Spokane Population Growth and Crime

FBI UCR Data (1985-2014)

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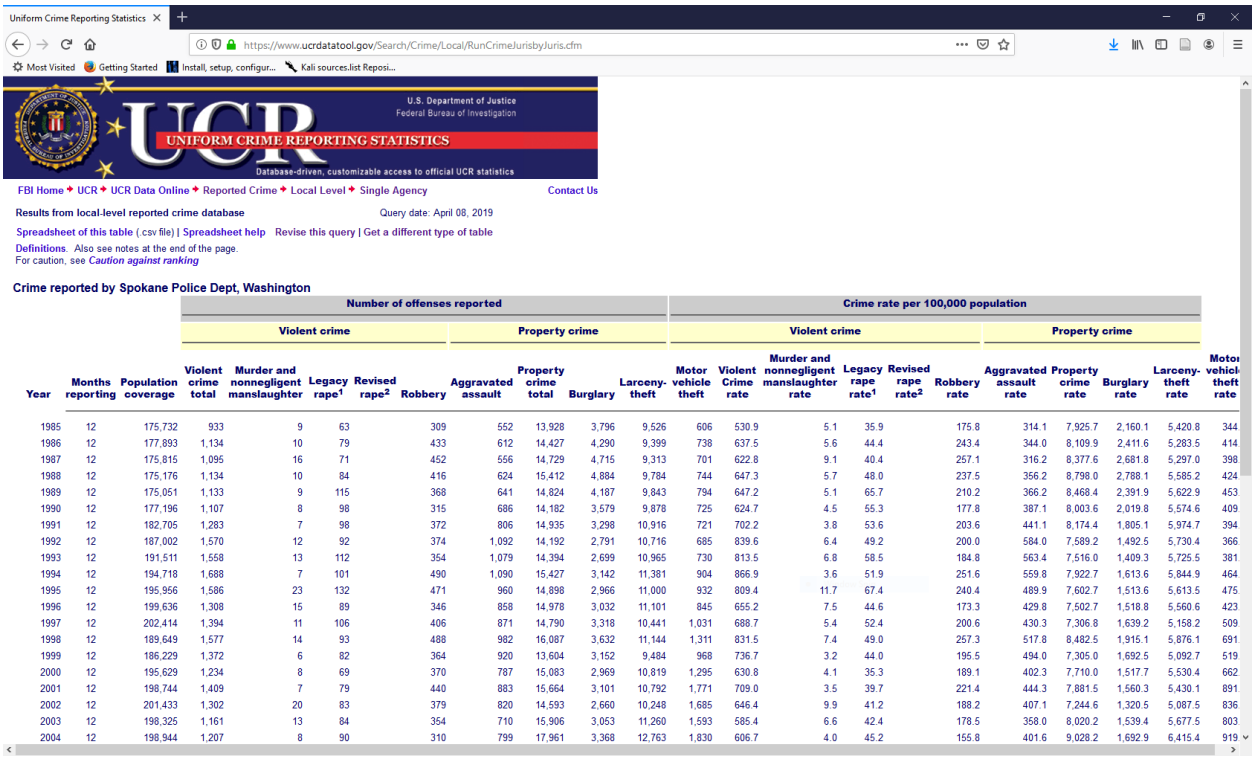
I was recently talking with someone about Spokane's economy and growth, and they mentioned their concern about crime increasing as the city grows. It's a concern that makes sense on the surface; More people could mean more criminals, and therefore more crime. However, there are many factors that contribute to an environment where criminality occurs. Unemployment, local education levels, and support programs for vulnerable members of the community all affect crime levels. Communities also experience a diversity of crime - violent and non-violent. Within each type are varying degrees of offense as well. Saying "crime went up" may be accurate, but within that trend violent crime (murder, robbery, etc.) could go down while non-violent crime (theft, malicious mischief) goes up. I decided to do a quick exploration of available data and what it says about changes in population and crime. I compared different types of crime, both violent and non-violent, with population data over time to see if correlations exist.

Data

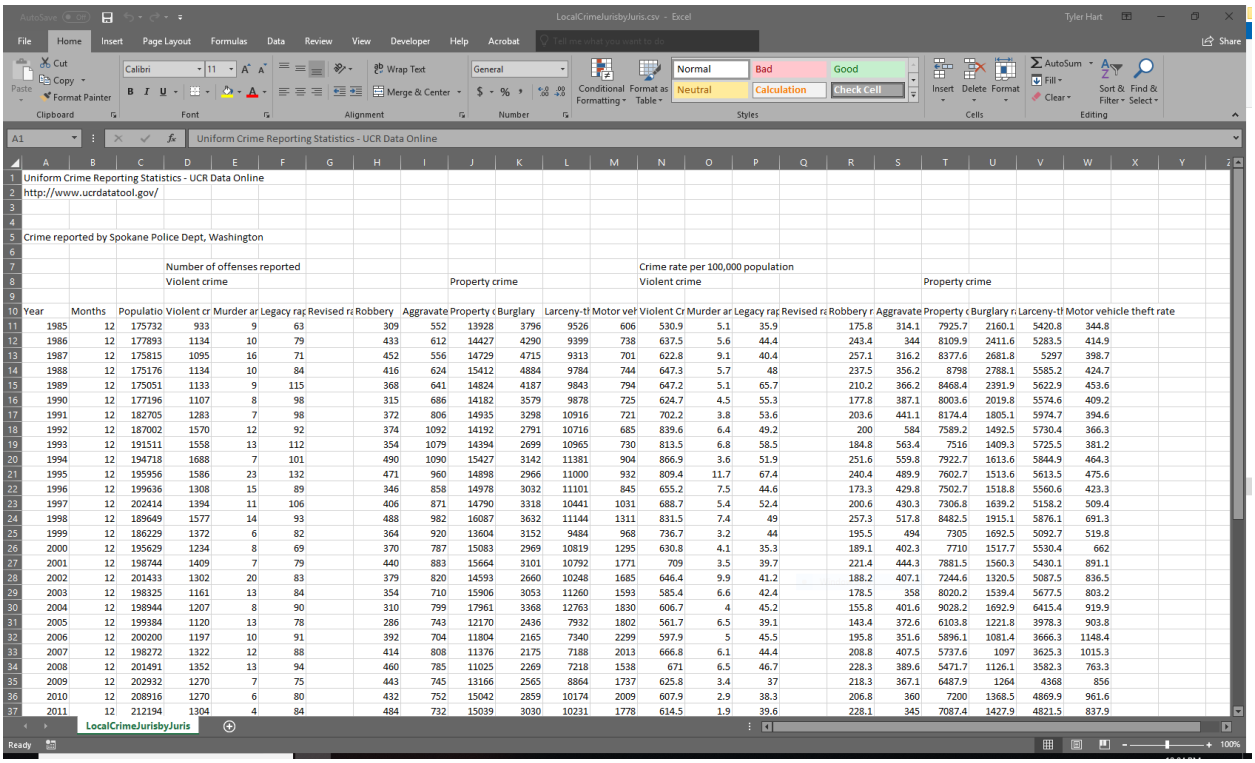
The Federal Bureau of Investigation (FBI) makes crime data available for many localities through the Uniform Crime Reporting (UCR) webpage. In the case of Spokane, WA there is data available from 1985 through 2014. All the data used in this report is sourced from the FBI UCR webpage. I was able to select from a number of different crime types, and for this report chose all available. The output of a search for Spokane data results in a simple HTML table output to the screen:



			Number of offenses reported										Crime rate per 100,000 population									
			Violent crime					Property crime					Violent crime					Property crime				
Year	Months reporting	Population coverage	Violent crime total	Murder and nonnegligent manslaughter	Legacy rape[1]	Revised rape[2]	Robbery	Aggravated assault	Property crime total	Burglary	Larceny-theft	Motor vehicle theft	Violent Crime rate	Murder and nonnegligent manslaughter rate	Legacy rape rate[1]	Revised rape rate[2]	Robbery rate	Aggravated assault rate	Property crime rate	Burglary rate	Larceny-theft rate	Motor vehicle theft rate
1985	12	175,732	933	9	63		309	552	13,928	3,796	9,526	606	530.9	5.1	35.9		175.8	314.1	7,925.7	2,160.1	5,420.8	344
1986	12	177,893	1,134	10	79		433	612	14,427	4,290	9,399	738	637.5	5.6	44.4		243.4	344.0	8,109.9	2,411.6	5,283.5	414
1987	12	175,815	1,095	16	71		452	556	14,729	4,715	9,313	701	622.8	9.1	40.4		257.1	316.2	8,377.6	2,681.8	5,297.0	398
1988	12	175,176	1,134	10	84		416	624	15,412	4,884	9,784	744	647.3	5.7	48.0		237.5	356.2	8,798.0	2,788.1	5,585.2	424
1989	12	175,051	1,133	9	115		368	641	14,824	4,187	9,843	794	647.2	5.1	65.7		210.2	366.2	8,468.4	2,391.9	5,622.9	453
1990	12	177,196	1,107	8	98		315	686	14,182	3,579	9,878	725	624.7	4.5	55.3		177.8	387.1	8,003.6	2,019.8	5,574.6	409
1991	12	182,705	1,283	7	98		372	806	14,935	3,298	10,916	721	702.2	3.8	53.6		203.6	441.1	8,174.4	1,805.1	5,974.7	394
1992	12	187,002	1,570	12	92		374	1,092	14,192	2,791	10,716	685	839.6	6.4	49.2		200.0	584.0	7,589.2	1,492.5	5,730.4	366
1993	12	191,511	1,558	13	112		354	1,079	14,394	2,699	10,965	730	813.5	6.8	58.5		184.8	563.4	7,516.0	1,409.3	5,725.5	381
1994	12	194,718	1,688	7	101		490	1,090	15,427	3,142	11,381	904	866.9	3.6	51.9		251.6	559.8	7,922.7	1,613.6	5,844.9	464
1995	12	195,956	1,586	23	132		471	960	14,898	2,966	11,000	932	809.4	11.7	67.4		240.4	489.9	7,602.7	1,513.6	5,613.5	475
1996	12	199,636	1,308	15	89		346	858	14,978	3,032	11,101	845	655.2	7.5	44.6		173.3	429.8	7,502.7	1,518.8	5,560.6	423
1997	12	202,414	1,394	11	106		406	871	14,790	3,318	10,441	1,031	688.7	5.4	52.4		200.6	430.3	7,306.8	1,639.2	5,158.2	509
1998	12	189,649	1,577	14	93		488	982	16,087	3,632	11,144	1,311	831.5	7.4	49.0		257.3	517.8	8,482.5	1,915.1	5,876.1	691
1999	12	186,229	1,372	6	82		364	920	13,604	3,152	9,484	968	736.7	3.2	44.0		195.5	494.0	7,305.0	1,692.5	5,092.7	519
2000	12	195,629	1,234	8	69		370	787	15,083	2,969	10,819	1,295	630.8	4.1	35.3		189.1	402.3	7,710.0	1,517.7	5,530.4	662
2001	12	198,744	1,409	7	79		440	883	15,664	3,101	10,792	1,771	709.0	3.5	39.7		221.4	444.3	7,881.5	1,560.3	5,430.1	891
2002	12	201,433	1,302	20	83		379	820	14,593	2,660	10,248	1,685	646.4	9.9	41.2		188.2	407.1	7,244.6	1,320.5	5,087.5	836
2003	12	198,325	1,161	13	84		354	710	15,906	3,053	11,260	1,593	585.4	6.6	42.4		178.5	358.0	8,020.2	1,539.4	5,677.5	803
2004	12	198,944	1,207	8	90		310	799	17,961	3,368	12,763	1,830	606.7	4.0	45.2		155.8	401.6	9,028.2	1,692.9	6,415.4	919

Fortunately, there is a handy link to download the data in CSV format so no web scraping is required. The download is named "LocalCrimeJurisbyJuris.csv". Unfortunately, some HTML header information from the

webpage is included in the CSV file, along with loads of extraneous spaces. The extra "data" is easily seen when opening the CSV file in Excel:



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
1	Uniform Crime Reporting Statistics - UCR Data Online																								
2	http://www.ucrdatatool.gov/																								
3																									
4																									
5	Crime reported by Spokane Police Dept, Washington																								
6																									
7				Number of offenses reported										Crime rate per 100,000 population											
8				Violent crime						Property crime				Violent crime							Property crime				
9																									
10	Year	Months	Populatio	Violent cr	Murder ar	Legacy ra	Revised ra	Robbery	Aggravate	Property c	Burglary	Larceny-th	Motor vel	Violent Cr	Murder ar	Legacy ra	Revised ra	Robbery r	Aggravate	Property c	Burglary ra	Larceny-th	Motor vehicle theft rate		
11	1985	12	175732	933	9	63		309	552	13928	3796	9526	606	530.9	5.1	35.9		175.8	314.1	7925.7	2160.1	5420.8	344.8		
12	1986	12	177893	1134	10	79		433	612	14427	4290	9399	738	637.5	5.6	44.4		243.4	344	8109.9	2411.6	5283.5	414.9		
13	1987	12	175815	1095	16	71		452	556	14729	4715	9313	701	622.8	9.1	40.4		257.1	316.2	8377.6	2681.8	5297	398.7		
14	1988	12	175176	1134	10	84		416	624	15412	4884	9784	744	647.3	5.7	48		237.5	356.2	8798	2788.1	5585.2	424.7		
15	1989	12	175051	1133	9	115		368	641	14824	4187	9843	794	647.2	5.1	65.7		210.2	366.2	8468.4	2391.9	5622.9	453.6		
16	1990	12	177196	1107	8	98		315	686	14182	3579	9878	725	624.7	4.5	55.3		177.8	387.1	8003.6	2019.8	5574.6	409.2		
17	1991	12	182705	1283	7	98		372	806	14935	3298	10916	721	702.2	3.8	53.6		203.6	441.1	8174.4	1805.1	5974.7	394.6		
18	1992	12	187002	1570	12	92		374	1092	14192	2791	10716	685	839.6	6.4	49.2		200	584	7589.2	1492.5	5730.4	366.3		
19	1993	12	191511	1558	13	112		354	1079	14394	2699	10965	730	813.5	6.8	58.5		184.8	563.4	7516	1409.3	5725.5	381.2		
20	1994	12	194718	1688	7	101		490	1090	15427	3142	11381	904	866.9	3.6	51.9		251.6	559.8	7922.7	1613.6	5844.9	464.3		
21	1995	12	195956	1586	23	132		471	960	14898	2966	11000	932	809.4	11.7	67.4		240.4	489.9	7602.7	1513.6	5613.5	475.6		
22	1996	12	199636	1308	15	89		346	858	14978	3032	11101	845	655.2	7.5	44.6		173.3	429.8	7502.7	1518.8	5560.6	423.3		
23	1997	12	202414	1394	11	106		406	871	14790	3318	10441	1031	688.7	5.4	52.4		200.6	430.3	7306.8	1639.2	5158.2	509.4		
24	1998	12	189649	1577	14	93		488	982	16087	3632	11144	1311	831.5	7.4	49		257.3	517.8	8482.5	1915.1	5876.1	691.3		
25	1999	12	186229	1372	6	82		364	920	13604	3152	9484	968	736.7	3.2	44		195.5	494	7305	1692.5	5092.7	519.8		
26	2000	12	195629	1234	8	69		370	787	15083	2969	10819	1295	630.8	4.1	35.3		189.1	402.3	7710	1517.7	5530.4	662		
27	2001	12	198744	1409	7	79		440	883	15664	3101	10792	1771	709	3.5	39.7		221.4	444.3	7881.5	1560.3	5430.1	891.1		
28	2002	12	201433	1302	20	83		379	820	14593	2660	10248	1685	646.4	9.9	41.2		188.2	407.1	7244.6	1320.5	5087.5	836.5		
29	2003	12	198325	1161	13	84		354	710	15906	3053	11260	1593	585.4	6.6	42.4		178.5	358	8020.2	1539.4	5677.5	803.2		
30	2004	12	198944	1207	8	90		310	799	17961	3368	12763	1830	606.7	4	45.2		155.8	401.6	9028.2	1692.9	6415.4	919.9		
31	2005	12	199384	1120	13	78		286	743	12170	2436	7932	1802	561.7	6.5	39.1		143.4	372.6	6103.8	1221.8	3978.3	903.8		
32	2006	12	200200	1197	10	91		392	704	11804	2165	7340	2299	597.9	5	45.5		195.8	351.6	5896.1	1081.4	3666.3	1148.4		
33	2007	12	198272	1322	12	88		414	808	11376	2175	7188	2013	666.8	6.1	44.4		208.8	407.5	5737.6	1097	3625.3	1015.3		
34	2008	12	201491	1352	13	94		460	785	11025	2269	7218	1538	671	6.5	46.7		228.3	389.6	5471.7	1126.1	3582.3	763.3		
35	2009	12	202932	1270	7	75		443	745	13166	2565	8864	1737	625.8	3.4	37		218.3	367.1	6487.9	1264	4368	856		
36	2010	12	208916	1270	6	80		432	752	15042	2859	10174	2009	607.9	2.9	38.3		206.8	360	7200	1368.5	4869.9	961.6		
37	2011	12	212194	1304	4	84		484	732	15039	3030	10231	1778	614.5	1.9	39.6		228.1	345	7087.4	1427.9	4821.5	837.9		

