governments should embrace a more intelligent data-driven approach to tax revenue, especially insofar as it pertains to earmarked special purpose taxes.

This study does not condemn special purpose local option sales taxes and does not exclude that they may work well in some instances. What this study shows is that three conditions must be met for a SPLOST system to be effective on its face. First, there must be a data-driven need for the additional tax revenue. Second, there must be evidence that additional tax revenue may alleviate the problem. Third, and most importantly, SPLOST revenue will inevitably flow unevenly and favor market dominant jurisdictions. Therefore, SPLOSTs are only fit to fund services that spatially move in the same direction as sales tax revenue. For example, the expectation is that a

SPLOST system could be an effective way to finance public transportation, a social service more needed and costly where more people live, work, and spend money.

Insofar as criminal justice is concerned, this study shows that the State of Washington and Washington counties must do better, for as long as they define criminal justice as a three-dimensional expression of police staffing, judicial bandwidth, and jail space, they will not successfully influence the multitudes of social clues that are truly indicative of criminal justice. These types of misguided policies are at the heart of the social movement to disband police. This study shows that the most effective action the state can take to ensure public safety and advance criminal justice is to leverage its power to tax to guarantee that every Washington child (a) eats, (b) learns English in order to have wider access to educational and employment opportunities, and (c) graduates from college.

REFERENCES

[1] *A History of Washington's Local Governments: Washington State Local Governance Study Commission Report.* (2007). Municipal Research and Services Center of Washington. Available at: https://tinyurl.com/ycwqcv3s [Accessed 17 Oct. 2019].

[2] Afonso, W. (2013). Diversification Toward Stability? The Effect of Local Sales Taxes on Own Source Revenue. *Journal of Public Budgeting, Accounting and Financial Management*, 25(4): 649-674.

[3] Afonso, W. (2014). Local Sales Taxes as a Means of Increasing Revenues and Predicting Property Tax Burdens: An Analysis Using Propensity Score Matching. *Public Budgeting & Finance*, 34(2): 24-43.

[4] Aichhorn, A. (1925). Verwahrloster Jugend Wien (English: *Wayward Youth of Vienna*). Vienna, Austria: Internationaler Psychoanalytischer Verlag.

[5] Alcorn, S. (2019). *Growth Management Planning's Effects on Employment Trends in Washington State Rural Counties*. Washington, DC: ProQuest LLC.

[6] Allen, R. (1996). Socioeconomic Conditions and Property Crime: A Comprehensive Review and Test of the Professional Literature. *American Journal of Economics and Sociology*, 55(3): 293-308.

[7] *Annexation by Washington Cities and Towns.* (2020). Municipal Research and Services Center of Washington. Available at: https://tinyurl.com/y5q5aukg [Accessed 27 Jul. 2020].

[8] Babbie, E. (2016). *The Practice of Social Research*, 14th edition. Boston, MA: Cengage.

[9] Barber, N. (2004). Single Parenthood as a Predictor of Cross-national Variation in Violent Crime. *Cross-Cultural Research*, 38(4): 343-358.

[10] Bellair, P. (1997). Social Interaction and Community Crime: Examining the Importance of Neighbor Networks. *Criminology,* 35(4): 677-703.

[11] Berg, B. (2005). Introduction to Markov Chain Monte Carlo Simulations and Their Statistical Analysis. In *Markov Chain Monte Carlo Innovations and Applications* (1-52). Singapore: World Scientific Publishing.

[12] BERK (2014). *Analysis of Statewide Adult Correctional Needs and Costs.* Submitted to the Office of Financial Management. Available at: https://tinyurl.com/yd9kw27t [Accessed 8 Jun. 2019].

[13] Biegeleisen, J.; Sjoquist, D. (1988). Rational Voting Applies to Choice of Taxes. *Public Choice*, 57(1): 39-47.

[14] Bierens, H. (1994). The Nadaraya–Watson Kernel Regression Function Estimator. In *Topics in Advanced Econometrics* (212-247). New York, NY: Cambridge University Press.

[15] Blau, P.; Blau, J. (1982). The Cost of Inequality: Metropolitan Structure and Violent Crime. *American Sociological Review*, 47(1): 114-129.

[16] Bonta, J.; Moira, L.; Hanson, K. (1998). The Prediction of Criminal and Violent Recidivism among Mentally Disordered Offenders: A Meta-Analysis. *Psychological Bulletin*, 123(2): 123-142.

[17] Buchanan, J. (1967). *Public Finance in a Democratic Process*. Chapel Hill, NC: University of North Carolina Press.

[18] Burge, G.; Piper, B. (2012). Strategic Fiscal Interdependence: County and Municipal Adoptions of Local Option Sales Taxes. *National Tax Journal*, 65(2): 387-416.

[19] Burge, G.; Rogers, C. (2010). Local Option Sales Taxes and Consumer Spending Patterns: Fiscal Interdependence Under Multi-tiered Local Taxation. *Regional Science and Urban Economics*, 41(1): 46-58.

[20] Burrough, B. (2009). *Public Enemies: America's Greatest Crime Wave and the Birth of the FBI, 1933-34.* Ney York, NY: Penguin Books.

[21] Bursik, R. (1988). Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects. *Criminology*, 26(4): 519-551.

[22] Carroll, L.; Jackson, P. (1983). Inequality, Opportunity, and Crime Rates in Central Cities. *Criminology*, 21(2): 178-194.

