

How Many Cameras Are On You? An Analysis of the Location of Surveillance Devices in the US in Relation to Various Demographic Categories

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Abstract

Throughout this research paper, we utilize data from Atlas of Surveillance (AoS) and demographic data from the American Community Survey 5-year estimates to determine whether there exists a correlation between the number of surveillance technologies in a county and the demographics of its residents. We utilize Ordinary Least Squares Regression (OLS) and train a K-Nearest Neighbors (KNN) machine learning model in order to answer our research question. With some demographic groups we find statistically significant correlations using OLS, but no explanation for the variance between variables. We conclude by making several recommendations for future research in this area.

1. Introduction

AoS is a database containing the records of multiple surveillance technologies owned and operated by local law enforcement agencies. Some of the surveillance technologies included in this database are drones, body-worn cameras, automated license plate readers, facial recognition, within others [1]. The American Community Survey 5-year estimates is a database containing county-wide demographic information in different categories such as gender, race, income, etc.

Throughout this research paper, we utilize these two data sets to determine whether there exists a correlation between the number of surveillance technologies in a county and the

demographics of its residents. In order to answer this question, we use two methods of evaluation: OLS Regression and training/testing a KNN model.

2. Related Work & Ethics

2.1 Related Work

There are multiple papers describing the increased use of surveillance technologies in the United States. For once, Rojas [5] wrote a report discussing how anyone with an Internet connection in Newark is able to access police surveillance cameras. Rojas emphasizes that the citizens of Newark have access to feeds of dozens of cameras in the public, and that citizens are encouraged to report anything suspicious. Rojas criticizes this program by making the observation that giving the public access to this information can rely on the heavily biased judgement of residents, leading to an increase in systemic racism and bias in the policing system.

In addition, Ghaffary [4] wrote about President Donald Trump's proposal to create a 'smart wall' containing multiple technologies across the border, ranging from drones and sensors to Artificial Intelligence technologies. Throughout his article, Ghaffary quotes Republican representative Hurd, who stated that because every mile of the border is different, there are different technologies that fit for different purposes. Ghaffary also mentions that

the technologies introduced into the border bring about privacy concerns for American citizens, particularly those living near border zones. While there is no proof that law enforcement is utilizing these technologies outside of the border, Ghaffary says, there are multiple examples of times where law enforcement agencies used surveillance technologies beyond their intended use [4].

Taking this work into account and looking at its relationship with the AoS database, we believe that the database does not contain a representative number of technologies per city or county. For example, in the case of Rojas's article we made a query of the number of policing technologies reported by citizens of Newark. We noticed, however, that there are only 14 technologies reported by residents. This contradicts Rojas' argument on the high number of technologies in Newark, and might demonstrate that the AoS database is not complete.

Given the privacy concerns expressed in Ghaffary's paper on surveillance technologies affecting citizens living in border zones, we also queried the AoS database to test the number of surveillance technologies reported in all of the American cities bordering with the Mexican border. The findings can be seen in Figure 1.

These findings demonstrate that there are some cities near the border that have a higher number of surveillance technologies than others. While these numbers might still be low relative to all of the cameras and technologies throughout the border, they demonstrate the presence of technologies near the US/Mexico border. All of these queries can be seen in Figure 2.

Lastly, predictive policing has been prevalent in the media. For example, Sam Biddle discusses *Dataminr*, a Twitter affiliated company and their involvement in allowing law enforcement to have access to data in order to predict the location of George Floyd Protests. This is a clear representation of the increasing of surveillance technologies within the US and the impact that it has on its citizens [3].

City	State	# Tech
San Diego	California	12
Calexico	California	1
San Luis	Arizona	1
Yuma	Arizona	4
Naco	Arizona	0
Nogales	Arizona	1
Douglas	Arizona	0
Columbus	New Mexico	18
Sunland Prk.	New Mexico	1
El Paso	Texas	9
Edinburg	Texas	4
Socorro	Texas	2
San Elizario	Texas	0
Brownsville	Texas	6
Del Rio	Texas	2
Eagle Pass	Texas	2
Presidio	Texas	0
Hidalgo	Texas	1
Laredo	Texas	10
El Cenizo	Texas	0
Roma	Texas	0
Escobares	Texas	0
Rio Grande City	Texas	1
La Grulla	Texas	0
Progresso Lakes	Texas	0

Figure 1: Number of surveillance technologies per city and state in AoS across cities in the US-Mexico border [2]

2.2 Ethics

We recognize that attempting to measure the correlation of surveillance technologies and demographic characteristics might not be representative of the true impact that these technologies have on different members of underrepresented groups and minorities. The quality of our conclusions are dependent on the quality of the data sets used. Furthermore, we attempt to conduct unbiased research methods.

3. Methods

3.1 Data

```

SELECT COUNT(Technology) AS
NumberOfTechnologies
FROM Atlas_of_Surveillance_20201007
WHERE
City='Newark';

SELECT COUNT(Technology) AS
NumberOfTechnologies
FROM
Atlas_of_Surveillance_20201007
WHERE
City='San Diego';

SELECT COUNT(Technology)
AS NumberOfTechnologies
FROM Atlas_of_Surveillance_20201007
WHERE City='Progresso Lakes';

```

Figure 2: Example of SQL queries used to test number of surveillance technologies per city

We use two data sets: AoS from the Electronic Frontier Foundation (EFF) and U.S. Census Demographic Data found on Kaggle which contains information from the American Community Survey 5-year estimates.

AoS contains a CSV file of 5,785 rows of data regarding surveillance devices throughout United States. The database contains multiple columns, the ones that we utilized were the following: *City*, *County*, *State*, *Agency*, and *Technology* (Gunshot Detection, Facial Recognition, etc) [2]. Over 500 students and volunteers compiled AoS from publicly available data sets. The census demographic data contains two CSV files from 2015 and 2017 with 3,221 rows each. From this database, we use the following columns: *State*, *County*, *TotalPop*, *Men*, *Women*, *Percent Hispanic*, *Percent White*, *Percent Black*, *Percent Native*, *Percent Asian*, *Percent Pacific*, *VotingAgeCitizen*, *Income*, *IncomeErr*, *IncomePerCap*, *IncomePerCapErr*, *Poverty*, *ChildPoverty*, *Professional*, *Service*, *Office*, *Construction*, *Production*, *Drive*, *Carpool*, *Transit*, *Walk*, *OtherTransport*, *WorkAtHome*, *MeanCommute*, *Employed*, *PrivateWork*, *PublicWork*, *SelfEmployed*,

FamilyWork, and *Unemployed* [6].