I need to strip out data from the first 10 rows in the file and the last 11 rows. Using Excel was the quickest way to drop the extra stuff and get to the data. Next, I imported raw data from the CSV and formatted the *Year* column:

```
df.crime_data <- read_csv(
  "LocalCrimeJurisbyJuris.csv",
  col_types = cols(Year = col_date(format = "%Y"))
  )
```

To make handling columns in the data frame easier I switched all the names from mixed-case to lower-case:

```
names(df.crime_data) <- tolower(names(df.crime_data))
```

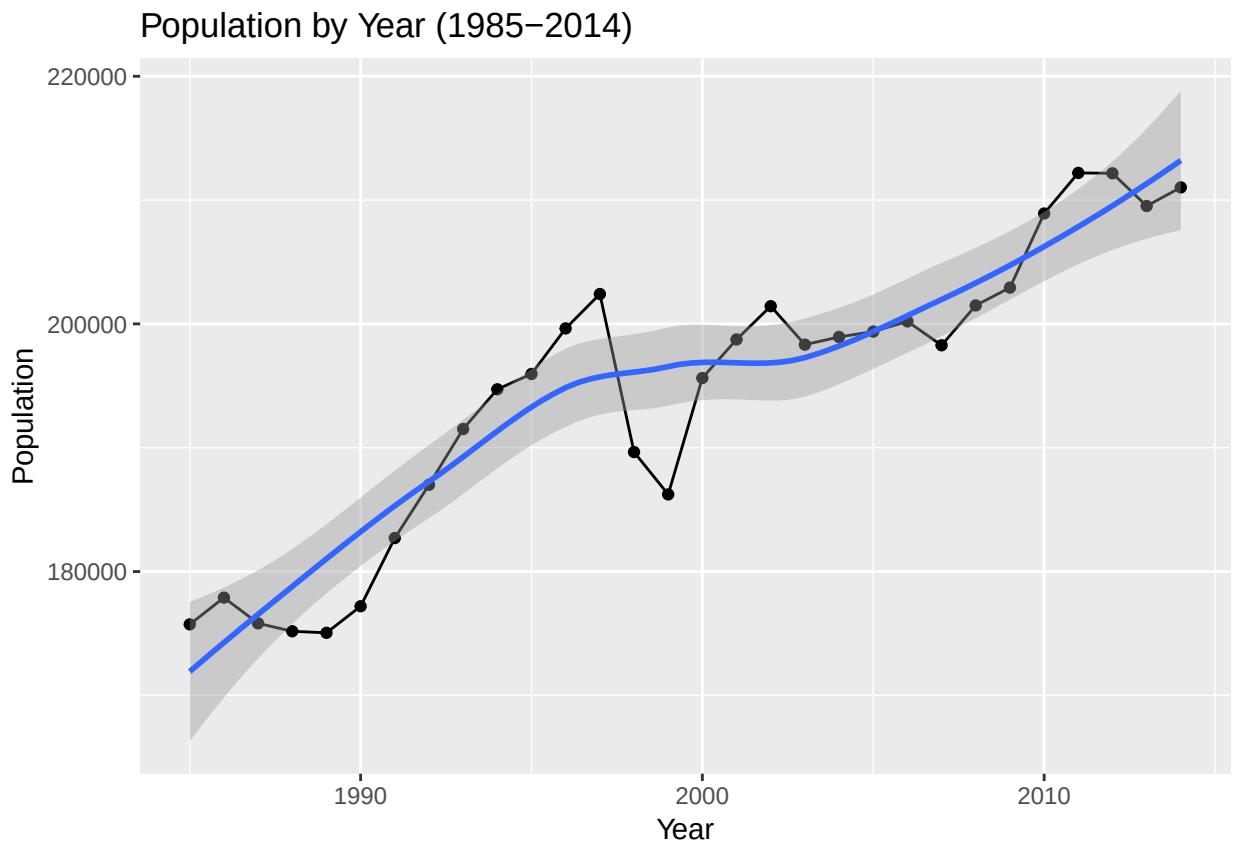
Next, I loaded up the *df.crime_data* data frame into a reusable ggplot object. In the process I also set the *year* column as the *X* aesthetic so it didn't need to be done repeatedly:

```
plot.annual_crime <- df.crime_data %>%
  ggplot(aes(year)) +
  xlab("Year")
```

I created a basic line plot of overall population, leveraging that reusable ggplot object. In the process I also include the data points to make the line more meaningful.

