The Association of Segregation and Urban Form with Crime

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Introduction

The study seeks to identify independent variables (IVs) associated with the dependent variables (DV) of rates per 100,000 population for violent crime (VCRMR) and homicide (MURDR) in the United States. More specifically, does racial/income segregation and population density or clustering have statistically significant relationships with these crime rates as measured across metropolitan statistical areas (MSAs)? The topic is of high interest to the public and politicians due in part to general decreases in crime, pockets of increasing violence, media coverage, police-related shootings, terror-inspired attacks, and the number of associated demonstrations related to the public's frustrations with crime. The audience is generally non-technical. The study will also be of interest to other researchers with technical backgrounds who have delved into the causes of crime. The findings show that dissimilarity index (unevenness of white-black population spread-DISSIM), Gini coefficient (unevenness of income distribution-GINI), and urbanized area (UA) average daily traffic per freeway lane mile (ADTFL) have statistically positive relationships with violent crime rates. Additionally, weighted population density changes (WPDC) from 2000 to 2010 have a statistically significant negative association with murder rates.

Literature Review

A review of the research below found that methodologies used included multi-variable regression analysis and meta-studies. Both approaches are appropriate given the nuances with data availability for the former and the value of summarizing an array of research. Lee and Shinn examined 1980s and 1990s international crime data for the U.S. and 13 other countries using multi-variable regression. They found that the Gini coefficient measure showing the positive association between income inequality and crime is overshadowed by the stronger relationship between loss of manufacturing jobs and crime. An underlying cause is low prospects for replacement employment which is evidence of the shrinking middle class and reduced mobility between income classes. Thus, low-income workers tend to resent high-wage earners which leads to increased crime.[1]

Shidadeh and Ousey used cross sectional ordinary least squares (OLS) regression to analyze 1980 data for the largest 136 U.S. cities/MSAs and identified a strong association between suburbanization and black center-city crime rates. The migration of wealthier white populations and employment to outlying areas was found to be a primary reason for the increasing social isolation of blacks. This tends to facilitate “hyperghettoization” which leads to increased crime rates in intercity black neighborhoods. Population and employment de-densification of UAs were facilitated by improvements in communications and the establishment of limited-access urban expressways. In relation, cheap exurban land enticed manufacturers to relocate (“industrial drift”) to take advantage of better road systems and larger spaces for expansive single-level facilities. City downtowns tended to lose clerical, sales and blue collar jobs while gaining managerial, professional, technical and administrative support center employment. This served to reduce incomes of black residents due to spatial mismatches that distanced them from employment opportunities. This primarily affected black males which reduced female incentives for marriage; both strong indicators of increased crime in those areas.[2]

Cullen and Levitt analyzed demographics and crime data from the 1970’s to the 1990’s for 127 U.S. cities/UAs using aggregated data and multi-variable regression analysis. They determined that in center cities there is a causal relationship between commission of a reported crime and a 1-person decline in population. Alternatively, a 10 percent increase in crime in a center city relates to a 1 percent decrease in population of that same area. The association is particularly strong for the migration of highly educated persons and their children.[3]

Klovers builds upon these and other studies using a series of longitudinal and time-series OLS regressions. Review of data for 53 U.S. cities and their suburbs covering 1970 to 2000 found that the association between decreasing population densities and increased poverty concentration are both a cause and a result of each other (bi-directional). This finding and the known strong relationship between poverty and crime serves to establish that de-densification of UAs is a strong indicator of worsening crime.[4]

Using cross-sectional multi-variable Federal Bureau of Investigation, Uniform Crime Reporting Program (UCRP) data averaged for 1994-1996, Stretesky and Lynch examined ambient lead levels and crime rates for 2,772 U.S. counties and found a positive association which concurred with other studies. Elevated lead exposure levels are known to cause brain dysfunction which appears to modify hormonal and neurotransmitter systems resulting in aggressive/violent conduct. Other research has identified a strong relationship between lead exposure in early youth with both juvenile delinquency and adult crime, including violent crime and murders. Other studies have determined that elevated lead levels in prison inmates showed a positive correlation of higher lead levels associated with higher crime rates.[5]