[23] Chamlin, M. (1988). Crime and Arrests: An Autoregressive Integrated Moving Average (ARIMA) Approach. *Journal of Quantitative Criminology*, 4(3): 247-258.

[24] Chamlin, M.; Cochran, J. (1995). Assessing Messner and Rosenfeld's Institutional Anomie Theory: A Partial Test. *Criminology*, 33(3): 411-429.

[25] Chetty, R.; Looney, A.; Kroft, K. (2009). Salience and Taxation: Theory and Evidence. *American Economic Review*, 99(4): 1145-1177.

[26] Cigler, B. (1993). Challenges Facing Fiscal Federalism in the 1990s. *Political Science and Politics*, 26(2): 181-186.

[27] Cleveland, W. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association*, 74(368):829-836.

[28] Cohen, L.; Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, 44(4): 588-608.

[29] Danziger, S.; Wheeler, D. (1975). The Economics of Crime: Punishment or Income Redistribution. *Review of Social Economy*, 33(2): 113-131.

[30] DeFronzo, J. (1983). Economic Assistance to Impoverished Americans: Relationship to Incidence of Crime. *Criminology*, 21(1): 119-136.

[31] Devereux, M.; Lockwood, B.; Redoano, M. (2007). Horizontal and Vertical Indirect Tax Competition: Theory and Some Evidence From the USA. *Journal of Public Economics*, 91(3-4): 451-479.

[32] Dickey, D.; Fuller, W (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, 74(366): 427-431.

[33] Downes, T.; Pogue, T. (1992). Intergovernmental Aid to Reduce Fiscal Disparities: Problems of Definition and Measurement. *Public Finance Review*, 20(4): 468–482.

[34] Dugdale, R. (1877). *The Jukes: A Study in Crime, Pauperism, and Heredity*. Ney York, NY: Putman.

[35] Ehrlich, I. (1973). Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*, 81(3): 521-565.

[36] Engle, R.; Granger, C. (1987). Co-integration and Error Correction: Representation, Estimation and Testing. *Econometrica: Journal of the Econometric Society*, 55(2): 251-276.

[37] Felson, M. (1993). Social Indicators for Criminology. *Journal of Research in Crime and Delinquency*, 30(4): 400-411.

[38] Finkelstein, A. (2007). E-ZTax: Tax Salience and Tax Rates. *National Bureau of Economic Research*. Working Paper 12924. Available at: https://tinyurl.com/yygxpa6u [Accessed 13 Nov. 2020].

[39] Gamage, D; Shanske, D. (2011). Three Essays on Tax Salience: Market Salience and Political Salience, *Tax Law Review*, 65(19): 19-98.

[40] Goddard, H. (1914). *Feeble-Mindedness*. New York, NY: Macmillan.

[41] Green, A. (2006). Life in the Fast Lane: Transportation Finance and the Local Option Sales Tax. *State and Local Government Review*, 38(2): 92-103.

[42] Green, A. (2014). County Governments and Democratic Decision Making: Explaining Why Counties Seek Approval of Local Option Sales Taxes. *State Politics & Policy Quarterly*, 14(1): 50-71.

[43] Hamideh, A.; Oh, J.; Labi, S.; Mannering, F. (2008). Public Acceptance of Local Government Transportation Sales Taxes: A Statistical Assessment. *State & Local Government Review*, 40(3): 150-159.

[44] Harvard Law Review (2005). Old Regionalism, New Regionalism, and Envision Utah: Making Regionalism Work. *Harvard Law Review*, 118(7): 2291-2313.

[45] Hirschi, T.; Gottfredson, M. (1983). Age and the Explanation of Crime. *American Journal of Sociology*, 89(3): 552-584.

[46] Hsieh, C.; Pugh, M. D. (1993). Poverty, Income Inequality, and Violent Crime: A Meta-analysis of Recent Aggregate Data Studies. *Criminal Justice Review*, 18(2): 182-202.

[47] Huebner, B.; Bynum, T. (2016). *The Handbook of Measurement Issues in Criminology and Criminal Justice*. New York, NY: Wiley.

[48] Krishna, A.; Slemrod, J. (2003) Behavioral Public Finance: Tax Design as Price Presentation. *International Tax and Public Finance*, 10(2): 189-203.

[49] Jackson, P. (1984). Opportunity and Crime: A Function of City Size. *Sociology and Social Research*, 68(2): 173-193.

[50] Jansen, A. (1991). Can Sales Tax Revenue Equitably Finance Education? *Journal of Education Finance*, 16(4): 478-496.

[51] Johnston, J.; Pagano, M.; Russo, P. (2000). State Limits and State Aid: An Exploratory Analysis of County Revenue Structures. *State and Local Government Review*, 32(2): 86-97.

[52] Jones, D.; McIntosh, M. (1974). Revenue Options for Georgia Localities. *Georgia Government Review*, 6(2): 6-8.

[53] Jung, C. (2001). Does the Local-Option Sales Tax Provide Property Tax Relief? The Georgia Case. *Public Budgeting & Finance*, 21(1): 73-86.

[54] Kendall M. (1975). *Multivariate Analysis*. London, UK: Charles Griffin & Company.

[55] Krahn, H.; Hartnagel, T.; Gartrell, J. (1986). Income Inequality and Homicide Rates: Cross-national Data and Criminological Theories. *Criminology*, 24(2): 269-295.