This plot gives us a feel for how Spokane has grown from 1985-2014, including a smoothed line showing the conditional mean:

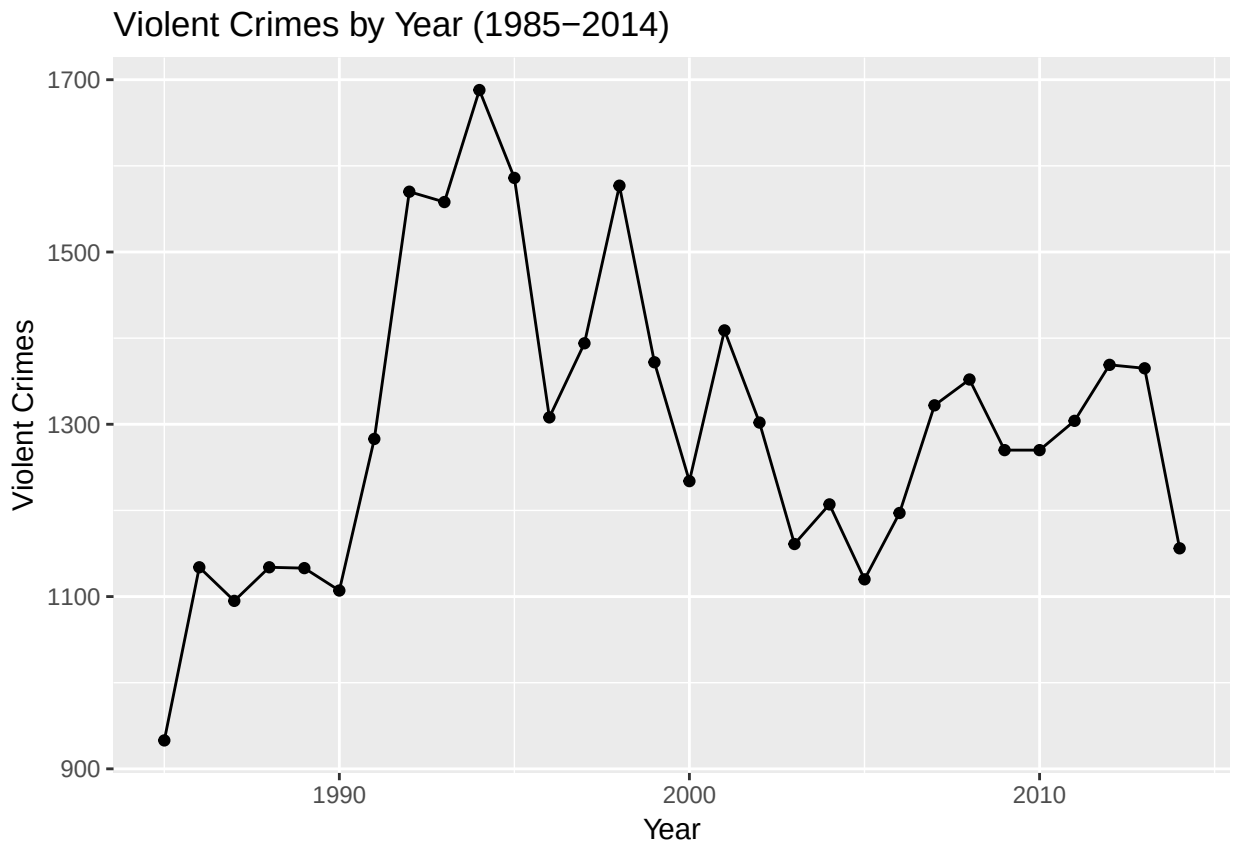
```
plot.annual_crime +
  geom_line(aes(y = population)) +
  geom_point(aes(y = population)) +
  geom_smooth(aes(y = population)) +
  ylab("Population") +
  ggtitle("Population by Year (1985-2014)")
```



From 1985 to 2014 (175,732 and 211,025 people, respectively) there was a 20% increase in Spokane's population.

I created the same plot, but with the total number of violent crimes per year instead of population numbers:

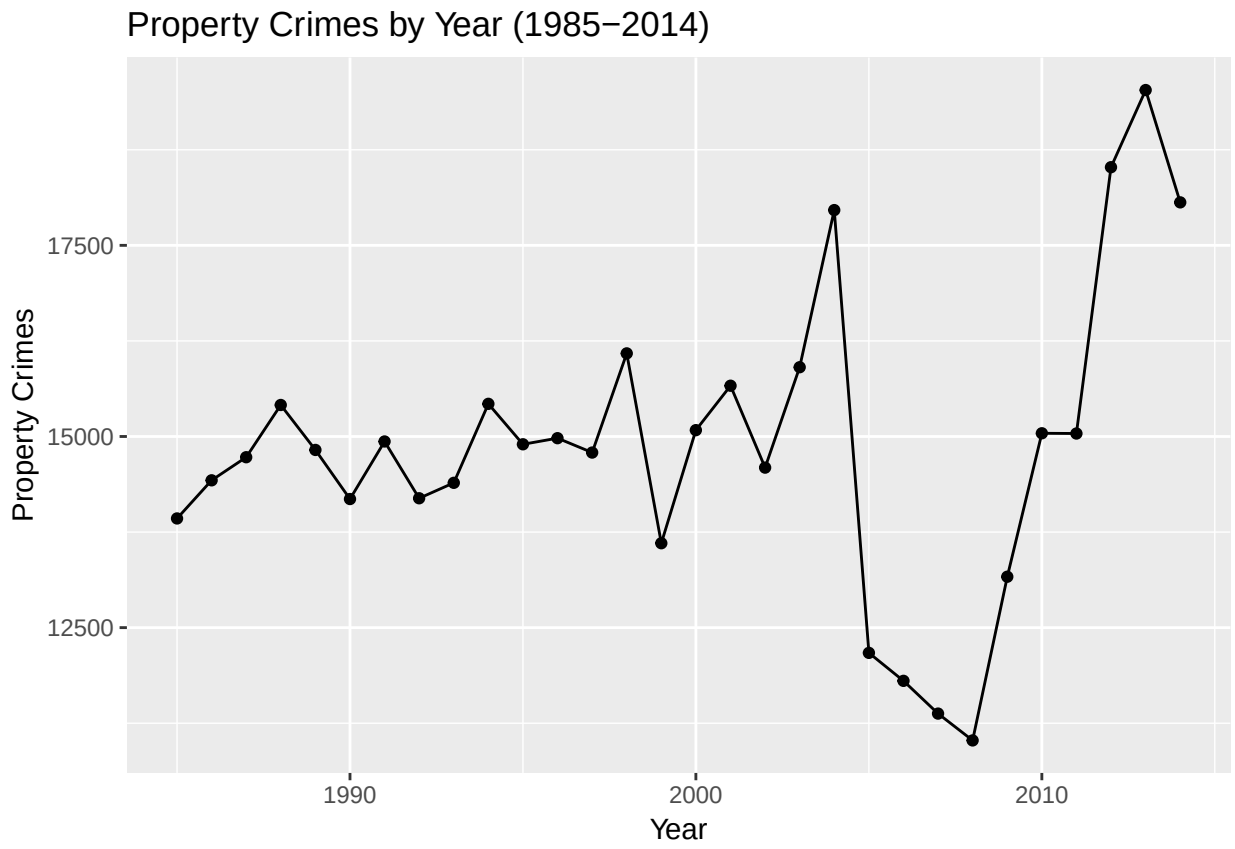
```
plot.annual_crime +
  geom_line(aes(y = `violent crime total`)) +
  geom_point(aes(y = `violent crime total`)) +
  ylab("Violent Crimes") +
  ggtitle("Violent Crimes by Year (1985-2014)")
```



From its peak in 1994 to 2014 (1,688 and 1,156 incidents, respectively) Spokane saw a 31.5% decrease in total violent crime. Over that same period Spokane's population grew 8.37%. When comparing violent crime against population number there doesn't appear to be a hard-and-fast association. Howerver, breaking down the types of violent crime yielded more insights into associations between population and crime.