Hu found in a study of employment accessibility in Los Angeles, using multi-variable Decennial Census1990/2000 and American Community Survey (ACS) 2007-11 data, that gradual desegregation has served to rectify spatial mismatches between areas of concentrated poverty and minorities with job opportunities. Consequently, moving these populations in larger proportions to outlying locations, improving employment opportunities in central cities, and offering improved mobility options may have positive impacts in relation to crime.[6]

Ferrel et al, analyzed 17 possible explanations based on review of other research across various countries for the occurrence of declining crime rates since the early 1990s: strong economy; concealed weapon laws; capital punishment; gun control laws; imprisonment; policing strategies; more police; legalization of abortion; immigration; consumer confidence; declining hard drug markets; lead poisoning; changing demographics; civilizing process; improved security; phone guardianship; and the internet. They found that only one of these appears to be substantially valid; improvements in security, especially for homes and automobiles. A contributing factor to this element may be increased cellular telephone usage. Others that appear to have a small influence consist of aging of the population and police strategies.[7]

Hypotheses

The null hypotheses to be tested, or $H_0: B_j = 0$, are that each of the IVs of DISSIM, GINI, WPD00 (2000), WPD10 (2010), WPDC, UA per capita vehicle miles traveled (PCVMT) and ADTFL do not have a relationship with VCRMR and MURDR and the slope of the population regression is 0. The alternative hypotheses are $H_1: B_j \neq 0$, meaning that each of these IVs do have a relationship with violent crime and murder rates, and the slope of the population regression is not 0. The level of significance for the test is .05.

Data and Empirical Approach

DV data is collected from crime statistics maintained by the UCRP. This resource is appropriate as it has been in place since 1930 and all municipal, county and state law enforcement agencies generally participate in the program.[8] Additionally, MSA data on demographics and other statistics with possible associations to crime are collected for testing from various public sources as listed in *Figure 1*. The geography of some MSAs has changed over the years, however, almost all data used is relatively recent. Available WPD data is restricted to the years of 2000 and 2010. Standard population density data for MSAs is available by census decennial years but was not used as it would mirror the tested IV of population (POP), and WPD has more value in measuring urban form.[9]

Figure 1 – Tested Independent Variables and Data Sources

Independent Variables	**Source/Description**	**Acronym**
Black Population Proportion	U.S. Census-ACS 2015 1-Yr Estimates	BKPOP
Dissimilarity Index	U.S. Census via Brown University	DISSIM
Gini Coefficient	U.S. Census-ACS 2015 1-Yr Estimates	GINI
Poverty Rate	U.S. Census-ACS 2015 1-Yr Estimates	POVR
Labor Force Participation Rate	U.S. Census-ACS 2015 1-Yr Estimates	LFPR
Employment Rate	U.S. Census-ACS 2015 1-Yr Estimates	EMPR
Unemployment Rate	U.S. Census-ACS 2015 1-Yr Estimates	UNEMP
% Population 25+ BS Degree	U.S. Census-ACS 2015 1-Yr Estimates	EDUBS
Per Capita Manufacturing	International Trade Administration	PCMAN
Weighted Pop. Density 2000	U.S. Census	WPD00
Weighted Pop. Density 2010	U.S. Census	WPD10
WPD Change 2000 to 2010	U.S. Census	WPDC
Population	U.S. Census – 2015 Estimates	POP
High School Dropout Rate	U.S. Census-ACS 2015 1-Yr Estimates	HSDO
Single Female Head/Household	U.S. Census-ACS 2015 1-Yr Estimates	SFHHC
UA Per Capita Veh. Miles. Trav.	FHWA 2014 Highway Stats. (HM-72)	PCVMT
UA Avg. Traf. per Fwy. Lane Mile	FHWA 2014 Highway Stats. (HM-72)	ADTFL
Per Capita Personal Income	Bureau of Economic Analysis – 2014	PCPI