We convert the CSV files from both data sets into SQL tables and place them all in the same database with 3 tables, which we name *atlas.db*. In order to clean up this database, we run SQL queries to convert all of the *County* names to the same format (i.e. we append "county" to the end of each county for uniformity). Second, we update the AoS *State* names such that for each state name it contains the two character state code instead of the full state names to match the U.S Census Demographic Data. Afterwards, we manually use the *sqlite3* command line interface in order to update these tables (Figure 3). Since each row of AoS represents one surveillance device, we are able to use this data set to count the number of devices per county. We choose not to remove outliers from our data sets given the context of what we are researching.

```

UPDATE Atlas_of_Surveillance_20201007 SET
State = "Wyoming" WHERE State == "WY";

UPDATE acs2017_county_data SET County =
County + ' County' WHERE NOT County LIKE
'%County%';

UPDATE acs2015_county_data SET County =
County + ' County' WHERE NOT County LIKE
'%County%';

```

Figure 3: Example of SQL queries used to clean data sets

3.2 Analysis Methods

We use the *statsmodels* module to run OLS regressions over different demographic categories from the county-wide data sets against the total number of surveillance devices used per county, and against different totals for each surveillance technology. We do this to see if there is a correlation between demographic categories and the number and type of surveillance devices.

Second, we use the *sklearn* and *numpy* modules in python in order to train a machine learning model using the k-nearest neighbors

algorithm. We do this in order to see if we can draw a relationship between multiple features available in our county-demographic tables and the number of surveillance devices in a county. We use the following features from the 2015 county-demographic data set: *TotalPop*, *Poverty*, *Men*, *Women*, *Black*, *White*, *Native*, *Hispanic*, *Asian*, *Pacific*, *Income*, *Drive*, *Walk*, *Transit*, *Professional*, *WorkAtHome*, *Unemployment*, *SelfEmployed*, *Professional*, *Employed* [6]. In order to label our data, we use numpy's percentile function to divide the number of devices per county into quartiles (25th, 50th, 75th, and 99th percentiles) in order to decrease the volatility of our labels. We use 80% of our data for training the model and 20% for testing which we randomly select using sklearn's *train_test_split* function. We automate the process of finding the optimal number of neighbors by looping through the possible options for neighbors within reason (from 1 neighbor to 250 neighbors) and selecting the best number based on the resulting accuracies.

4. Analysis

We analyze the results from our ordinary least squared regression tests and the KNN machine learning model.

4.1 Ordinary Least Squared Regression:

We run multiple tests comparing demographic groups against different total numbers of police surveillance technologies per county, but we focus on four significant results in this section based on 2015 demographic data. For more regression results, please see the appendix.

For each result, we include four values and the corresponding regression plot. The *R-squared* value describes the percentage of variance in the change of the dependent variable that can be explained by the independent variable. We list the the *p-value* for the independent variable which tests our null hypothesis.

Finally, we list the regression parameters. We include the constant parameter b and the parameter m linked to the independent variable for the fitted regression line $y = mx + b$.

1. We compare the percentage of Black residents against the total sightings of policing technologies per county.

- **R-squared value:** $R^2 = 0.005$
- **P-value:** $p = 0.012$
- **Regression parameters:**
 - $b = 3.8236$
 - $m = 0.0384$

We notice that we have a low R^2 value, but a significant p value (our significance level is 0.05). This indicates that while there is a significant correlation between our two variables, changes in the percentage of the population that is Black can not explain the variability of the number of policing technologies well.

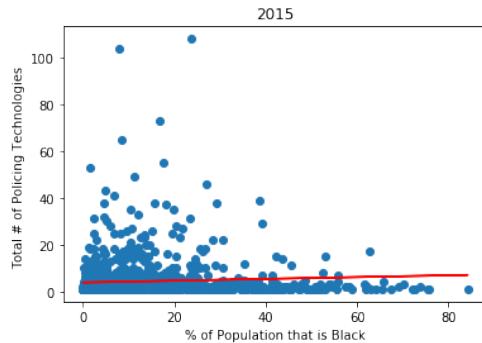


Figure 4: OLS Regression results for Percentage of Population that is Black as the independent variable and Total number of Policing technologies as the dependent variable

We see a slight positive correlation between our two variables indicating that the number of policing technologies grows slightly in counties with greater percentages of Black residents. However, the regression line does not well describe outliers and data which is skewed to the right. Note that we also have similar significant results for 2017 demographic data.

2. We compare the percentage of White residents against the total sightings of policing technologies per county.

- **R-squared value:** $R^2 = 0.096$
- **P-value:** $p = 0.000$
- **Regression parameters:**
 - $b = 13.5607$
 - $m = -0.1258$

Again, we notice a low R^2 value, but significant p value. This indicates that while there is a significant correlation between the two variables, changes in the percentage of the population that is White cannot explain the variability of the number of policing technologies well.

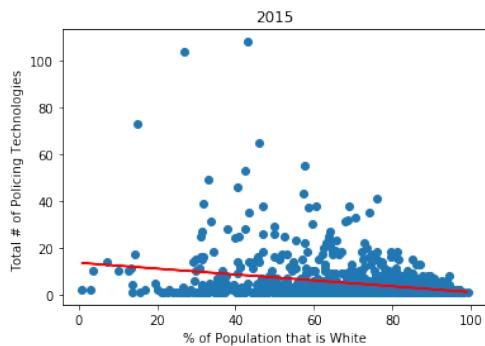


Figure 5: OLS Regression results for Percentage of Population that is White as the independent variable and Total number of Policing technologies as the dependent variable

Unlike our analysis on the percentage of Black residents against the total sightings of policing technologies per county where we found a positive correlation, we see a negative correlation between our two variables in this case. This indicates that the number of policing technologies diminishes in counties with greater percentages of White residents. Note that we also have similar significant results for 2017 demographic data.