[56] Krane, D.; Ebdon, C.; Bartle, J. (2004). Devolution, Fiscal Federalism, and Changing Patterns of Municipal Revenues: The Mismatch Between Theory and Reality. *Journal of Public Administration Research and Theory*, 14(4): 513-533.

[57] Krohn, M. (1976). Inequality, Unemployment and Crime: A Cross- National Analysis. *Sociological Quarterly*, 17(3): 303-313.

[58] Levine, N. (2013). *Spatial Autocorrelation Statistics* (CrimeStat IV: A Spatial Statistics Program for the Analysis of Crime Incident Locations, Version 4.0). National Institute of Justice (NIJ). Available at: https://tinyurl.com/yywq78fn [Accessed 6 Apr. 2020].

[59] Lilly, J.; Cullen, F.; Ball, R. (1995). *Criminological Theory: Context and Consequences*. Thousand Oaks, CA: Sage.

[60] Lockwood, B. (1993). Commodity Tax Competition under Destination and Origin Principles. *Journal of Public Economics*, 52(2): 141-162.

[61] Lockwood, B. (2000). Commodity Tax Competition and Tax Coordination under Destination and Origin Principles. *Center for Economic Policy Research,* Discussion Paper No. 2256.

[62] Lombroso-Ferrero, G. (1991). *Criminal Man, According to the Classification of Cesare Lombroso*. New York, NY: G.P. Putnam's Sons.

[63] Luna, L.; Bruce, D.; Hawkins, R. (2007). Maxing Out: An Analysis of Local-Option Sales Tax Rate Increases. *National Tax Journal*, 60(1): 45-63.

[64] Mackey, S. (1997). *Critical Issues in State-Local Fiscal Policy: A Guide to Local Option Taxes.* Denver, CO: National Conference of State Legislatures.

[65] Mann H. (1945). Nonparametric Tests Against Trend. *Econometrica: Journal of the Econometric Society*, 13(3): 245-259.

[66] Martinell, TJ. (2017). A retrospective look at the Growth Management Act. *The Business Institute of Washington*. Available at: https://tinyurl.com/y3asgysq [Accessed 27 Jul. 2020].

[67] Merton, R. (1938). Social Structure and Anomie. *American Sociological Review*, 3(5): 672-682.

[68] Messner, S.; Rosenfeld, R. (1997). *Crime and the American Dream*. Belmont, CA: Wadsworth.

[69] McHugh, P.; Jolley, G. (2012). The Sheriff of Nottingham's Favorite Tax: How Local Option Sales Taxes Exacerbate Budgetary Inequalities Between Local Governments. *Journal of Public Budgeting, Accounting and Financial Management*, 24(3): 466-488.

[70] Morrow, J. (2012). The Interaction of Theory and Data. In *Guide to the Scientific Study of International Processes*, 1st ed., by Sara McLaughlin Mitchell, Paul F. Diehl, and James D. Morrow (81-90). Malden, MA: Wiley-Blackwell.

[71] Nivette, A. (2011). Cross-national Predictors of Crime: A Meta-Analysis. *Homicide Studies,* 15(2): 103-131.

[72] Pagano, M.; Johnston, J. (2000). Life at the Bottom of the Fiscal Food Chain: Examining City and County Revenue Decisions. *Publius: The Journal of Federalism*, 330(1): 159-170.

[73] Patterson, E. (1991). Poverty, Income Inequality, and Community Crime Rates. *Criminology*, 29(4): 755-776.

[74] Peevely, G.; Ray, J. (1989). Equity As Determined By Locally Funded Teaching Positions in Tennessee Schools. *Journal of Education Finance*, 15(2): 189-204.

[75] Peterson, R.; Bailey, W. (1988). Forcible Rape, Poverty, and Economic Inequality in U.S. Metropolitan Communities. *Journal of Quantitative Criminology*, 4(2): 99-119.

[76] Pratt, C. (2001). *Assessing the Relative Effects of Macro-level Predictors of Crime: A Meta-Analysis.* Washington, DC: ProQuest LLC.

[77] Pratt, C.; Cullen, F. (2005). Assessing Macro-Level Predictors and Theories of Crime: A Meta-Analysis. *Crime and Justice*, 32(1): 373-450.

[78] Raphael, S.; Winter-Ebmer, R. (2001). Identifying the Effect of Unemployment on Crime. *The Journal of Law & Economics*, 44(1): 259-283.

[79] Rogers, C. (2004). Local Option Sales Tax (LOST) Policy on the Urban Fringe. *The Journal of Regional Analysis and Policy*, 34(1): 27-50.

[80] Rubenstein, R.; Freeman, C. (2003). Do Local Sales Taxes for Education Increase Inequities? The Case of Georgia's ESPLOST. *Journal of Education Finance*, 28(3): 425-441.

[81] Sampson, R. (1986). Neighborhood Family Structure and the Risk of Personal Victimization. In *The Social Ecology of Crime* (25-46). New York: Springer-Verlag.

[82] Sampson, R. (1987). Urban Black Violence: The Effect of Male Joblessness and Family Disruption. *American Journal of Sociology*, 93(2): 348-82.

[83] Sampson, R.; Groves, W. (1989). Community Structure and Crime: Testing Social Disorganization Theory. *American Journal of Sociology*, 94(4): 774-802.

[84] Sampson, R.; Laub, J. (1993). Turning Points in the Life Course: Why Change Matters to the Study of Crime. *Criminology*, 31(3): 301-325.

[85] Sanders, R.; Lee, S. (2009). Determinants of Public Support for Education Sales Tax Initiatives in Georgia. *Journal of Education Finance*, 34(3): 267-288.