The UA FHWA data in *Figure 1* and related statistics were converted to the MSA levels but exclude coverage for the non-UAs within them. Additionally, time series or longitudinal linear regression was explored for measuring violent crime and murder rates against standard population density for 1950 and differences compared to 2015. However, it was not found to improve the models as part of pooled regression. Also, that data is only available for 133 areas and it would have substantively reduced the number of observations in the study. Additionally, it is expected that crime conditions will depend upon both current and historic local circumstances which may be difficult to measure beyond the identified IVs. Other IVs that could be explored include per capita numbers of policeman/gang members, county/complete MSA

VMT estimates, incarceration and gentrification rates in addition to local drug and firearms laws. These additional IVs are not used in the study due to difficulties in obtaining comprehensive data at MSA levels.

Data is collected for all 381 MSAs. Due to data gaps, the total MSAs used in the study is 352. The main methodology of analysis is multi-variable cross-sectional linear or OLS regression for the MSA populations. The multi-variable OLS regression methodology is appropriate as there is a need to control for one or more IVs to test the hypotheses. The functional form for much of the data analyzed are proportions, rates or per capita to account for the different population sizes of MSAs. The actual data formats or metrics are used for DISSIM, GINI, POP, WPDC, and ADTFL. Summary or descriptive statistics are calculated for each of the IVs and DVs (*Appendix* 1). A Pearson correlation coefficient (*R*) matrix is created to measure the strength of one-on-one relationships of all IVs and DVs and for an initial check of multicollinearity (*Appendix 2*). Those IVs with the strongest potential relationships were included in initial runs of the respective models. Reverse stepwise regression was then applied by incrementally removing those IVs from the models that do not have statistically significant associations with the DVs as shown by the separate *t stats* and *P-values* in addition to the *F* and *Significance F* statistics.

Results

The final model specifications are as shown below and in the detailed regression summaries in *Figure 2* and *Figure 3*:

- ***VCRMR = -121.482 + 432.4952(BKPOP) + 1.3451(DISSIM) + 991.8704(GINI) – 463.978(EDUBS) + 0.005392(ADTFL);***
- ***(ln)MURDR = 0.586999 + 1.480216(BKPOPP) – 0.74042(EDUBS) – 0.00015(WPDC).***

Figure 2

VIOLENT CRIME SUMMARY OUTPUT - FINAL

Regression Statistics	
Multiple R	0.496206
R Square	0.24622
Adjusted R	0.235328
Standard E	142.7991
Observatio	352

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	5	2304660	460932	22.60403	1.26E-19
Residual	346	7055487	20391.58		
Total	351	9360147			

	Coefficients	*andard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*Ipper 95.0%*
Intercept	-121.482	142.3336	-0.8535	0.39397	-401.43	158.4656	-401.43	158.4656
BKPOP	432.4952	79.54169	5.437339	1.02E-07	276.0491	588.9412	276.0491	588.9412
DISSIM	1.345093	0.661809	2.03245	0.042871	0.043419	2.646768	0.043419	2.646768
GINI	991.8704	326.9063	3.034113	0.002595	348.8968	1634.844	348.8968	1634.844
EDUBS	-463.978	98.79894	-4.69618	3.83E-06	-658.3	-269.656	-658.3	-269.656
ADTFL	0.005392	0.001989	2.711284	0.007037	0.001481	0.009304	0.001481	0.009304

Figure 3

MURDER SUMMARY OUTPUT - FINAL

Regression Statistics	
Multiple R	0.57577
R Square	0.331511
Adjusted R	0.325748
Standard E	0.258371
Observatio	352

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	3	11.5205	3.840167	57.52575	3.18E-30
Residual	348	23.23096	0.066756		
Total	351	34.75146			