3. We compare the percentage of Black residents against the total sightings of Ring technologies per county.

- **R-squared value:** $R^2 = 0.014$
- **P-value:** $p = 0.007$
- **Regression parameters:**
 - $b = 2.3364$
 - $m = 0.0413$

We next looked at demographics against individual technologies. In this case, we look at the percentage of Black residents against the number of Ring technologies, the only case of positive correlation between percentage of Black residents against an individual technology. Here we have the same pattern of low R^2 value and significant p value indicating that while there is a significant correlation between the two variables, the variability is not well explained. It might be worth noting that looking at the percentage of White residents against the number of Ring technologies, there was a negative correlation.

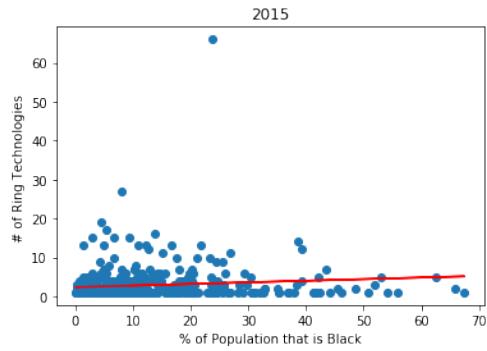


Figure 6: OLS Regression results for Percentage of Population that is Black as the independent variable and Total number of Ring Policing technologies as the dependent variable

We see a slight positive correlation between our variables indicating that the number of Ring technologies grows slightly in counties with greater percentages of Black residents.

4. We compare the percentage of White residents against the total sightings of facial recognition technologies per county.

- **R-squared value:** $R^2 = 0.049$

- **P-value:** $p = 0.012$
- **Regression parameters:**
 - $b = 5.8946$
 - $m = -0.0493$

In this case, we look at the percentage of White residents against the number of facial recognition technologies. Here we have the same pattern of low R^2 value and significant p value indicating that while there is a significant correlation between the two variables, the variability is not well explained. It might be worth noting that looking at the percentage of Black residents against the number of facial recognition technologies, there was no significant correlation.

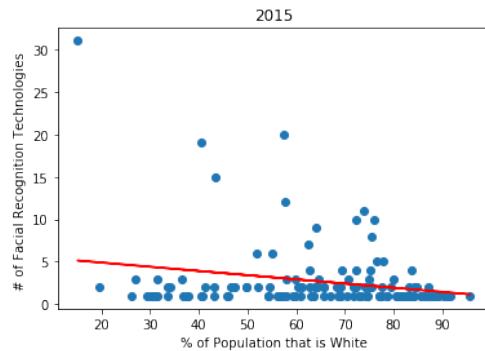


Figure 7: OLS Regression results for Percentage of Population that is White as the independent variable and Total number of Ring Policing technologies as the dependent variable

We see a slight negative correlation between our variables indicating that the number of facial recognition technologies diminishes slightly in counties with greater percentages of White residents.

Additional Results: The following tests also had statistically significant results.

- Percentage of the population that is Asian vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Percentage of the population that is Hispanic vs. total number of policing

technologies for both 2015 and 2017 demographic data.

- Percentage of the population that is Native vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Percentage of the population living in poverty vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Percentage of the population that drives vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Percentage of the population that is employed vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Percentage of the population that is self-employed vs. total number of policing technologies for both 2015 and 2017 demographic data.
- Average income per capita vs. total number of policing technologies for both 2015 and 2017 demographic data.

4.2 K-Nearest Neighbors Machine Learning Model:

After determining the optimal number of neighbors (121), our model is able to predict with about 60% accuracy which quartile a county will fall in when given its features: *Percent Black, Percent White, Percent Native, Percent Hispanic, Percent Asian, Percent Pacific, TotalPop, Poverty, Men, Women, Income, Driving to Work, Walking to Work, Taking Transit to Work, Professional Jobs, Work at Home, Unemployed, Self-Employed, and Employed in 2015*. Because we are working with quartiles, purely guessing a category would yield 25% accuracy, whereas our model predicted with over double that accuracy. This shows that our model was able to pick up on patterns within the features.

Limitations:

As mentioned in the Related Works section, we identify that there are limitations of our data set. We must keep in mind these limitations of our analysis. The AoS data set is sparse (from 2006-2020) and based on citizen observations which are unreliable and may not cover the true distribution of surveillance technology. We also note that the AoS website acknowledges the limitations.

5. Conclusions & Implications

In conclusion, analyzing the AoS and U.S. Census Demographic Data through OLS regressions and the KNN model allowed us to gain some insight on the correlations between AoS technologies and demographic data. While technically there are some significant findings, we believe that our results are not representative of reality due to the limitations of the database. We also believe that our results might not be representative because of the variability of the data and the fact that we did not consider the possibility of pursuing a multiple regression that took into account multiple variables at the same time.

We want to reiterate that we do not believe that these results are representative of the effects that surveillance technologies have on the members of the American community.

6. Future Work

Looking at our results, we find the potential of taking our work one step further by looking into the relationship between the AoS data, U.S. Census Data, and other relevant metrics. Some of the branches of investigation that we consider are:

- **Crime Rate:** We could consider the addition of the crime rate metric for each county and determine whether there exists a correlation between a county's crime rate and the number of surveillance technologies reported.

- **Predictive Policing:** We could analyze which of the technologies reported in the AoS database are also utilized for predictive policing. This could give us insight on whether there is a relationship between the technologies used for predictive policing and the technologies reported by citizens for the database.
- **Relationship to County's Income:** We also consider the idea of analyzing the number and type of surveillance technologies of a given county in comparison to the county's income. Since a county's funding comes mostly from taxes [7], it would be interesting to determine whether these two elements are related as well as the impact that taxes may have on surveillance.
- **Another Database for Surveillance Technologies:** One of the biggest limitations we face in this research was that the years in the AoS database were highly sparse (from 2006-2020), and not that close to the 2015 and 2017 U.S. Census Database; therefore, future work might seek to find a database that is more representative of those two years which could lead to more accurate and insightful results. Additionally, we consider limiting the AoS database to come closer to the 2015 and 2017 years, but we decide against it given that it would limit the amount of information to create a significant finding.
- **Consider political leaning:** It would be interesting to consider the relationship between the number and types of surveillance technologies along with the political beliefs shared with the majority of the county. For once, it would be interesting to continue this project next year and analyze the results of the 2020 elections and compare that data with AoS information.
- **Multiple Regression:** As mentioned in our conclusion, we believe that pursuing a Multiple Regression model could lead to greater insights into the data sets.