[86] Savolainen, J. (2000). Inequality, Welfare State, and Homicide: Further Support for the Institutional Anomie Theory. *Criminology*, 38(4): 1021-1042.

[87] Schneider, M. (1989). Fragmentation and the Growth of Local Government. *Public Choice,* 48(1): 255-264.

[88] Schwarz, G. (1978). Estimating the Dimension of a Model. *Annals of Statistics*, 6(2): 461–464.

[89] Serpa, S.; Ferreira, C. (2019). Micro, Meso and Macro Levels of Social Analysis. *International Journal of Social Science Studies*, 7(3): 120-124.

[90] Settle, R.; Gavigan, C. (1993) The Growth Management Revolution in Washington: Past, Present, and Future. *Seattle University Law Review,* 16(3): 867-948.

[91] Shadbegian, R. (1999). The Effect of Tax and Expenditure Limitations on the Revenue Structure of Local Government, 1962-87. *National Tax Journal*, 52(2): 221-238.

[92] Shadish, W.; Cook, T.; Campbell, D. (2002). *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Boston, MA: Houghton Mifflin.

[93] Shannon, J. (1987). The Return to Fend-for-yourself Federalism: The Reagan Mark. *Intergovernmental Perspective*, 13(3-4): 34-37.

[94] Shaw, C.; McKay, H. (1972). *Juvenile Delinquency and Urban Areas*. Chicago, IL: University of Chicago Press.

[95] Shaw, C.; Zorbaugh, F.; McKay H.; Cottrell, L. (1929). *Delinquency Areas: A Study of the Geographic Distribution of School Truants, Juvenile Delinquents, and Adult Offenders in Chicago*. Chicago, IL: University of Chicago Press.

[96] Shock, D. (2013). The Significance of Opposition Entrepreneurs on Local Sales Tax Referendum Outcomes. *Politics & Policy*, 41(4): 588-614.

[97] Sielke, C. (2004). Rural Factors in State Funding Systems. *Journal of Education Finance*, 29(3): 223-236.

[98] Taylor, R. (1997). Social Order and Disorder of Street Blocks and Neighborhoods: Ecology, Microecology, and the Systemic Model of Social Disorganization. *Journal of Research in Crime and Delinquency*, 34(1): 113-155.

[99] Tovar, J. (2014). GMA at 25: Looking Back, Looking Forward. *Municipal Research and Services Center of Washington*. Available at: https://tinyurl.com/yypc9tqa [Accessed 27 Jul. 2020].

[100] Trohimovic, T. (2002). The Growth Management Act (GMA) After More than 10 Years: Another Look & A Response to Criticisms. *1000 Friends of Washington (Futurewise)*. Available at: https://tinyurl.com/y24jg4v4 [Accessed 27 Jul. 2020].

[101] Turk, A. (1969). *Criminality and the Legal Order*. Chicago, IL: Rand McNally.

[102] *Understanding the Basics of County and City Revenues.* (2013). Institute for Local Government. Available at: https://tinyurl.com/y9e6g2fz [Accessed 9 Sep. 2019].

[103] Van Buuren S. (2007). Multiple Imputation of Discrete and Continuous Data by Fully Conditional Specification. *Statistical Methods in Medical Research,* 16(3): 219–242.

[104] Vieraitis, L. (1999). *Inequality and Urban Crime: Labor Stratification, Income Inequality, Poverty, and Violent Crime in Large United States Cities, 1990*. Washington, DC: ProQuest LLC.

[105] Wagner, A. (1936). Crime and Economic Change in Philadelphia, 1925-1934. *Journal of Criminal Law and Criminology*, 27(4): 83-89.

[106] Wang, W.; Zhao, Z. (2011). Fiscal Effects of Local Option Sales Tax on School Facilities Funding: Evidence from North Carolina. *Journal of Public Budgeting, Accounting and Financial Management*, 23(4): 507-533.

[107] Wolman, H.; Swanstrom, T.; Weir, M.; Lyon, N. (2004). The Calculus of Coalitions: Cities and States and the Metropolitan Agenda. *The Brookings Institution Center on Urban and Metropolitan Policy*, Discussion Paper. Available at: https://tinyurl.com/y4g8om6w [Accessed 10 Jan. 2020].

[108] Wong, J. (1996). The Impact of Local Option Sales Taxes on Retail Sales, Employment, Payrolls, and Establishments: The Case for Kansas. *The Review of Regional Studies*, 26(2): 165-176.

[109] Yurdusev, A. (1993). Level of Analysis and Unit of Analysis: A Case for Distinction. *Millennium: Journal of International Studies*, 22(1): 77–88.

[110] Zhao, B. (2010). The Fiscal Impact of Potential Local-Option Taxes in Massachusetts. *New England Public Policy Center*, Working Paper 10-2. Available at: https://tinyurl.com/yyaeqlqe [Accessed 19 Oct. 2019].

[111] Zhao, Z. (2005). Motivations, Obstacles, and Resources: The Adoption Of The General-Purpose Local Option Sales Tax in Georgia Counties. *Public Finance Review*, 33(6): 721-746.

[112] Zhao, Z.; Hou, Y. (2008). Local Option Sales Taxes and Fiscal Disparity: The Case of Georgia Counties. *Public Budgeting & Finance*, 28(1): 39-57.