	Coefficients	*andard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*Ipper 95.0%*
Intercept	0.586999	0.050722	11.57295	2E-26	0.48724	0.686759	0.48724	0.686759
BKPOP	1.480216	0.130818	11.31506	1.73E-25	1.222922	1.737509	1.222922	1.737509
EDUBS	-0.74042	0.164496	-4.50116	9.23E-06	-1.06396	-0.41689	-1.06396	-0.41689
WPDC	-0.00015	6.57E-05	-2.3377	0.019969	-0.00028	-2.4E-05	-0.00028	-2.4E-05

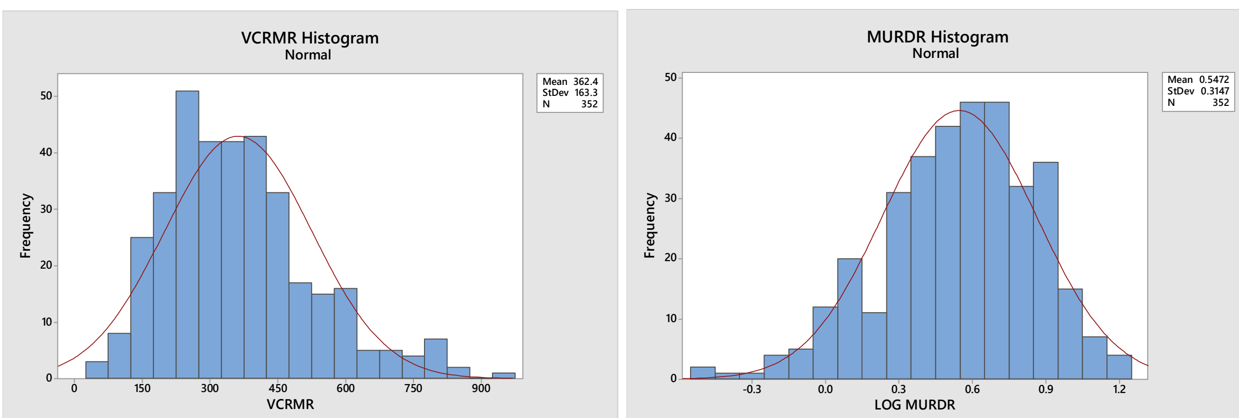
Individually, the following associations are evident when controlling for other factors: an increase of 0.01(1 percent) in DISSIM (unevenness of white-black population spread) with an increase in VCRMR by 1.35 percent; an increase of 0.01 (1 percent) in GINI (unevenness of income distribution) with an increase in VCRMR by 9.92 percent; an increase in ADTFL of 1 vehicle with an increase of VCRMR by 0.0000148 (0.00539/365); and a decrease in WPDC of 1 (weighted average of Census tract population density, i.e. weighted by the tract's share of the MSA population) with an increase in MURDR by 0.0015. Considering the robustness checks below, residential racial and income segregation have statistically significant positive relationships with violent crime rates while weighted population density has a statistically significant negative association with murder rates. Thus, the null hypothesis for VCRMR is rejected for DISSIM, GINI, and ADTFL but accepted for WPD00, WPD10, PCVMT and WPDC while the null hypothesis for MURDR is rejected for WPDC but accepted for DISSIM, GINI, WPD00, WPD10, PCVMT and ADTFL. It is interesting to note that if the Chicago MSA WPD declines by 1,216 from 2010-2020 as it did from 2000-2010, the MURDR model predicts that homicides per 100,000 in population will increase by 1.8. Ceteris paribus for the control IVs, an increase in BKPOP of 0.01 (1 percent) predicts VCRMR and MURDR increases of 4.33 and 14.80 percent, respectively, and an increase of 0.01 (1 percent) in EDUBS (proportion of population 25+ with a BS degree and above) predicts decreases in VCRMR by 4.64 percent and MURDR by 7.40 percent.