6. Try It Out Yourself!

We created a command-line script where people are able to enter information from a hypothetical county to see in which percentile of number of surveillance technologies their county would fall into. The repository can be accessed from [this link](#), and the instructions are in the Description section.

7. Appendix

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.037			
Model:	OLS	Adj. R-squared:	0.036			
Method:	Least Squares	F-statistic:	49.11			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	3.90e-12			
Time:	17:04:10	Log-Likelihood:	-4439.3			
No. Observations:	1288	AIC:	8883.			
Df Residuals:	1286	BIC:	8893.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
const	24.4783	2.898	8.446	0.000	18.793	30.164
x1	-0.2516	0.036	-7.008	0.000	-0.332	-0.181
<hr/>						
Omnibus:	1534.100	Durbin-Watson:	1.687			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	180886.267			
Skew:	6.053	Prob(JB):	0.00			
Kurtosis:	59.780	Cond. No.	1.10e+03			
<hr/>						
Notes:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						
[2] The condition number is large, 1.1e+03. This might indicate that there are strong multicollinearity or other numerical problems.						

Figure 8: OLS Regression results for amount of individuals that drive to work as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.001			
Model:	OLS	Adj. R-squared:	-0.000			
Method:	Least Squares	F-statistic:	0.7197			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.396			
Time:	16:53:48	Log-Likelihood:	-4463.1			
No. Observations:	1288	AIC:	8930.			
Df Residuals:	1286	BIC:	8941.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
const	4.1920	0.219	19.142	0.000	3.762	4.622
x1	0.3259	0.384	0.848	0.396	-0.428	1.080
<hr/>						
Omnibus:	1575.942	Durbin-Watson:	1.611			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	200963.679			
Skew:	6.330	Prob(JB):	0.00			
Kurtosis:	62.870	Cond. No.	1.80			
<hr/>						
Notes:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						

Figure 9: OLS Regression results for percentage of the population that is Pacific as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.091			
Model:	OLS	Adj. R-squared:	0.090			
Method:	Least Squares	F-statistic:	129.1			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.44e-28			
Time:	17:01:55	Log-Likelihood:	-4401.9			
No. Observations:	1288	AIC:	8808.			
Df Residuals:	1286	BIC:	8818.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
const	-6.9006	1.001	-6.897	0.000	-8.864	-4.938
x1	0.3434	0.030	11.361	0.000	0.284	0.403
<hr/>						
Omnibus:	1616.083	Durbin-Watson:	1.701			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	247450.693			
Skew:	6.550	Prob(JB):	0.00			
Kurtosis:	69.628	Cond. No.	161.			
<hr/>						
Notes:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						

Figure 10: OLS Regression results for percentage of the population that is working as professional as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.169			
Model:	OLS	Adj. R-squared:	0.169			
Method:	Least Squares	F-statistic:	261.5			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.10e-53			
Time:	16:52:56	Log-Likelihood:	-4344.3			
No. Observations:	1288	AIC:	8693.			
Df Residuals:	1286	BIC:	8703.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
const	2.3359	0.229	10.209	0.000	1.887	2.785
x1	0.9136	0.056	16.171	0.000	0.803	1.024
<hr/>						
Omnibus:	1539.831	Durbin-Watson:	1.790			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	233237.455			
Skew:	5.976	Prob(JB):	0.00			
Kurtosis:	67.832	Cond. No.	4.79			
<hr/>						
Notes:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						

Figure 11: OLS Regression results for percentage of the population that is Asian as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.005			
Model:	OLS	Adj. R-squared:	0.004			
Method:	Least Squares	F-statistic:	6.355			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.0118			
Time:	16:03:19	Log-Likelihood:	-4460.3			
No. Observations:	1288	AIC:	8925.			
Df Residuals:	1286	BIC:	8935.			
Df Model:	1					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
const	3.8236	0.267	14.296	0.000	3.299	4.248
x1	0.0384	0.015	2.521	0.012	0.009	0.068
<hr/>						
Omnibus:	1574.453	Durbin-Watson:	1.606			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	200846.286			
Skew:	6.319	Prob(JB):	0.00			
Kurtosis:	62.856	Cond. No.	21.8			
<hr/>						
Warnings:						
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.						

Figure 12: OLS Regression results for percentage of the population that is Black as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.627				
Model:	OLS	Adj. R-squared:	0.626				
Method:	Least Squares	F-statistic:	215.6				
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	2.29e-277				
Time:	16:57:41	Log-Likelihood:	-3829.1				
No. Observations:	1288	AIC:	7662.				
Df Residuals:	1286	BIC:	7672.				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	1.6053	0.143	11.191	0.000	1.324	1.887	
x1	2.7296e-05	5.58e-07	46.454	0.000	2.61e-05	2.84e-05	
Omnibus:	916.646	Durbin-Watson:	1.890				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	64745.534				
Skew:	2.601	Prob(JB):	0.00				
Kurtosis:	37.342	Cond. No.	2.66e+05				

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 2.66e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 13: OLS Regression results for percentage of the population that is employed as the independent variable and total number of Policing technologies as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.021				
Model:	OLS	Adj. R-squared:	0.014				
Method:	Least Squares	F-statistic:	2.789				
Date:	Wed, 21 Oct 2020	Prob (F-statistic):	0.0974				
Time:	22:15:58	Log-Likelihood:	-362.17				
No. Observations:	129	AIC:	728.3				
Df Residuals:	127	BIC:	734.1				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	2.0422	0.547	3.733	0.000	0.960	3.125	
x1	0.0551	0.013	1.670	0.097	-0.010	0.120	
Omnibus:	144.453	Durbin-Watson:	1.831				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2724.803				
Skew:	4.130	Prob(JB):	0.00				
Kurtosis:	23.945	Cond. No.	25.6				

Warnings:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 14: OLS Regression results for percentage of the population that is Black as the independent variable and total number of Policing technologies which are facial recognition as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.015				
Model:	OLS	Adj. R-squared:	0.007				
Method:	Least Squares	F-statistic:	1.945				
Date:	Wed, 21 Oct 2020	Prob (F-statistic):	0.166				
Time:	22:13:29	Log-Likelihood:	-362.59				
No. Observations:	129	AIC:	729.2				
Df Residuals:	127	BIC:	734.9				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	1.2467	1.126	1.107	0.270	-0.982	3.475	
x1	0.0972	0.070	1.395	0.166	-0.041	0.235	
Omnibus:	144.629	Durbin-Watson:	1.914				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2653.938				
Skew:	4.156	Prob(JB):	0.00				
Kurtosis:	23.607	Cond. No.	51.2				