I did the same type of graph for property crime totals:

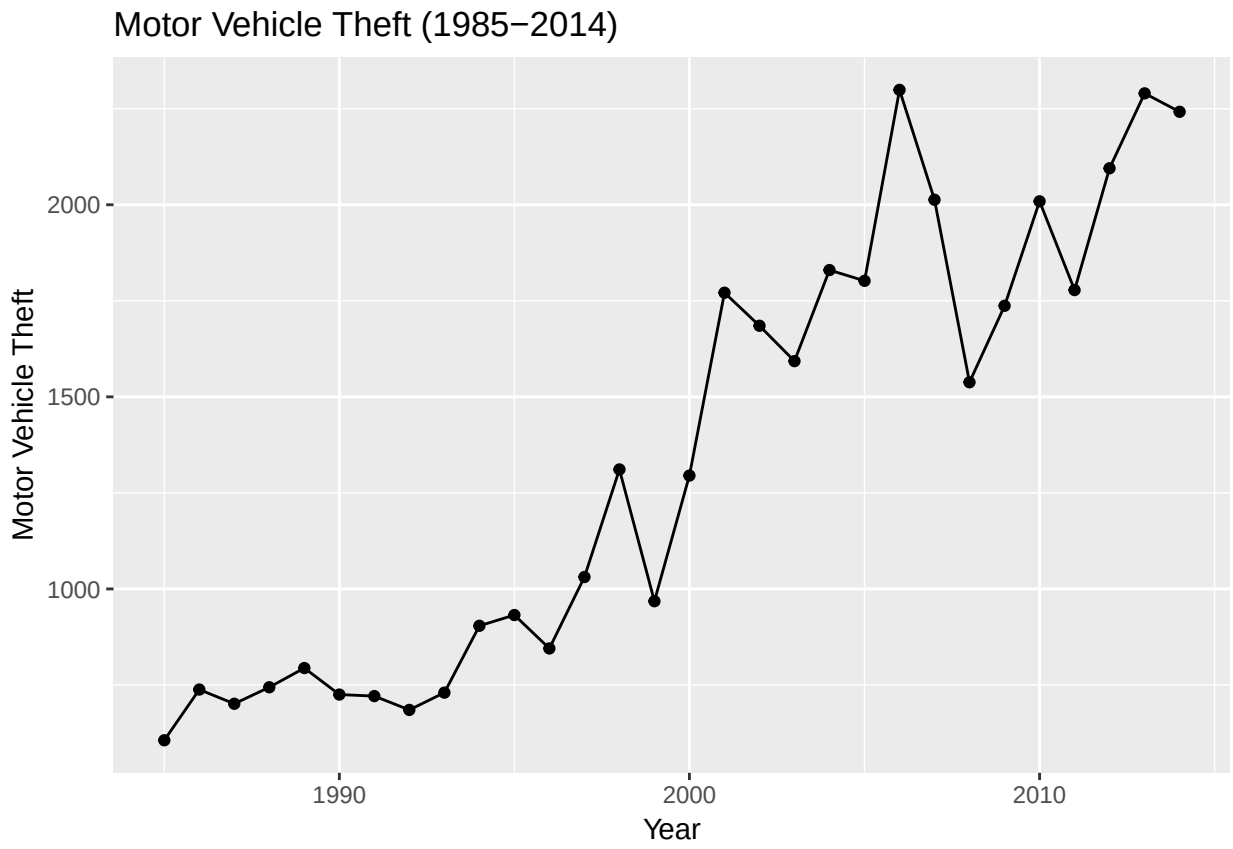
```
plot.annual_crime +
  geom_line(aes(y = `property crime total`)) +
  geom_point(aes(y = `property crime total`)) +
  ylab("Property Crimes") +
  ggtitle("Property Crimes by Year (1985-2014)")
```



Again, there doesn't appear to be an immediately-apparent link between population growth and this type of crime overall. Any insights into the relationship between crime and population will probably be found within individual types of crime. First I broke out a graph for motor vehicle thefts, then for larceny-theft and burglaries.

Here is the plot just for motor vehicle thefts:

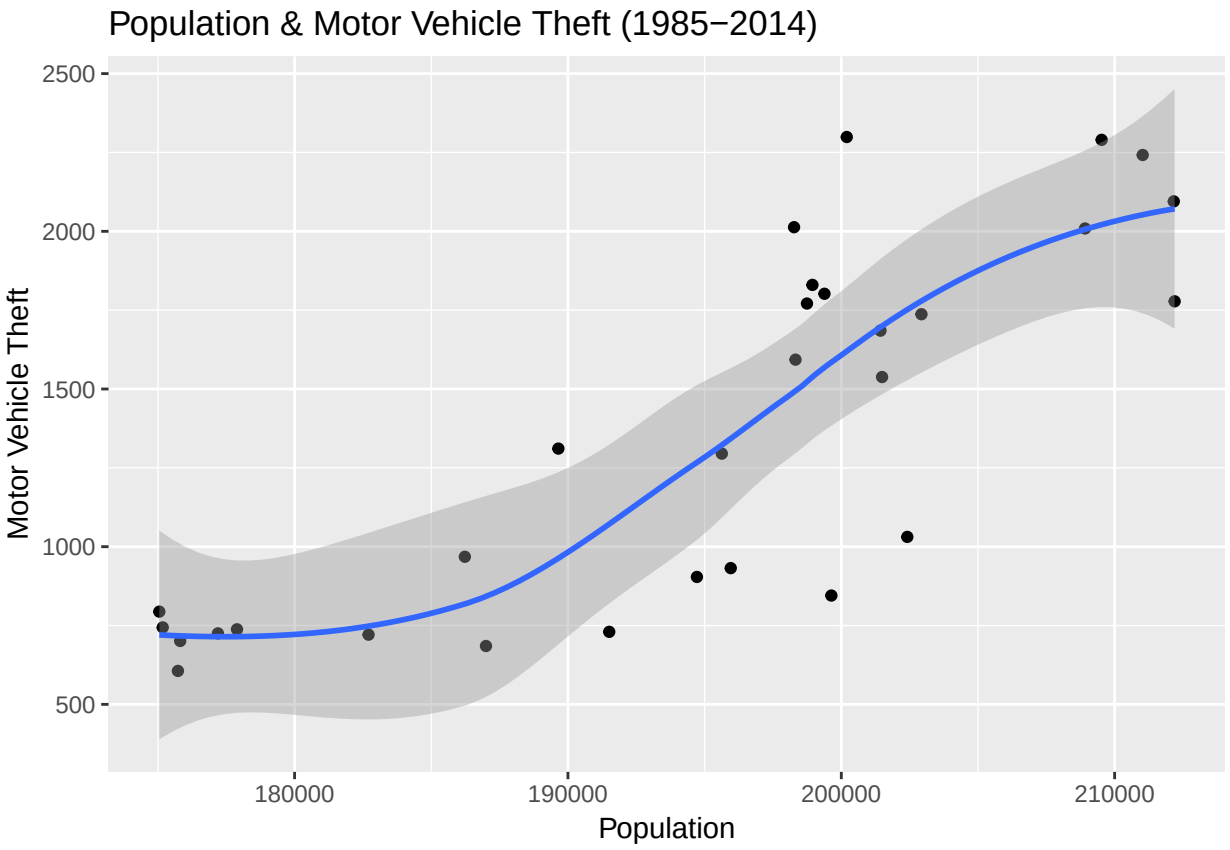
```
plot.annual_crime +
  geom_line(aes(y = `motor vehicle theft`)) +
  geom_point(aes(y = `motor vehicle theft`)) +
  ylab("Motor Vehicle Theft") +
  ggtitle("Motor Vehicle Theft (1985-2014)")
```



In the case of motor vehicle theft there does appear to be a steady upward trend that resembles population growth. From 1985 to 2014 (606 and 2,242 incidents, respectively) there was a 269.9% increase in motor vehicle thefts.