<u>Robustness Checks</u>

The aforementioned initial check for multicollinearity in the attached Pearson correlation matrix identified some relationships amongst the IVs with very high *R* values such as LFPR-EMPPR-UNEMP and WPD00-WPD10-WPDC-POP. However, the reverse stepwise regression did not show value in retaining more than one of these from each grouping. Those IVs retained in the models did not have *R* values between them of above 0.37 which is one indicator that the degree of multicollinearity likely is low. Another indicator of high multicollinearity, high R^2 but few significant *t stat* values, is not evident in either model.[10]

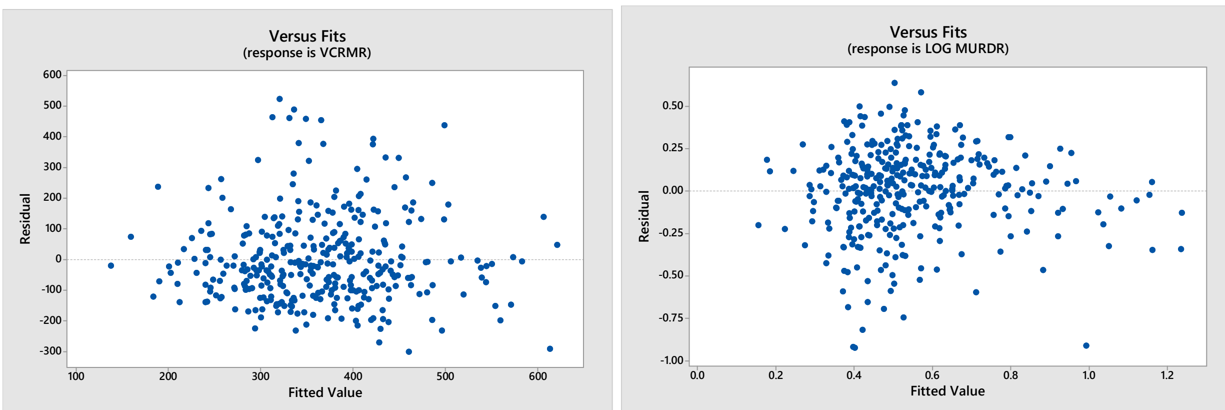
There are four standard assumptions of regression that were used to test validity of the data. The first is to determine that the variables are distributed normally, not skewed, and do not have excessive outliers. The second concerns the assumption that the IVs and DVs variables have a linear relationship. The third is to ensure that the variables have been reliably measured without error. The fourth is to confirm that homoscedasticity is evident, i.e. consistent variance of errors for the IVs, by looking at the pertinent scatterplots.[11] Histograms for the DVs are in *Figure 4* below and show the data to be relatively normal but some skewness is evident.

Figure 4



The second assumption can be addressed by looking at the residual plots as a function of predicted values to see if non-linear patterns are prevalent. In both models, these residuals appear to be linear to an extent, with no slope and residuals that average zero (*Figure 4* and *Appendix 3*). However, there is some evidence of heteroscedasticity or unequal variance of the residuals due to a slight cone-like spread to the right for VCRMR and to the left (and more pronounced) for MURDR that appears to be driven to an extent by several outliers. The MURDR DV was converted to log values as results of a Park Test showed that heteroscedasticity was evident. Generally, the data appeared to be reliably measured despite some outliers. There were occasions in which MSAs had to be removed from the study due to unavailable data.

Figure 5



The Park Test was performed to check further for heteroscedasticity in each model by squaring the residuals or errors, converting them to log format, and regressing the results against the predicted *Y* values. In the case of VCRMR, the resulting R^2 is 0.001387, the *t stat* value is 0.6972 which is not above the t table threshold of 1.960, and the *P-value/Significance F* value is 0.486138 which is above 0.05. In the case of log MURDR, the resulting R^2 is 0.00382, the *t stat* value is -1.1585 which is not above the t table threshold of 1.960, and the *P-value/Significance F* value is 0.2475 which is above 0.05. Thus, the relationships are not statistically significant and there is no evidence of heteroskedasticity in the two models. When ADTFL was added to the MURDR model, the *t stat* and *P-value* metrics in the multivariable regression showed it to be positively associated with the DV as with the VCRMR model. However, the Park Test showed R^2 decreased to 0.012399, the *t stat* value increased to -2.09618 which is above the t table threshold of 1.960, and the *P-value/Significance F* value decreased to 0.036784 which is below

0.05. Thus, there was evidence of heteroskedasticity in the log MURDR model with the addition of ADTFL and it was removed.