[113] Zhao, Z.; Jung, C. (2008). Does Earmarked Revenue Provide Property Tax Relief? Long-Term Budgetary Effects of Georgia's Local Option Sales Tax. *Public Budgeting & Financ*e, 28(4): 52-70.

BIBLIOGRAPHY

[1] Aaron, H. (1975). *Who pays the Property Tax?* Washington, DC: Brookings Institution Press.

[2] Addinsoft, (2019). *XLSTAT Manual 2019.* Available at: https://tinyurl.com/y8m53yyo [Accessed 6 Jan. 2020].

[3] Agrawal, D. (2014). LOST in America: Evidence on Local Sales Taxes from National Panel Data. *Regional Science and Urban Economics*, 49(2014), 147-163.

[4] Akaike, H. (1974). A New Look at the Statistical Model Identification. *IEEE Transactions on Automatic Control*, 19(6): 716-723.

[5] Alm, J.; Buschman, R.; Sjoquist, D. (2011). Rethinking Local Government Reliance on the Property Tax. *Regional Science and Urban Economics*, 41(4): 320-331.

[6] Anderson, J. (1994). *Fiscal Equalization for State and Local Government Finance*. Westport, CT: Praeger Publishers.

[7] Andreoni, A.; Postorino, M.; (2006). A Multivariate ARIMA Model to Forecast Air Transport Demand. *Proceedings of the Association for European Transport and contributors*. Available at: https://tinyurl.com/y89hu5hq [Accessed 17 Feb. 2020].

[8] Batt, W. (1993). User Fees: The Nontax Revenue Alternative. *State Tax Notes*, 4(14): 787-794.

[9] Berman, D. (2000). *State and Local Politics*. Armonk, NY: M.E. Sharpe.

[10] Bernard, T. (1990). Angry aggression among the 'truly disadvantaged.' *Criminology*, 28(1): 73-95.

[11] Bingham, R.; Hawkins, B.; Hebert, F. (1978). *The Politics of Raising State and Local Revenue*. New York, NY: Praeger Publishers.

[12] Bowman, J.; Mikesell, J. (1978). Fiscal Disparities and Local Non-Property Taxes. In *Proceedings of the 70th Annual Conference on Taxation*. Washington, DC: National Tax Association.

[13] Box, G.; Jenkins, G.; Reinsel, G.; Ljung, G. (2015). *Time Series Analysis: Forecasting and Control*, 5th ed. New York, NY: Wiley.

[14] Bradbury, K.; Zhao, B. (2009). Measuring Non-School Fiscal Disparities among Municipalities. *National Tax Journal*, 62(1): 25-56.

[15] Braithwaite, J. (1979). *Inequality, Crime, and Public Policy*. London: Routledge and Kegan Paul.

[16] Brockwell, P.; Davis, R. (2002). *Introduction to Time Series and Forecasting*. New York, NY: Springer Verlag.

[17] Brueckner, J.; Saavedra, L. (1983). Do Local Governments Engage in Strategic Property-Tax Competition? *National Tax Journal,* 54(2): 203-229.

[18] Brunori, D. (2004). History of the Property Tax in America. In *Property Taxation*, 3rd ed., edited by Jerry Jana (1-44). Atlanta, GA: Institute for Professionals in Taxation.

[19] Brunori, D. (2013). *Local Tax Policy: A Federalist Perspective*, 3rd ed. Washington, D.C.: Urban Institute Press.

[20] Carlberg, C. (2015). *More Predictive Analytics: Microsoft Excel*. Indianapolis, IN: Que Publishing.

[21] Changhoon, J. (2001). Does the Local-Option Sales Tax Provide Property Tax Relief? The Georgia Case. *Public Budgeting and Finance,* 21(1): 73-86.

[22] Chapman, J. (2003). Local Government Autonomy and Fiscal Stress: The Case of California Counties. *State and Local Government Review*, 35(1): 15-25.

[23] Chasin, B. (1997). *Inequality and Violence in the United States: Casualties of Capitalism*. Atlantic Highlands, NJ: Humanities Press.

[24] Chatfield, C.; Xing, H. (2019). *The Analysis of Time Series*. New York, NY: Routledge.

[25] Chiricos, T. (1987). Rates of Crime and Unemployment: an Analysis of Aggregate Research Evidence. *Social Problems*, 34(2): 187-212.

[26] Citrin, J. (1979). Do People Want Something for Nothing? Public Options on Taxes and Spending. *National Tax Journal*, 32(2): 113-130.

[27] Cohen, L.; Land, K. (1987). Age Structure and Crime. *American Sociological Review*, 52(2): 170-183.

[28] Craft, M. (2002). LOST and Found: The Unequal Distribution of Local Option Sales Tax Revenue among Iowa Schools. *Iowa Law Review*, 88(1): 199-216.

[29] Crutchfield, R. (1989). Labor Stratification and Violent Crime. *Social Forces*, 68(2): 489-512.

[30] Dye, R.; McGuire, T. (1997). The Effect of Property Tax Limitation Measures on Local Government Fiscal Behavior. *Journal of Public Economics*, 66(3): 469-487.

[31] Figlio, D. (1997). Did the 'Tax Revolt' Reduce School Performance? *Journal of Public Economics*, 65(3): 245-269.

[32] Fischel, W. (2006). *Erosion of the Kansas Property Tax Base*. Topeka, KS: Kansas Department of Revenue.

[33] Fowles, R.; Merva, M. (1996). Wage Inequality and Criminal Activity: An Extreme Bounds Analysis for the United States, 1975-1990. *Criminology*, 34(2): 163-182.