I used a scatter plot to visualize the population and motor vehicle thefts, and added a smoothed conditional means (*geom_smooth*) plot over the top:

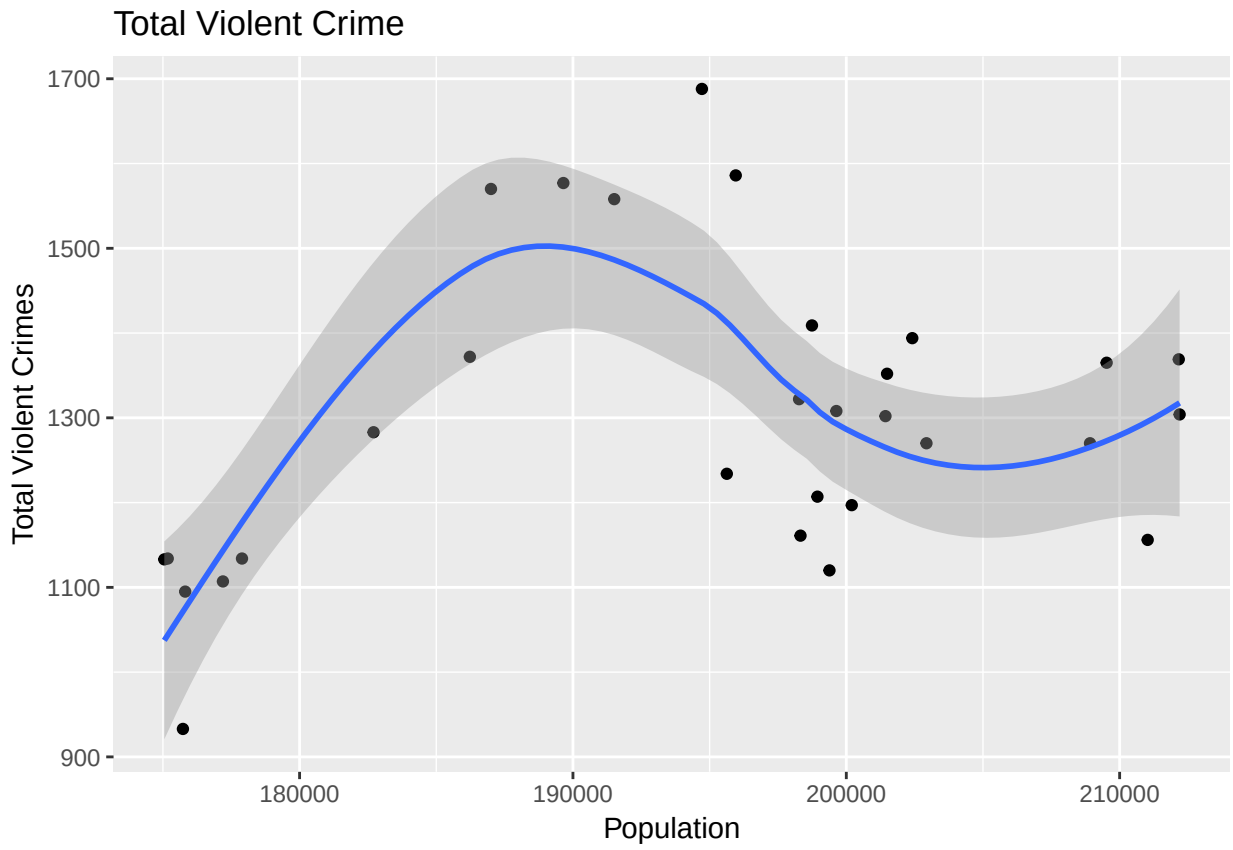
```
df.crime_data %>%
  ggplot(aes(population, `motor vehicle theft`)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Motor Vehicle Theft") +
  ggtitle("Population & Motor Vehicle Theft (1985-2014)")
```



It appears that a relationship may exist between population and vehicle thefts.

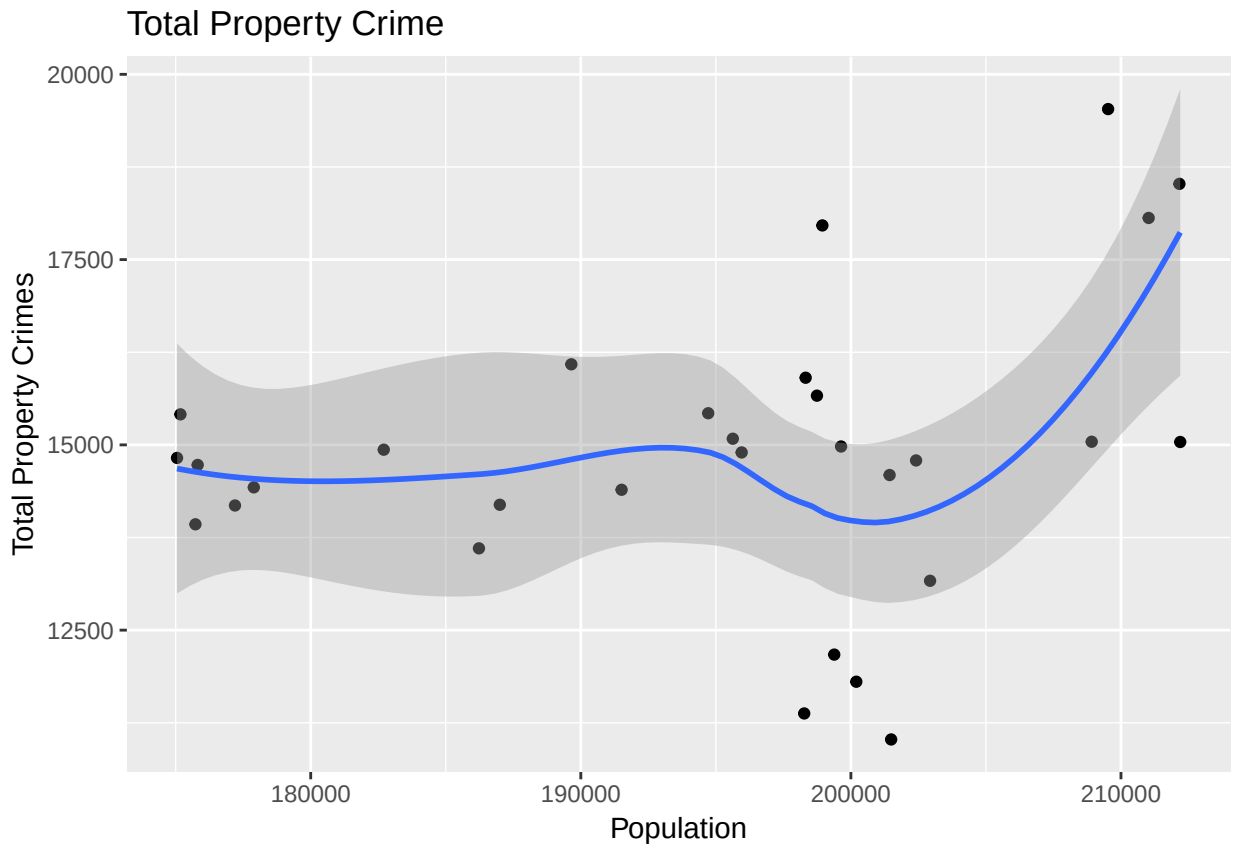
I used code for the previous scatter plot with other types of crime, including total violent crime:

```
df.crime_data %>%
  ggplot(aes(population, `violent crime total`)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Total Violent Crimes") +
  ggtitle("Total Violent Crime")
```