Warnings:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 15: OLS Regression results for percentage of the population that are living in Poverty as the independent variable and total number of Policing technologies which are facial recognition as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.013				
Model:	OLS	Adj. R-squared:	-0.003				
Method:	Least Squares	F-statistic:	0.7991				
Date:	Wed, 21 Oct 2020	Prob (F-statistic):	0.455				
Time:	22:18:57	Log-Likelihood:	-71.494				
No. Observations:	62	AIC:	147.0				
Df Residuals:	60	BIC:	151.2				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	1.5251	0.168	9.054	0.000	1.188	1.862	
x1	-0.0271	0.008	-0.894	0.375	-0.023	0.009	
Omnibus:	38.122	Durbin-Watson:	1.954				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	83.16				
Skew:	2.078	Prob(JB):	8.53e-19				
Kurtosis:	6.865	Cond. No.	36.2				

Warnings:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 16: OLS Regression results for percentage of the population that are Black as the independent variable and total number of Policing technologies which are gunshot detection as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.022				
Model:	OLS	Adj. R-squared:	0.006				
Method:	Least Squares	F-statistic:	1.381				
Date:	Wed, 21 Oct 2020	Prob (F-statistic):	0.245				
Time:	22:19:46	Log-Likelihood:	-71.399				
No. Observations:	62	AIC:	146.4				
Df Residuals:	60	BIC:	150.7				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	1.8029	0.354	5.092	0.000	1.095	2.511	
x1	-0.0256	0.022	-1.175	0.245	-0.069	0.018	
Omnibus:	0.000	Durbin-Watson:	0.889				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.569				
Skew:	2.020	Prob(JB):	1.58e-17				
Kurtosis:	6.692	Cond. No.	58.7				

Warnings:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 17: OLS Regression results for percentage of the population that are living in poverty as the independent variable and total number of Policing technologies which are gunshot detection as the dependent variable in 2015

OLS Regression Results							
Dep. Variable:	y	R-squared:	0.042				
Model:	OLS	Adj. R-squared:	0.026				
Method:	Least Squares	F-statistic:	2.616				
Date:	Wed, 21 Oct 2020	Prob (F-statistic):	0.111				
Time:	22:17:53	Log-Likelihood:	-70.581				
No. Observations:	62	AIC:	145.2				
Df Residuals:	60	BIC:	149.4				
Df Model:	1						
Covariance Type:	nonrobust						
coef	std err	t	P> t	[0.025	0.975]		
const	1.9671	0.362	5.434	0.000	1.243	2.691	
x1	-0.0097	0.006	-1.617	0.111	-0.022	0.002	
Omnibus:	37.954	Durbin-Watson:	1.964				
Prob(Omnibus):	0.000	Jarque-Bera (JB):	82.937				
Skew:	2.064	Prob(JB):	9.78e-19				
Kurtosis:	6.882	Cond. No.	224.				

Warnings:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 18: OLS Regression results for percentage of the population that is White as the independent variable and total number of Policing technologies which are gunshot detection as the dependent variable in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.070					
Model:	OLS	Adj. R-squared:	0.070					
Method:	Least Squares	F-statistic:	97.43					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	3.35e-22					
Time:	16:50:26	Log-Likelihood:	-4416.4					
No. Observations:	1288	AIC:	8837.					
Df Residuals:	1286	BIC:	8847.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	2.6858	0.260	10.331	0.000	2.176	3.196		
x1	0.1523	0.015	9.871	0.000	0.122	0.183		
=====								
Omnibus:	1531.798	Durbin-Watson:	1.720					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	186499.844					
Skew:	6.021	Prob(JB):	0.00					
Kurtosis:	60.707	Cond. No.	21.1					
=====								
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 19: OLS Regression results for percentage of the population that is Hispanic as the independent variable and total number of Policing technologies in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.010					
Model:	OLS	Adj. R-squared:	0.010					
Method:	Least Squares	F-statistic:	13.57					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.000240					
Time:	16:53:13	Log-Likelihood:	-4456.7					
No. Observations:	1288	AIC:	8917.					
Df Residuals:	1286	BIC:	8928.					
Df Model:	1							
Covariance Type:	nonrobust							
=====								
coef	std err	t	P> t	[0.025	0.975]			
const	6.3591	0.618	10.286	0.000	5.146	7.572		
x1	-0.1320	0.036	-3.683	0.000	-0.202	-0.062		
=====								
Omnibus:	1586.166	Durbin-Watson:	1.619					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	210084.089					
Skew:	6.390	Prob(JB):	0.00					
Kurtosis:	64.248	Cond. No.	49.8					
=====								

Figure 22: OLS Regression results for percentage of the population that is living in Poverty as the independent variable and total number of Policing technologies in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.097					
Model:	OLS	Adj. R-squared:	0.096					
Method:	Least Squares	F-statistic:	137.6					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	2.90e-30					
Time:	16:55:57	Log-Likelihood:	-4398.0					
No. Observations:	1288	AIC:	8800.					
Df Residuals:	1286	BIC:	8810.					
Df Model:	1							
Covariance Type:	nonrobust							
=====								
coef	std err	t	P> t	[0.025	0.975]			
const	-5.5876	0.861	-6.487	0.000	-7.277	-3.898		
x1	0.0004	3.26e-05	11.728	0.000	0.000	0.000		
=====								
Omnibus:	1615.976	Durbin-Watson:	1.685					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	250431.666					
Skew:	6.543	Prob(JB):	0.00					
Kurtosis:	70.046	Cond. No.	1.11e+05					
=====								
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								
[2] The condition number is large, 1.11e+05. This might indicate that there are strong multicollinearity or other numerical problems.								