[34] Fox, W.; McGuire, T. (2010). Special Issue on Mobility and Taxes. *National Tax Journal*, 63(4): 839-841.

[35] Gibbs, J.; Erickson, M. (1976). Crime Rates of American Cities in an Ecological Context. *American Journal of Sociology*, 82(3): 605-620.

[36] Gilks, W.; Richardson, S.; Spiegelhalter, D. (1996). *Markov Chain Monte Carlo in Practice*. London: Chapman & Hall/CRC Press.

[37] Golden, R.; Messner, S. (1987). Dimensions of Racial Inequality and Rates of Violent Crime. *Criminology*, 25(3): 525-541.

[38] Gordon, D. (1971). Class and the Economics of Crime. *The Review of Radical Political Economy*, 3(3): 51-72.

[39] Goldman, T.; Wachs, M. (2003). A Quiet Revolution in Transportation Finance: The Rise of Local Option Transportation Taxes. *Transportation Quarterly*, 57(1): 1-32.

[40] Hagan, J. (1993). The Social Embeddedness of Crime and Unemployment. *Criminology*, 31(4): 465-491.

[41] Hagan, J.; Peterson, R. (1995). *Crime and Inequality*. Stanford, CA: Stanford University Press.

[42] Hirschi, T. (1969). *Causes of Delinquency*. Berkeley, CA: University of California Press.

[43] Hyndman, R.; Athanasopoulos, G. (2019). *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts.

[44] Jacobs, D. (1981). Inequality and Economic Crime. *Social and Social Research*, 66(1): 12-28.

[45] Jose, J.; Lal, S. (2013). Application of ARIMA (1,1,0) Model for Predicting Time Delay of Search Engine Crawlers. *Informatica Economica*, 17(4): 26-38.

[46] Kovandzic, T.; Vieraitis, L.; Yeisley, M. (1998). The Structural Covariates of Homicide: Reassessing the Impact of Income Inequality and Poverty in the post-Reagan era. *Criminology*, 36(3): 569-600.

[47] Kposowa, A.; Breault, K.; Harrison, B. (1995). Reassessing the Structural Covariates of Violent and Property Crimes in the USA: A County Level Analysis. *British Journal of Sociology*, 46(1): 79-105.

[48] Levin, J.; Fox, J.; Forde, D. (2009). *Elementary Statistics in Social Research*, 11th ed. Boston, MA: Allyn & Bacon.

[49] *Local Tax Reference Guide: Information on Local Taxes in Washington State*. (2018). Washington State Department of Revenue. Available at: https://tinyurl.com/yy5kljew [Accessed 13 Dec. 2019].

[50] Lynch, M. (1988). Surplus Value, Crime, and Punishment: A Preliminary Examination. *Contemporary Crises*, 12(4): 329-344.

[51] Lynch, M.; Byron, G.; Lizotte, A. (1994). The Rate of Surplus Value and Crime: A Theoretical and Empirical Examination of Marxian Economic Theory and Criminology. *Crime, Law, and Social Change*, 21(1): 15-48.

[52] Massey, D. (1990). American Apartheid: Segregation and the Making of the Underclass. *American Journal of Sociology*, 96(2): 329-357.

[53] Massey, D.; Eggers, M. (1990). The Ecology of Inequality: Minorities and the Concentration of Poverty, 1970-1980. *American Journal of Sociology*, 95(5): 1153-1188.

[54] Messner, S. (1983). Regional Differences in the Economic Correlates of the Urban Homicide Rate. *Criminology*, 21(4): 477-488.

[55] Nadaraya, E. (1964). On Estimating Regression. *Theory of Probability and Its Applications*, 9(1):141-14.

[56] Nigel, B. (2004). Single Parenthood as a Predictor of Cross-national Variation in Violent Crime. *Cross-Cultural Research*, 38(4): 343-358.

[57] Oates, W. (1993). Fiscal Decentralization and Economic Development. *National Tax Journal*, 46(2): 23-43.

[58] Oats, L. (2012). *Taxation: A Fieldwork Research Handbook*. New York: Routledge.

[59] Render, B.; Stair, R. Jr.; Hanna, M. (2011). *Quantitative Analysis for Management*, 11th ed. Upper Saddle River, NJ: Prentice Hall.

[60] *Revenue Guide for Washington Counties.* (2019). Municipal Research and Services Center of Washington. Available at: https://tinyurl.com/ycw9vrnh [Accessed 6 Mar 2020].

[61] Shumway, R.; Stoffer, D. (2017). *Time Series Analysis and its Applications: With R Examples*, 4th ed. New York, NY: Springer.

[62] Søren, B.; Murat, C. (2011). *Time Series Analysis and Forecasting by Example*. New York, NY: Wiley.

[63] Spitzer, S. (1975). Toward a Marxian Theory of Deviance. *Social Problems*, 22(5): 638-651.

[64] *Tax Reference Manual*. (2019). Washington State Department of Revenue. Available at: https://tinyurl.com/y4r2vlk7 [Accessed 8 Apr. 2020].

[65] Teetor, P. (2010). *R Cookbook*. Sebastopol, CA: O'Reilly.

[66] Thomas, J. (1991). Financing County Government: An Overview. *Intergovernmental Perspective*, 17 (winter): 10-13.

[67] Tsay, R. (2013). *Multivariate Time Series Analysis: With R and Financial Applications*. New York, NY: Wiley.