As shown in *Figure 2* and *Figure 3*, the attached regression tables for both the VCRMR and MURDR models, at the 0.05 level of significance, the *t Stat* numbers for the IVs are all above the 1.960 statistical level of significance threshold. Confirmation is provided by all the IV *P-values* as they are below the 0.05 level. The respective models selected achieved the highest *F* values compared to their predecessor iterations and the significance *F statistic* or *P-value* for the models are well below the 0.05 level of significance. The R^2 value, or the coefficient of determination indicating the proportion of variability explained, for the VCRMR and MURDR models is 0.24622 and 0.3315, respectively. Thus, it is likely that there are other unidentified IVs that could improve R^2 in the models.

Conclusion

Controlling for race and education and using cross-sectional data, the study revealed statistically significant positive relationships for both DISSIM and GINI with the rate of violent crime. Further, using the same control IVs and data, WPDC has a statistically significant negative relationship with MURDR. A shortcoming of the research is that, apart from the WPDC data, information was restricted to the years of 2014 or 2015. Thus, the lack of other longitudinal data does not provide any insight on the metrics associated with violent crime and murder rates over extended periods. A recommendation is to build upon the cumulative research by using more robust decennial data back to 1960 when crime began to escalate. A confounding part of this study is that the amount of violent crime and murder explained by the two models is relatively small. This is consistent with research that has found it difficult to identify substantive explanations for why crime rates in general have been declining in recent years.[12] The ability to locate sufficient data for other potential IVs as identified in the Data and Empirical Approach section could provide more explanative information. In terms of social policy, it is recommended that local governments consider the social costs of crime within their regions before making decisions to expand borders of municipalities in exurban and suburban areas. A related recommendation for local officials in addressing crime is to ensure that there are not barriers to affordable housing, racial integration, and public transportation in their communities. The ability for all racial and income classes to assimilate within all portions of MSAs appears beneficial in reducing crime.

Appendix 1 – Summary Statistics

STATISTIC	*BKPOP*	*DISSIM*	*GINI*	*POVR*	*LFPR*	*EMPR*	*UNEMP*	*EDUBS*	*PCMAN*	*WPD00*	*WPD10*
Mean	0.106169	45.08693	0.458345	0.157543	0.620239	0.575688	0.062895	0.277801	3831.229	2465.575	2408.508
Standard Error	0.005686	0.697558	0.001352	0.002277	0.002759	0.002999	0.001071	0.004484	240.6462	123.0704	120.6223
Median	0.069854	45.6	0.4594	0.153	0.62	0.578	0.0615	0.265	2378.864	1949.747	1906.869
Mode	#N/A	49.3	0.4731	0.157	0.616	0.561	0.065	0.256	#N/A	#N/A	#N/A
Standard Deviation	0.10668	13.08734	0.02536	0.042715	0.051767	0.056259	0.020097	0.084122	4514.922	2309.006	2263.075
Sample Variance	0.011381	171.2786	0.000643	0.001825	0.00268	0.003165	0.000404	0.007076	20384522	5331510	5121507
Kurtosis	2.188466	-0.36458	0.319584	1.218168	0.570997	0.138516	1.908207	0.782459	10.5286	74.83872	77.08191
Skewness	1.559479	0.036179	0.106182	0.782026	-0.38979	-0.15317	0.904506	0.78423	3.006398	6.759518	6.897145
Range	0.537776	64.5	0.1475	0.258	0.308	0.317	0.142	0.487	28915.7	31171.75	30728.7
Minimum	0.001566	15.1	0.3929	0.066	0.439	0.388	0.023	0.119	111.2394	511.8603	522.7306
Q1	0.02761	35.9	0.44112	0.129	0.587	0.537	0.049	0.21625	1356	1290	1290
Q3	0.14971	54.25	0.4743	0.18275	0.657	0.61475	0.073	0.32875	4401	2935	2879
Maximum	0.539342	79.6	0.5404	0.324	0.747	0.705	0.165	0.606	29026.94	31683.61	31251.44
Sum	37.3715	15870.6	161.3376	55.455	218.324	202.642	22.139	97.786	1348593	867882.3	847795
Count	352	352	352	352	352	352	352	352	352	352	352