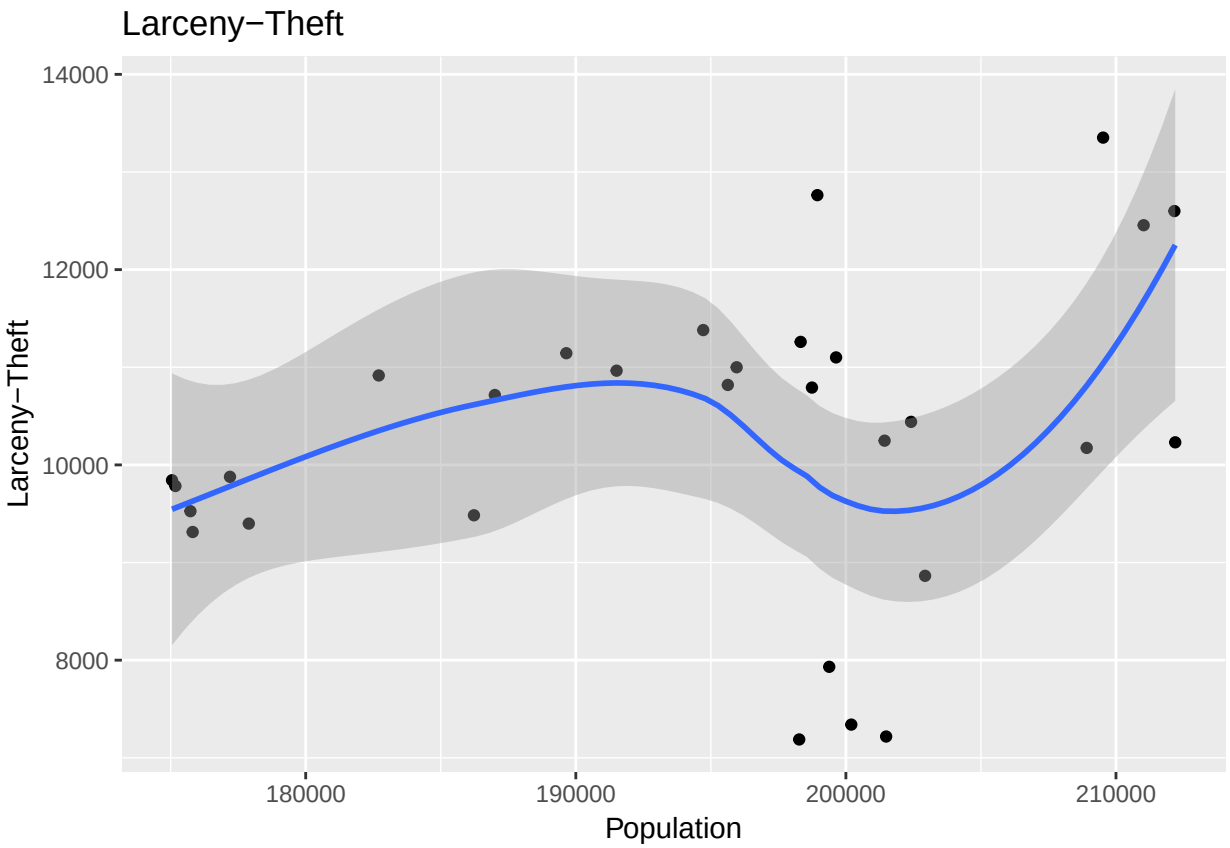
Total property crime:

```
df.crime_data %>%
  ggplot(aes(population, `property crime total`)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Total Property Crimes") +
  ggtitle("Total Property Crime")
```



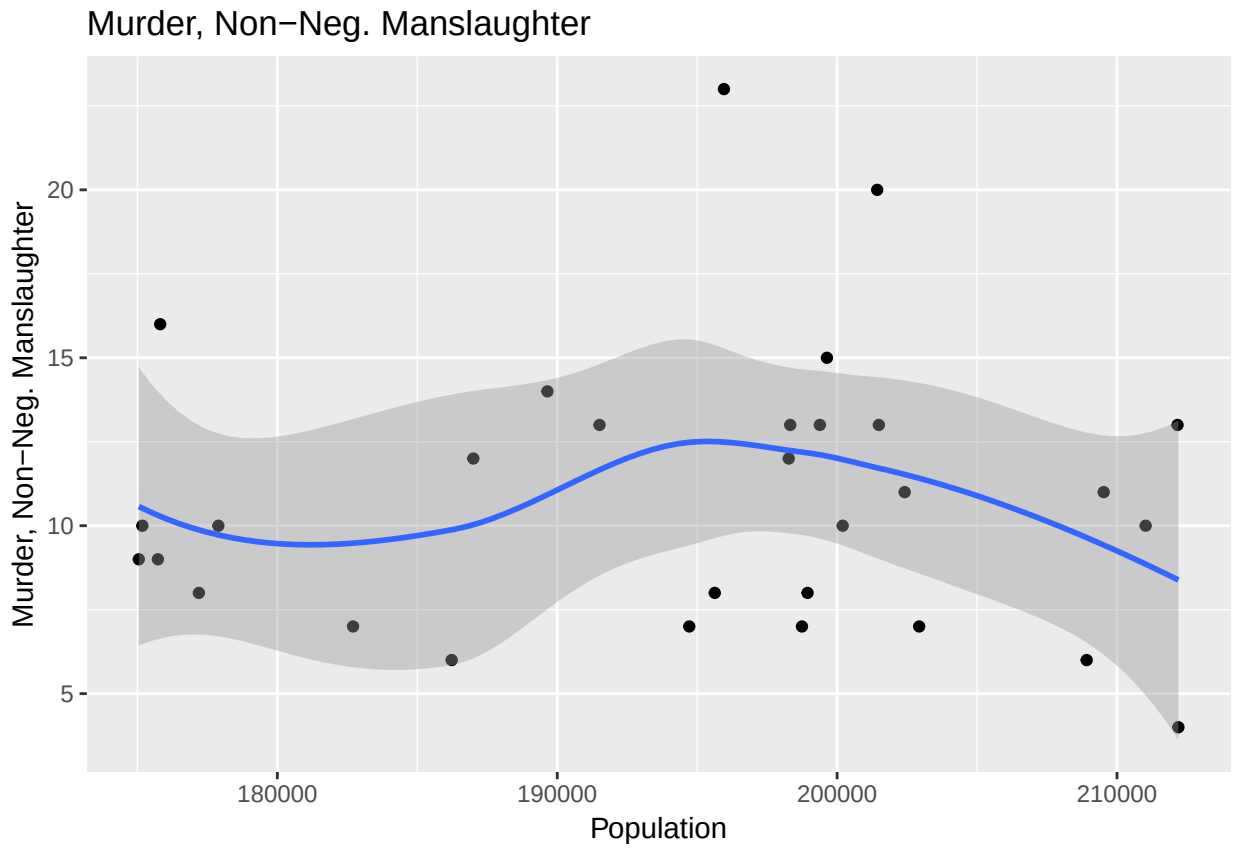
Larceny-theft:

```
df.crime_data %>%
  ggplot(aes(population, `larceny-theft`)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Larceny-Theft") +
  ggtitle("Larceny-Theft")
```