[68] *Humanity Divided: Confronting Inequality in Developing Countries.* (2015). United Nations Development Programme. Available at: https://tinyurl.com/yy3aa2fv [Accessed 31 Oct. 2020].

[69] U.S. Department of Commerce, National Institute of Standards and Technology (2003). *Engineering Statistics Handbook.* Available at: https://www.itl.nist.gov/div898/handbook/ [Accessed 4 Jan. 2020].

[70] Watson, G. (1964). Smooth Regression Analysis. *The Indian Journal of Statistics, Series A*, 26(4): 359-372.

[71] Watts, A.; Watts, T. (1981). Minorities and Urban Crime. *Urban Affairs Quarterly*, 16(4): 423-436.

[72] Wei, W. (2019). *Multivariate Time Series Analysis and Applications*. New York, NY: Wiley.

[73] Williams, K.; Drake, S. (1980). Social Structure, Crime and Criminalisation: An Empirical Examination of the Conflict Perspective. *Sociology Quarterly*, 21(4): 563-575.

[74] Williams, K.; Drake, S. (1988). The Social Production of Criminal Homicide: A Comparative Study of Disaggregated Rates in American Cities. *American Sociological Review*, 53(3): 421-431.

DATA SOURCES

[1] Children's Alliance and Washington State Budget & Policy Center, Kids Count in Washington.

[2] Municipal Research and Services Center of Washington.

[3] Office of the Washington State Auditor, Local Government Financial Reporting System.

[4] The Annie E. Casey Foundation, Kids Count Data Center.

[5] The National Center for Education Statistics.

[6] The Robert Wood Johnson Foundation and The University of Wisconsin Population Health Institute, County Health Rankings & Roadmaps.

[7] The Washington Statistical Analysis Center, Criminal Justice Databook.

[8] University of Washington Institute for Health Metrics and Evaluation, Global Health Data Exchange.

[9] United States Bureau of Labor Statistics.

[10] United States Census Bureau.

[11] United States Center for Disease Control and Prevention, Behavioral Risk Factor Surveillance System.

[12] United States Center for Disease Control and Prevention, National Center for Health Statistics.

[13] United States Department of Agriculture Economic Research Service, County-level Data Sets.

[14] United States Department of Commerce, Bureau of Economic Analysis.

[15] United States Department of Housing and Urban Development, Office of Policy Development & Research.

[16] United States Department of Justice, Office of Juvenile Justice and Delinquency Prevention.

[17] United States Federal Bureau of Investigation Uniform Crime Reporting System.

[18] Washington Administrative Office of the Courts.

[19] Washington Association of Sheriffs and Police Chiefs.

[20] Washington Office of Superintendent of Public Instruction.

[21] Washington Secretary of State, Voter Turnout.

[22] Washington State Department of Health, Center for Health Statistics.

[23] Washington State Department of Revenue, Statistics and Reports.

[24] Washington State Employment Security Department, Labor Market and Economic Analysis Branch.

[25] Washington State Fiscal Information (fiscal.wa.gov).

[26] Washington State Office of Financial Management.

[27] Washington State Open Data Platform (data.wa.gov).

APPENDIX A: TABLE OF OBSERVED VARIABLES

CRIME DATA		SOCIAL DATA		REVENUE DATA
• CJ VC: Homicide Superior Court Filings per 100,000 People		• FD: % of Total Births to Unmarried Teenage Mothers (15-19)		• RC: Total Taxable Retail Sales per 1,000 People
• CJ VC: Sex Crimes Superior Court Filings per 100,000 People		• FD: % of Total Births to Unmarried Mothers		• RC: Presumed SALTAX Spillover Index
• CJ VC: Assault Superior Court Filings per 100,000 People		• FD: Children in Foster Care Placement per 1,000 People		• RC: Total Tax Revenue per 1,000 People
• CJ VC: Robbery Superior Court Filings per 100,000 People		• FD: Divorce per 1,000 People		• RC: Sales and Use Tax Revenue Total (SALTAX) per 1,000 People
• CJ NVC: Property Crimes Superior Court Filings per 100,000 People		• SD: Population Density (PPL/Sq mi)		• RC: Degree of Reliance on Sales Tax
• CJ: Total Superior Court Filings per 100,000 People		• SD: % Binge Drinking (4+ drinks for women, 5+ drinks for men)		• SPLOST CJ: Criminal Justice SPLOST?
• JD: Total Juvenile Arrests per 100,000 People		• SD: Average Reported Poor Mental Health Days		• SPLOST CJ: RCW 82.14.340 Revenue (Criminal Justice) per 1,000 People
• JD: Juvenile Dispositions per 100,000 People		• SD: Income Inequality Ratio (80th Percentile Income/20th Percentile)		• SPLOST JD: Juvenile Detention SPLOST?
		• SD: Residential Segregation Index - Black/White		• SPLOST JD: RCW 82.14.350 Revenue (Juvenile Facilities) per 1,000 People
		• SD: Residential Segregation Index - non-white/White		
		• SD: High School Graduation Rate		
		• SD: % of Population with Some College Education		
		• SD: % of Population with 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: Relevant Previous Presidential Election Turnout		

APPENDIX B: LIST OF ACRONYMS

AR - Autoregressive

ARD - Absolute and Relative Deprivation

ARIMA - Autoregressive Integrated Moving Average

ARIMAX - Autoregressive Integrated Moving Average with Explanatory Variable(s)