Figure 20: OLS Regression results for income per capita as the independent variable and total number of Policing technologies in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.014					
Model:	OLS	Adj. R-squared:	0.013					
Method:	Least Squares	F-statistic:	17.62					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	2.88e-05					
Time:	16:59:54	Log-Likelihood:	-4454.7					
No. Observations:	1288	AIC:	8913.					
Df Residuals:	1286	BIC:	8924.					
Df Model:	1							
Covariance Type:	nonrobust							
=====								
coef	std err	t	P> t	[0.025	0.975]			
const	6.6799	0.623	10.720	0.000	5.457	7.902		
x1	-0.3753	0.089	-4.198	0.000	-0.551	-0.200		
=====								
Omnibus:	1594.448	Durbin-Watson:	1.623					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	214411.125					
Skew:	6.446	Prob(JB):	0.00					
Kurtosis:	64.879	Cond. No.	20.6					
=====								
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 23: OLS Regression results for percentage of the population that is living self employed as the independent variable and total number of Policing technologies in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.005					
Model:	OLS	Adj. R-squared:	0.004					
Method:	Least Squares	F-statistic:	5.866					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.0156					
Time:	16:51:21	Log-Likelihood:	-4460.5					
No. Observations:	1288	AIC:	8925.					
Df Residuals:	1286	BIC:	8935.					
Df Model:	1							
Covariance Type:	nonrobust							
=====								
coef	std err	t	P> t	[0.025	0.975]			
const	4.3722	0.224	19.524	0.000	3.933	4.812		
x1	-0.1509	0.062	-2.422	0.016	-0.273	-0.029		
=====								
Omnibus:	1576.564	Durbin-Watson:	1.607					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	201892.020					
Skew:	6.333	Prob(JB):	0.00					
Kurtosis:	63.013	Cond. No.	3.76					
=====								
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 21: OLS Regression results for percentage of the population that is Native as the independent variable and total number of Policing technologies in 2015

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.001					
Model:	OLS	Adj. R-squared:	-0.000					
Method:	Least Squares	F-statistic:	0.8469					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.358					
Time:	17:03:11	Log-Likelihood:	-4463.1					
No. Observations:	1288	AIC:	8930.					
Df Residuals:	1286	BIC:	8940.					
Df Model:	1							
Covariance Type:	nonrobust							
=====								
coef	std err	t	P> t	[0.025	0.975]			
const	4.4898	0.361	12.442	0.000	3.782	5.198		
x1	-0.1083	0.118	-0.920	0.358	-0.339	0.123		
=====								
Omnibus:	1577.957	Durbin-Watson:	1.606					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	202485.780					
Skew:	6.343	Prob(JB):	0.00					
Kurtosis:	63.101	Cond. No.	5.49					
=====								
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 24: OLS Regression results for percentage of the population that walk to work as the independent variable and total number of Policing technologies in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.096			
Model:	OLS	Adj. R-squared:	0.095			
Method:	Least Squares	F-statistic:	136.5			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	4.92e-30			
Time:	16:48:06	Log-Likelihood:	-4398.5			
No. Observations:	1288	AIC:	8801.			
Df Residuals:	1286	BIC:	8811.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	13.5607	0.825	16.432	0.000	11.942	15.180
x1	-0.1258	0.011	-11.681	0.000	-0.147	-0.105
<hr/>						
Omnibus:	1526.494	Durbin-Watson:	1.716			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	189308.465			
Skew:	5.973	Prob(JB):	0.00			
Kurtosis:	61.179	Cond. No.	308.			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 25: OLS Regression results for percentage of the population that is White as the independent variable and total number of Policing technologies in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.005			
Model:	OLS	Adj. R-squared:	0.004			
Method:	Least Squares	F-statistic:	6.303			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.0122			
Time:	17:22:40	Log-Likelihood:	-4460.3			
No. Observations:	1288	AIC:	8925.			
Df Residuals:	1286	BIC:	8935.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	3.8252	0.267	14.301	0.000	3.300	4.350
x1	0.0381	0.015	2.511	0.012	0.008	0.068
<hr/>						
Omnibus:	1574.706	Durbin-Watson:	1.606			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	201004.392			
Skew:	6.320	Prob(JB):	0.00			
Kurtosis:	62.880	Cond. No.	21.9			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 28: OLS Regression results for percentage of the population that are Black as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.007			
Model:	OLS	Adj. R-squared:	0.006			
Method:	Least Squares	F-statistic:	9.291			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.00235			
Time:	17:00:45	Log-Likelihood:	-4458.8			
No. Observations:	1288	AIC:	8922.			
Df Residuals:	1286	BIC:	8932.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	2.8056	0.513	5.474	0.000	1.800	3.811
x1	0.3440	0.113	3.048	0.002	0.123	0.565
<hr/>						
Omnibus:	1574.849	Durbin-Watson:	1.622			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	202018.823			
Skew:	6.319	Prob(JB):	0.00			
Kurtosis:	63.038	Cond. No.	11.3			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 26: OLS Regression results for percentage of the population that work from home as the independent variable and total number of Policing technologies in 2015