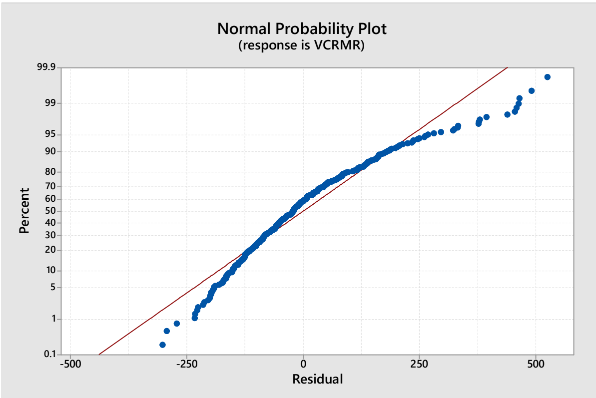
Appendix 1 – Summary Statistics

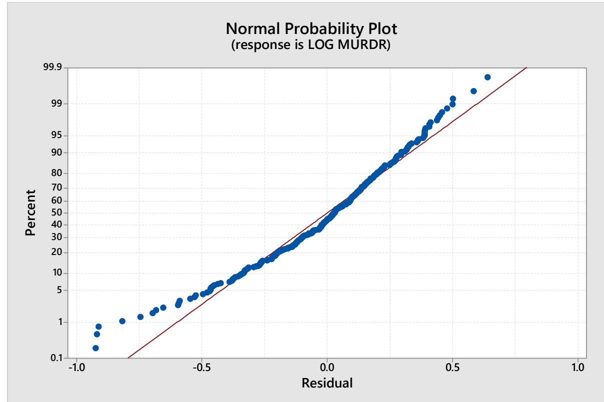
STATISTIC	*WPDC*	*POP*	*HSDO*	*SFHHC*	*PCVMT*	*DATF*	*ADTFL*	*PCPI*	*VCRMR*	*MURDR*	*LOG MURDR*
Mean	-57.0664	764721	0.121341	0.069574	28.70877	47001.9	9563.747	43182.99	362.3776	4.443182	0.5472205
Standard Error	11.29154	90720.12	0.002844	0.000981	0.46905	1503.987	226.9567	485.3329	8.703951	0.157068	0.0167711
Median	-44.2212	267008	0.109	0.068	26.71347	42944.1	9582.321	41691.5	334.2	3.8	0.5797836
Mode	#N/A	#N/A	0.095	0.05	38.06898	0	0	46076	231.8	2	0.30103
Standard Deviation	211.8481	1702060	0.053352	0.018399	8.800158	28217.3	4258.085	9105.653	163.3006	2.946853	0.3146538
Sample Variance	44879.61	2.9E+12	0.002846	0.000339	77.44279	7.96E+08	18131290	82912908	26667.09	8.683942	0.099007
Kurtosis	13.88456	58.16241	4.601733	0.85292	1.988571	2.36468	-0.13065	13.38151	0.53349	1.626107	0.2595237
Skewness	-2.03466	6.548843	1.74925	0.612294	1.173624	1.146307	0.080353	2.673323	0.811175	1.220645	-0.5304506
Range	2319.363	20035821	0.353	0.106	58.05122	188794.6	21840.57	81803	874.8	16	1.7350663
Minimum	-1748.66	34867	0.029	0.029	13.23269	0	0	24579	61.6	0.3	-0.5228787
Q1	-164.6	149682	0.091	0.058	22.757	2660	6503	37355	242.93	2.3	0.3617
Q3	62.1	621284	0.14275	0.07975	32,533	61095	12410	46351	447.63	6.075	0.7835
Maximum	570.7	20070688	0.382	0.135	71.28391	188794.6	21840.57	106382	936.4	16.3	1.2121876
Sum	-20087.4	2.69E+08	42.712	24.49	10105.49	16544667	3366439	15200411	127556.9	1564	192.62163
Count	352	352	352	352	352	352	352	352	352	352	352