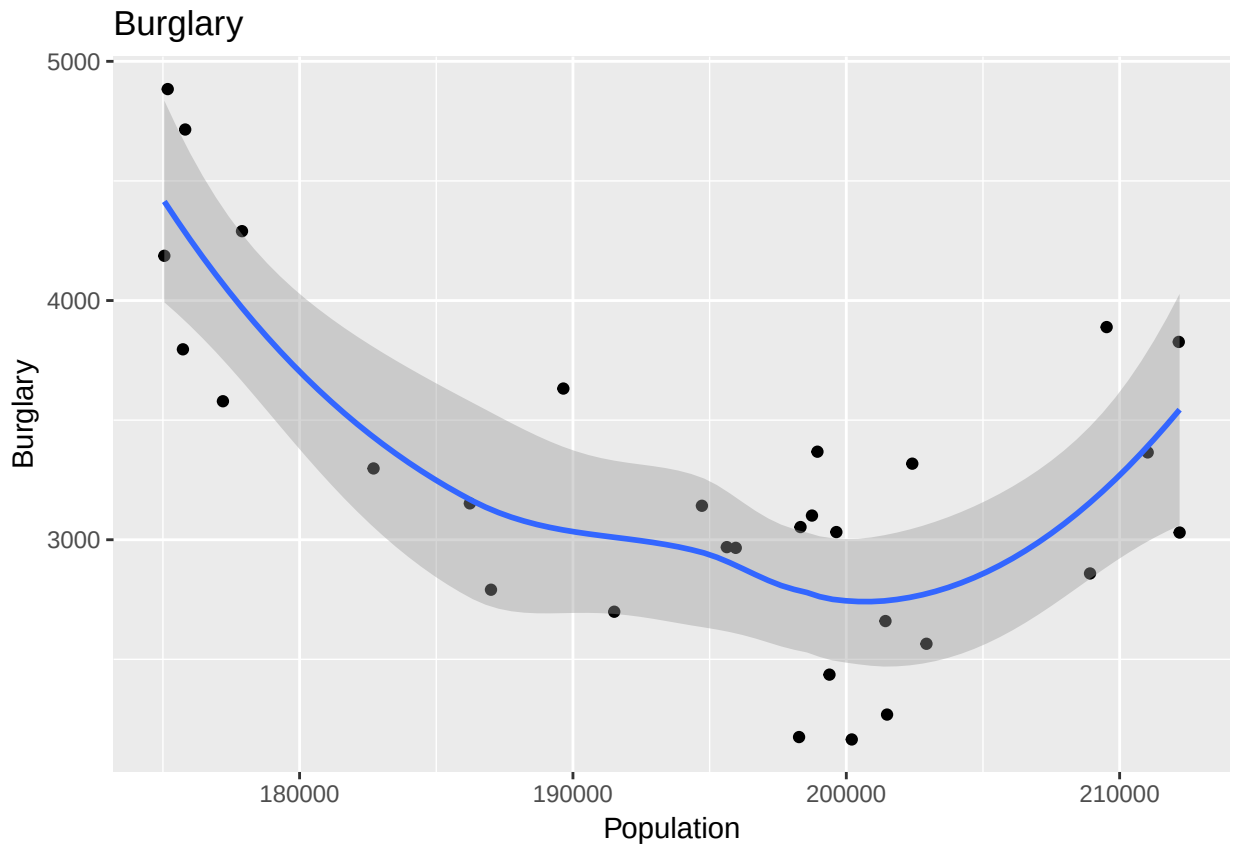
Murder and non-negligent manslaughter:

```
df.crime_data %>%
  ggplot(aes(population, `murder and nonnegligent manslaughter`)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Murder, Non-Neg. Manslaughter") +
  ggtitle("Murder, Non-Neg. Manslaughter")
```



Burglary:

```
df.crime_data %>%
  ggplot(aes(population, burglary)) +
  geom_point() +
  geom_smooth() +
  xlab("Population") +
  ylab("Burglary") +
  ggtitle("Burglary")
```



While the first scatter plot we looked at seemed clear, I'm not confident there is much positive correlation between crime and population outside of motor vehicle theft.

Correlations

The Pearson correlation coefficient quantifies (possible) relationships between the two sets of data. I used this built-in R feature so there would be a numeric value for easy comparison. The coefficient value is always in the range of negative-one to one (-1:1). Values less than zero mean there is a negative correlation; When one value increases, the other decreases. Values above zero indicate a positive correlation; When one value increases, the other does as well. A zero value indicates no correlation at all, and values near zero are "weak". First, I looked at overall correlation values for total violent and property crimes:

```
corr.crimes <- c(
  cor(
    df.crime_data$population,
    df.crime_data$`violent crime total`
  ),

  cor(
    df.crime_data$population,
    df.crime_data$`property crime total`
    )
)

df.correlation_values <- data.frame(
  crime_type = c("Total Violent Crime", "Total Property Crime"),
  correlation_coef = corr.crimes
)

kable(df.correlation_values, caption = "Total Crime Correlations")
```

Table 1: Total Crime Correlations

crime_type	correlation_coef
Total Violent Crime	0.2959880
Total Property Crime	0.2520579

There is a weak positive correlation between total violent crime and population. An even weaker correlation exists for property crime. Given more recent data and the continuing downturn in crime, it's possible they have become weaker or even turned negative. I wouldn't be confident making and defending the blanket statement, "crime goes up along with population in Spokane".

Finally, I looked at correlation values for individual types of crime and built a table:

```
corr.specific_crimes <- c(
  cor(
    df.crime_data$population,
    df.crime_data$`motor vehicle theft`
    ),

  cor(
    df.crime_data$population,
    df.crime_data$`larceny-theft`
    ),

  cor(
    df.crime_data$population,
    df.crime_data$`murder and nonnegligent manslaughter`
    ),

  cor(
    df.crime_data$population,
    df.crime_data$`aggravated assault`
    ),

  cor(
    df.crime_data$population,
    df.crime_data$`burglary`
    ),

  cor(
    df.crime_data$population,
    df.crime_data$`robbery`
    )
)

df.correlation_values <- data.frame(
  crime_type = c(
    "Motor Vehicle Theft",
    "Larceny-Theft",
    "Murder & Non-Negl. Manslaughter",
    "Aggravated Assault",
    "Burglary",
    "Robbery"
    ),
  correlation_coef = corr.specific_crimes
)

kable(
  df.correlation_values[
    order(-df.correlation_values$correlation_coef),
    ], caption = "Crime-Type Correlations"
  )
```

Table 2: Crime-Type Correlations

	crime_type	correlation_coef
1	Motor Vehicle Theft	0.8206645
6	Robbery	0.3820753
2	Larceny-Theft	0.2500194
4	Aggravated Assault	0.1753144
3	Murder & Non-Negl. Manslaughter	0.0112465
5	Burglary	-0.5400008

There was a strong positive correlation between motor vehicle theft and population. I could comfortably make the statement, "more cars were being stolen while the population increased." However, it's important to remember that *correlation is not causation.* More research is needed before I could say definitively that more cars were being stolen *because of* population growth. A positive correlation existed for robbery as well, though it was less than half as strong. The coefficient for murder and non-negligent manslaughter was almost zero - I wouldn't really say, "more people were being murdered as the population grew". Nor would I say, "fewer people were being murdered as the population grew", because it was pretty much static.

One surprising result was the negative correlation between population and burglaries. As the population grew, burglaries went down. Again, I can't say the population change was the *cause* of a reduction in burglaries. However, I might be comfortable saying, "burglaries went down as the population increased".

Summary

Was there a correlation between population growth and crime? **Yes**. Can I argue for the blanket statement that crime *in-general* went up along with the population? **No**. While motor vehicle theft and robbery increased along with the population, murders stayed the same, while burglaries went down.