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.626			
Model:	OLS	Adj. R-squared:	0.625			
Method:	Least Squares	F-statistic:	2149.			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.14e-276			
Time:	17:09:41	Log-Likelihood:	-3830.7			
No. Observations:	1288	AIC:	7665.			
Df Residuals:	1286	BIC:	7676.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	1.6191	0.144	11.281	0.000	1.338	1.901
x1	2.619e-05	5.65e-07	46.362	0.000	2.51e-05	2.73e-05
<hr/>						
Omnibus:	918.241	Durbin-Watson:	1.890			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	64892.817			
Skew:	2.608	Prob(JB):	0.00			
Kurtosis:	37.380	Cond. No.	2.76e+05			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 2.76e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 29: OLS Regression results for percentage of the population that are Employed as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.171			
Model:	OLS	Adj. R-squared:	0.170			
Method:	Least Squares	F-statistic:	264.5			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	3.16e-54			
Time:	17:21:25	Log-Likelihood:	-4343.0			
No. Observations:	1288	AIC:	8690.			
Df Residuals:	1286	BIC:	8700.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	2.3041	0.229	10.049	0.000	1.854	2.754
x1	0.8896	0.055	16.263	0.000	0.782	0.997
<hr/>						
Omnibus:	1544.335	Durbin-Watson:	1.790			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	235190.597			
Skew:	6.007	Prob(JB):	0.00			
Kurtosis:	68.101	Cond. No.	4.97			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 27: OLS Regression results for percentage of the population that are Asian as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.071			
Model:	OLS	Adj. R-squared:	0.071			
Method:	Least Squares	F-statistic:	98.88			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.70e-22			
Time:	17:23:51	Log-Likelihood:	-4415.8			
No. Observations:	1288	AIC:	8836.			
Df Residuals:	1286	BIC:	8846.			
Df Model:	1					
Covariance Type:	nonrobust					
coef std err t P> t [0.025 0.975]						
const	2.6489	0.261	10.133	0.000	2.136	3.162
x1	0.1514	0.015	9.944	0.000	0.122	0.181
<hr/>						
Omnibus:	1532.480	Durbin-Watson:	1.724			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	187114.732			
Skew:	6.024	Prob(JB):	0.00			
Kurtosis:	60.805	Cond. No.	21.6			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 30: OLS Regression results for percentage of the population that are Hispanic as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.076			
Model:	OLS	Adj. R-squared:	0.075			
Method:	Least Squares	F-statistic:	105.4			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	8.00e-14			
Time:	17:20:01	Log-Likelihood:	-4412.8			
No. Observations:	1288	AIC:	8830.			
Df Residuals:	1286	BIC:	8840.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-3.4464	0.775	-4.445	0.000	-4.968	-1.925
x1	0.0001	1.4e-05	10.266	0.000	0.000	
Omnibus:	1610.687	Durbin-Watson:	1.688			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	242008.919			
Skew:	6.517	Prob(JB):	0.00			
Kurtosis:	68.876	Cond. No.	2.07e+05			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 2.07e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 31: OLS Regression results for the average income as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.000			
Model:	OLS	Adj. R-squared:	-0.000			
Method:	Least Squares	F-statistic:	0.5400			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.461			
Time:	17:20:45	Log-Likelihood:	-4463.2			
No. Observations:	1288	AIC:	8930.			
Df Residuals:	1286	BIC:	8941.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	4.1950	0.219	19.132	0.000	3.765	4.625
x1	0.2803	0.380	0.737	0.461	-0.466	1.026
Omnibus:	1575.924	Durbin-Watson:	1.411			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	200911.304			
Skew:	6.330	Prob(JB):	0.00			
Kurtosis:	62.861	Cond. No.	1.79			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 34: OLS Regression results for the percentage that is Pacific as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.099			
Model:	OLS	Adj. R-squared:	0.099			
Method:	Least Squares	F-statistic:	142.0			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	4.02e-31			
Time:	17:19:15	Log-Likelihood:	-4396.0			
No. Observations:	1288	AIC:	8796.			
Df Residuals:	1286	BIC:	8806.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-5.6344	0.852	-6.610	0.000	-7.307	-3.962
x1	0.0004	3e-05	11.915	0.000	0.000	0.000
Omnibus:	1615.635	Durbin-Watson:	1.686			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	250513.325			
Skew:	6.540	Prob(JB):	0.00			
Kurtosis:	70.059	Cond. No.	1.18e+05			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 1.18e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Figure 32: OLS Regression results for the income per capita as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.013			
Model:	OLS	Adj. R-squared:	0.012			
Method:	Least Squares	F-statistic:	16.31			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	5.69e-05			
Time:	17:18:39	Log-Likelihood:	-4455.4			
No. Observations:	1288	AIC:	8915.			
Df Residuals:	1286	BIC:	8925.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	6.5159	0.607	10.739	0.000	5.326	7.706
x1	-0.1490	0.037	-4.039	0.000	-0.221	-0.079
Omnibus:	1586.838	Durbin-Watson:	1.620			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	210935.573			
Skew:	6.393	Prob(JB):	0.00			
Kurtosis:	64.376	Cond. No.	46.7			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 35: OLS Regression results for the percentage that is living in poverty as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.005			
Model:	OLS	Adj. R-squared:	0.004			
Method:	Least Squares	F-statistic:	6.102			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.0036			
Time:	17:22:02	Log-Likelihood:	-4460.4			
No. Observations:	1288	AIC:	8925.			
Df Residuals:	1286	BIC:	8935.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	4.3733	0.224	19.549	0.000	3.934	4.812
x1	-0.1495	0.061	-2.470	0.014	-0.268	-0.031
Omnibus:	1576.654	Durbin-Watson:	1.608			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	201983.014			
Skew:	6.334	Prob(JB):	0.00			
Kurtosis:	63.027	Cond. No.	3.86			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 33: OLS Regression results for the percentage that is Native as the independent variable and total number of Policing technologies in 2017

OLS Regression Results						
Dep. Variable:	y	R-squared:	0.090			
Model:	OLS	Adj. R-squared:	0.089			
Method:	Least Squares	F-statistic:	127.0			
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	3.68e-28			
Time:	17:17:53	Log-Likelihood:	-4402.8			
No. Observations:	1288	AIC:	8810.			
Df Residuals:	1286	BIC:	8820.			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-6.7644	0.997	-6.789	0.000	-8.719	-4.809
x1	0.3327	0.030	11.270	0.000	0.275	0.391
Omnibus:	1615.816	Durbin-Watson:	1.694			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	246633.929			
Skew:	6.550	Prob(JB):	0.00			
Kurtosis:	69.514	Cond. No.	163.			

Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 36: OLS Regression results for the percentage that is working a professional job as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.011					
Model:	OLS	Adj. R-squared:	0.011					
Method:	Least Squares	F-statistic:	14.79					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.000126					
Time:	17:09:02	Log-Likelihood:	-4456.1					
No. Observations:	1288	AIC:	8916.					
Df Residuals:	1286	BIC:	8927.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	6.4651	0.621	10.408	0.000	5.246	7.684		
x1	-0.3495	0.091	-3.845	0.000	-0.528	-0.171		
Omnibus:	1592.878	Durbin-Watson:	1.622					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	213185.575					
Skew:	6.437	Prob(JB):	0.00					
Kurtosis:	64.698	Cond. No.	20.2					
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 37: OLS Regression results for the percentage that is working self employed job as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.045					
Model:	OLS	Adj. R-squared:	0.044					
Method:	Least Squares	F-statistic:	60.67					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.38e-14					
Time:	17:07:07	Log-Likelihood:	-4433.8					
No. Observations:	1288	AIC:	8872.					
Df Residuals:	1286	BIC:	8882.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	26.6025	2.881	9.235	0.000	20.951	32.254		
x1	-0.2770	0.036	-7.789	0.000	-0.347	-0.207		
Omnibus:	1530.580	Durbin-Watson:	1.703					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	180827.017					
Skew:	6.026	Prob(JB):	0.00					
Kurtosis:	59.782	Cond. No.	1.1e+03					
Notes:								
[1] The condition number is large, 1.1e+03. This might indicate that there are strong multicollinearity or other numerical problems.								