Appendix 2 – Pearson Correlation Matrix

	BKPOPP	*DISSIM*	*GINI*	*POVR*	*LFPR*	*EMPPR*	*UNEMP*	*EDUBS*	*PCMAN*	*WPD00*	*WPD10*	*WPDC*	*POP*	*HSDO*	*SFHHC*	*PCVMT*	*ADTFL*	*PCPI*	*VCRIMR*	*MURDR*
BKPOPP	1																			
DISSIM	0.372504	1																		
GINI	0.284871	0.21602	1																	
POVR	0.268005	-0.08906	0.431509	1																
LFPR	-0.09592	0.001235	-0.20812	-0.50162	1															
EMPPR	-0.21435	0.032441	-0.15205	-0.53401	0.910867	1														
UNEMP	0.376627	0.098519	0.145355	0.485036	-0.44396	-0.6621	1													
EDUBS	-0.08149	-0.01706	0.227162	-0.34435	0.52606	0.553825	-0.3785	1												
PCMAN	0.018904	0.126783	0.025652	0.078171	0.066255	0.089199	0.024591	-0.05416	1											
WPD00	-0.06856	0.259045	0.18066	-0.16897	0.266158	0.245817	-0.03161	0.335339	0.126774	1										
WPD10	-0.08313	0.233163	0.181398	-0.16619	0.260425	0.239694	-0.03316	0.342381	0.106295	0.995884	1									
WPDC	-0.14045	-0.33179	-0.03123	0.066167	-0.11868	-0.11843	-0.00967	0.002452	-0.24561	-0.26026	-0.17168	1								
POP	0.113782	0.376463	0.215586	-0.15366	0.198698	0.185778	0.005603	0.260481	0.095025	0.799262	0.790549	-0.26579	1							
HSDO	0.091794	0.039087	0.17499	0.49272	-0.34065	-0.34915	0.392139	-0.52092	0.186824	0.02918	0.037238	0.079528	0.069031	1						
SFHHC	0.491604	0.19664	0.10653	0.474373	-0.13449	-0.26528	0.466984	-0.4443	0.124218	-0.05989	-0.06775	-0.07081	0.006855	0.53025	1					
PCVMT	0.332129	0.063994	0.122151	0.002608	-0.15344	-0.11396	0.061536	-0.0357	-0.10711	-0.29703	-0.29066	0.132235	-0.03599	0.098025	0.020355	1				
ADTFL	0.113323	0.315361	0.165805	-0.20364	0.180915	0.176261	0.040227	0.295134	0.103895	0.446737	0.445108	-0.11403	0.462654	0.074592	-0.02515	0.186861	1			
PCPI	-0.09707	0.228399	0.157177	-0.60593	0.439508	0.444102	-0.25692	0.541835	0.021324	0.432774	0.438129	-0.0366	0.336639	-0.23766	-0.29003	-0.07358	0.377167	1		
VCRIMR	0.418343	0.294357	0.232057	0.233126	-0.11895	-0.16888	0.29214	-0.18181	0.019416	0.058833	0.048915	-0.11839	0.092282	0.238428	0.363839	0.075616	0.16627	-0.0459	1	
MURDR	0.596229	0.333125	0.202173	0.209794	-0.10108	-0.18156	0.323368	-0.21613	0.031701	0.016371	-0.00696	-0.25204	0.097118	0.21945	0.39504	0.142996	0.155971	-0.06673	0.552868	1

Appendix 3





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