BARS - Budget, Accounting and Reporting System

CJ - Criminal Justice

CJ SPLOST - Criminal Justice Special Purpose Local Option Sales Tax

DG - Demographics

FD - Family Disruption

JD - Juvenile Detention

JD SPLOST - Juvenile Detention Special Purpose Local Option Sales Tax

LGFRS - Local Government Finance Reporting System

LOST - Local Option Sales Taxes

MA - Moving Average

NVC - Non-violent Crime

RCC - Revenue Composition

RCW - Revised Code of Washington

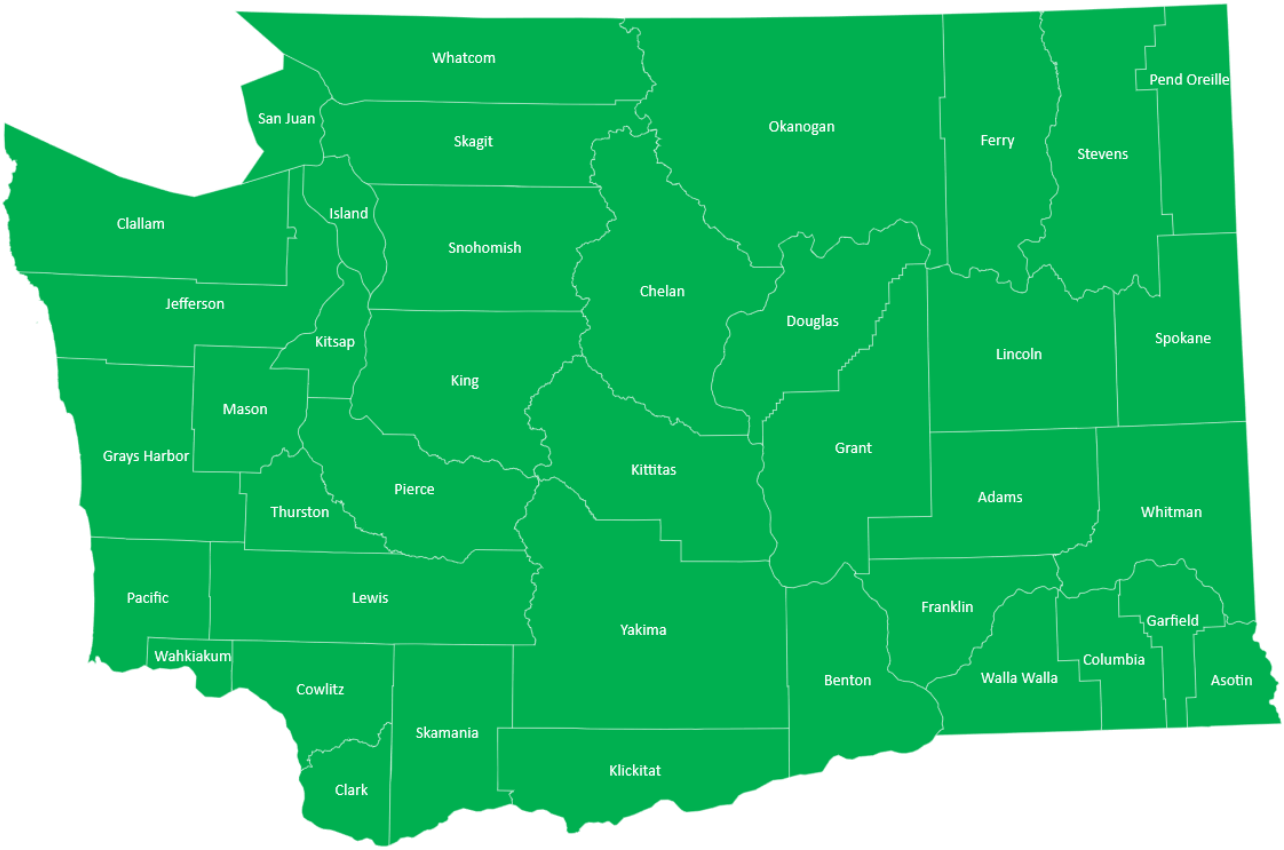
SALTAX - Sales Tax

SD - Social Disruption

SPLOST - Special Purpose Local Option Sales Taxes

VC - Violent Crime

APPENDIX C: MAP OF WASHINGTON COUNTIES



APPENDIX D: STATEMENT OF ASSUMPTIONS AND LIMITING CONDITIONS

This study is subject to the following assumptions and limiting conditions:

- Data retrieved from the referenced third-party sources was assumed to be accurate and complete without independent verification.
- Information and statements provided in the referenced publications were assumed to be true and correct without independent verification.
- The study did not differentiate between online sales and retail sales and it is unclear whether doing so would alter the empirical findings.
- The study did not account for the mitigating impact, if any, derived from the Streamlined Sales and Use Tax Agreement, to which Washington is a full member.
- The study did not explore what impact, if any, tax exempt sales may have on the revenue portfolio composition of Washington counties.
- The study did not explore horizontal tax competition in terms of county sales tax rates but in terms of revenue per $1,000 People.
- In instances where an observation was not available, the analyses either ignored the missing observation or estimated it using the multiple imputation algorithm based on the Markov Chain Monte Carlo (MCMC) approach, also called fully conditional specification (Berg 2004; Van Buuren, 2007).
- The legislative recommendations are purely the informed opinion of the author and do not promote a specific political agenda.

VITA

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