Figure 40: OLS Regression results for the percentage that drive to work as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.001					
Model:	OLS	Adj. R-squared:	-0.000					
Method:	Least Squares	F-statistic:	0.7491					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.387					
Time:	17:17:13	Log-Likelihood:	-4463.1					
No. Observations:	1288	AIC:	8930.					
Df Residuals:	1286	BIC:	8941.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	4.4702	0.357	12.508	0.000	3.769	5.171		
x1	-0.1028	0.119	-0.865	0.387	-0.336	0.130		
Omnibus:	1577.852	Durbin-Watson:	1.605					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	202390.287					
Skew:	6.342	Prob(JB):	0.00					
Kurtosis:	63.086	Cond. No.	5.34					
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 38: OLS Regression results for the percentage that walk to work as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.001					
Model:	OLS	Adj. R-squared:	0.000					
Method:	Least Squares	F-statistic:	1.281					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.258					
Time:	17:08:04	Log-Likelihood:	-4464.8					
No. Observations:	1288	AIC:	8930.					
Df Residuals:	1286	BIC:	8940.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	3.5493	0.634	5.601	0.000	2.306	4.793		
x1	0.1029	0.091	1.132	0.258	-0.075	0.281		
Omnibus:	1572.948	Durbin-Watson:	1.613					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	199010.866					
Skew:	6.311	Prob(JB):	0.00					
Kurtosis:	62.573	Cond. No.	20.8					
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 41: OLS Regression results for the percentage that is unemployed as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.098					
Model:	OLS	Adj. R-squared:	0.097					
Method:	Least Squares	F-statistic:	139.4					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	1.30e-30					
Time:	17:23:15	Log-Likelihood:	-4397.2					
No. Observations:	1288	AIC:	8798.					
Df Residuals:	1286	BIC:	8809.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	13.4830	0.811	16.632	0.000	11.893	15.073		
x1	-0.1257	0.011	-11.806	0.000	-0.147	-0.105		
Omnibus:	1527.764	Durbin-Watson:	1.720					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	190616.042					
Skew:	5.979	Prob(JB):	0.00					
Kurtosis:	61.385	Cond. No.	301.					
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 39: OLS Regression results for the percentage that works from home as the independent variable and total number of Policing technologies in 2017

OLS Regression Results								
Dep. Variable:	y	R-squared:	0.011					
Model:	OLS	Adj. R-squared:	0.010					
Method:	Least Squares	F-statistic:	13.80					
Date:	Tue, 20 Oct 2020	Prob (F-statistic):	0.000212					
Time:	17:10:17	Log-Likelihood:	-4456.6					
No. Observations:	1288	AIC:	8917.					
Df Residuals:	1286	BIC:	8928.					
Df Model:	1							
Covariance Type:	nonrobust							
coef	std err	t	P> t	[0.025	0.975]			
const	2.4867	0.515	4.833	0.000	1.477	3.496		
x1	0.3993	0.107	3.715	0.000	0.188	0.610		
Omnibus:	1575.452	Durbin-Watson:	1.626					
Prob(Omnibus):	0.000	Jarque-Bera (JB):	203275.233					
Skew:	6.321	Prob(JB):	0.00					
Kurtosis:	63.232	Cond. No.	11.9					
Notes:								
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.								

Figure 42: OLS Regression results for the percentage that works from home as the independent variable and total number of Policing technologies in 2017

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OLS Regression Results
=====
Dep. Variable:      y   R-squared:       0.049
Model:              OLS   Adj. R-squared:    0.041
Method:             Least Squares   F-statistic:     6.521
Date:          Wed, 21 Oct 2020   Prob (F-statistic): 0.0118
Time:            22:17:08   Log-Likelihood:   -360.34
No. Observations: 127   AIC:             724.7
Df Residuals:     127   BIC:             730.4
Df Model:          1
Covariance Type:  nonrobust
=====
            coef  std err      t  P>|t|    [0.025  0.975]
const    5.8946   1.286   4.585  0.000   3.351   8.439
x1      -0.0493   0.019  -2.554  0.012  -0.088  -0.011
=====
Omnibus:        130.404   Durbin-Watson:    1.723
Prob(Omnibus):           0.000   Jarque-Bera (JB): 1797.02
Skew:           3.673   Prob(JB):       0.00
Kurtosis:       19.745   Cond. No.       244.
=====
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

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Figure 43: OLS Regression results for the percentage that are White as the independent variable and total number of Policing technologies that were facial recognition in 2015

REFERENCES

- [1] Atlas of Surveillance. [Atlasofsurveillance.org.](https://atlasofsurveillance.org/) (2020). Retrieved 26 October 2020, from <https://atlasofsurveillance.org/>.
- [2] Atlas of Surveillance. (2006-2020). US Census Demographic Data [CSV]. Location: Atlas of Surveillance.
- [3] Biddle, S. (2020). Police Surveilled George Floyd Protests With Help From Twitter-Affiliated Startup Dataminr. The Intercept. Retrieved 2 November 2020 from https://theintercept.com/2020/07/09/twitter-dataminr-police-spy-surveillance-black-lives-matter-protests/?utm_campaign=theinterceptutm_medium=socialutm_source=twitter.
- [4] Ghaffary, S. (2020). The "smarter" wall: How drones, sensors, and AI are patrolling the border. Vox. Retrieved 27 October 2020, from <https://www.vox.com/recode/2019/5/16/18511583/smart-border-wall-drones-sensors-ai>.
- [5] Rojas, R. (2018). In Newark, Police Cameras, and the Internet, Watch You. New York Times. Retrieved 27 October 2020, from <https://www.nytimes.com/2018/06/09/nyregion/newark-surveillance-cameras-police.html>.
- [6] The Census Bureau. (2015-2017). US Census Demographic Data (Version 3) [CSV]. Location: Kaggle.
- [7] Welcome to Your County. [Welcometoyourcounty.org.](http://www.welcometoyourcounty.org) (2020). Retrieved 27 October 2020, from http://www.welcometoyourcounty.org/content/how_is_a_county_funded.shtm.