FBI NICS Firearm Background Check Data Analysis

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Introduction

The data in this project comes from the FBI's National Instant Criminal Background Check System (https://www.fbi.gov/about-us/cjis/nics). The NICS is used to determine whether a prospective buyer is eligible to buy firearms or explosives. Gun shops call into this system to ensure that each customer does not have a criminal record or isn't otherwise ineligible to make a purchase. The data has been supplemented with state level data from census.gov (https://www.google.com/url?q=https://www.census.gov/&sa=D&ust=1532469042127000).

> Mandated by the Brady Handgun Violence Prevention Act of 1993 and launched by the FBI on November 30, 1998, NICS is used by Federal Firearms Licensees (FFLs) to instantly determine whether a prospective buyer is eligible to buy firearms or explosives. Before ringing up the sale, cashiers call in a check to the FBI or to other designated agencies to ensure that each customer does not have a criminal record or isn't otherwise ineligible to make a purchase. More than 100 million such checks have been made in the last decade, leading to more than 700,000 denials.

In [1]:

```
# import libraries
import pandas as pd
import numpy as np
import datetime
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Data Wrangling

In this section of the report, I load in the data, check for cleanliness, and then trim and clean the datasets for analysis.

General Properties

In [2]:

```
# Load data
gun = pd.read_excel('data/gun_data.xlsx')
census = pd.read_csv('data/U.S. Census Data.csv', thousands=',')
```

Gun dataset

In [3]:

```
# print out a shape of dataframe
gun.shape
```

Out[3]:

```
(12485, 27)
```

In [4]:

```
# print out a few lines
gun.head(5)
```

Out[4]:

	month	state	permit	permit_recheck	handgun	long_gun	other	multiple
0	2017-09	Alabama	16717.0	0.0	5734.0	6320.0	221.0	317
1	2017-09	Alaska	209.0	2.0	2320.0	2930.0	219.0	160
2	2017-09	Arizona	5069.0	382.0	11063.0	7946.0	920.0	631
3	2017-09	Arkansas	2935.0	632.0	4347.0	6063.0	165.0	366
4	2017-09	California	57839.0	0.0	37165.0	24581.0	2984.0	0

5 rows × 27 columns

In [5]:

```
# display summary of the dataframe
gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12485 entries, 0 to 12484
Data columns (total 27 columns):
month                        12485 non-null object
state                        12485 non-null object
permit                       12461 non-null float64
permit_recheck               1100 non-null float64
handgun                      12465 non-null float64
long_gun                     12466 non-null float64
other                        5500 non-null float64
multiple                     12485 non-null int64
admin                        12462 non-null float64
prepawn_handgun              10542 non-null float64
prepawn_long_gun             10540 non-null float64
prepawn_other                5115 non-null float64
redemption_handgun           10545 non-null float64
redemption_long_gun          10544 non-null float64
redemption_other             5115 non-null float64
returned_handgun             2200 non-null float64
returned_long_gun            2145 non-null float64
returned_other               1815 non-null float64
rentals_handgun              990 non-null float64
rentals_long_gun             825 non-null float64
private_sale_handgun         2750 non-null float64
private_sale_long_gun        2750 non-null float64
private_sale_other           2750 non-null float64
return_to_seller_handgun     2475 non-null float64
return_to_seller_long_gun    2750 non-null float64
return_to_seller_other       2255 non-null float64
totals                       12485 non-null int64
dtypes: float64(23), int64(2), object(2)
memory usage: 2.6+ MB
```

In [6]:

```
# check for duplicates
gun.duplicated().sum()
```

Out[6]:

```
0
```

Gun dataset is pretty clean. In the Data Cleaning section I will fix the following issues:

- 'month' column contains both year and month;
- 'handgun' column contains null values;
- 'long_gun' column contains null values;

Despite those small issues, I can get some statistics already.

In [7]:

```
# display basic stats
gun.describe()
```

Out[7]:

	permit	permit_recheck	handgun	long_gun	other
count	12461.000000	1100.000000	12465.000000	12466.000000	5500.000000
mean	6413.629404	1165.956364	5940.881107	7810.847585	360.471636
std	23752.338269	9224.200609	8618.584060	9309.846140	1349.478273
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	865.000000	2078.250000	17.000000
50%	518.000000	0.000000	3059.000000	5122.000000	121.000000
75%	4272.000000	0.000000	7280.000000	10380.750000	354.000000
max	522188.000000	116681.000000	107224.000000	108058.000000	77929.000000

8 rows × 25 columns

Census dataset

In [8]:

```
# print out dataframe
census.head(5)
```

Out[8]:

	Fact	Fact Note	Alabama	Alaska	Arizona	Arkansas	California	Colorado	C
0	Population estimates, July 1, 2016, (V2016)	NaN	4,863,300	741,894	6,931,071	2,988,248	39,250,017	5,540,545	3,
1	Population estimates base, April 1, 2010, (V2...	NaN	4,780,131	710,249	6,392,301	2,916,025	37,254,522	5,029,324	3,
2	Population, percent change - April 1, 2010 (es...	NaN	1.70%	4.50%	8.40%	2.50%	5.40%	10.20%	0.
3	Population, Census, April 1, 2010	NaN	4,779,736	710,231	6,392,017	2,915,918	37,253,956	5,029,196	3,
4	Persons under 5 years, percent, July 1, 2016, ...	NaN	6.00%	7.30%	6.30%	6.40%	6.30%	6.10%	5.

5 rows × 52 columns

In [9]:

```
# display summary of the dataframe
census.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85 entries, 0 to 84
Data columns (total 52 columns):
Fact              80 non-null object
Fact Note         28 non-null object
Alabama           65 non-null object
Alaska            65 non-null object
Arizona           65 non-null object
Arkansas          65 non-null object
California        65 non-null object
Colorado          65 non-null object
Connecticut       65 non-null object
Delaware          65 non-null object
Florida           65 non-null object
Georgia           65 non-null object
Hawaii            65 non-null object
Idaho             65 non-null object
Illinois          65 non-null object
Indiana           65 non-null object
Iowa              65 non-null object
Kansas            65 non-null object
Kentucky          65 non-null object
Louisiana         65 non-null object
Maine             65 non-null object
Maryland          65 non-null object
Massachusetts     65 non-null object
Michigan          65 non-null object
Minnesota         65 non-null object
Mississippi       65 non-null object
Missouri          65 non-null object
Montana           65 non-null object
Nebraska          65 non-null object
Nevada            65 non-null object
New Hampshire     65 non-null object
New Jersey        65 non-null object
New Mexico        65 non-null object
New York          65 non-null object
North Carolina    65 non-null object
North Dakota      65 non-null object
Ohio              65 non-null object
Oklahoma          65 non-null object
Oregon            65 non-null object
Pennsylvania      65 non-null object
Rhode Island      65 non-null object
South Carolina    65 non-null object
South Dakota      65 non-null object
Tennessee         65 non-null object
Texas             65 non-null object
Utah              65 non-null object
Vermont           65 non-null object
Virginia          65 non-null object
Washington        65 non-null object
West Virginia     65 non-null object
Wisconsin         65 non-null object
Wyoming           65 non-null object
dtypes: object(52)
memory usage: 34.6+ KB
```

In [10]:

```
# check for duplicates
census.duplicated().sum()
```

Out[10]:

3

Census dataset is messy. In the Data Cleaning section I will fix the following issues:

- 'Fact Note' column will not be useful for analysis and can be removed;
- rows starting from the row 65 will not be useful for analysis and can be removed;
- dateset would be easier to use when transposed;
- column names can be simplified;
- all columns are strings, while some hold numeric values;

Data Cleaning

Census Dataset

In [11]:

```
# keep all rows up to 65
census = census.iloc[:65,:]

# drop 'Fact note' column
census = census.drop(columns = ['Fact Note'])

# transpose dataframe
census = census.transpose()

# convert first row to column's header
census.rename(columns=census.iloc[0], inplace=True)
census.drop(census.index[0], inplace=True)
```

In [12]:

```
# display full list of columns
census.columns.values
```

Out[12]:

```
array(['Population estimates, July 1, 2016,  (V2016)',
       'Population estimates base, April 1, 2010,  (V2016)',
       'Population, percent change - April 1, 2010 (estimates base) to Jul
y 1, 2016,  (V2016)',
       'Population, Census, April 1, 2010',
       'Persons under 5 years, percent, July 1, 2016,  (V2016)',
       'Persons under 5 years, percent, April 1, 2010',
       'Persons under 18 years, percent, July 1, 2016,  (V2016)',
       'Persons under 18 years, percent, April 1, 2010',
       'Persons 65 years and over, percent,  July 1, 2016,  (V2016)',
       'Persons 65 years and over, percent, April 1, 2010',
       'Female persons, percent,  July 1, 2016,  (V2016)',
       'Female persons, percent, April 1, 2010',
       'White alone, percent, July 1, 2016,  (V2016)',
       'Black or African American alone, percent, July 1, 2016,  (V2016)',
       'American Indian and Alaska Native alone, percent, July 1, 2016,
(V2016)',
       'Asian alone, percent, July 1, 2016,  (V2016)',
       'Native Hawaiian and Other Pacific Islander alone, percent, July 1,
2016,  (V2016)',
       'Two or More Races, percent, July 1, 2016,  (V2016)',
       'Hispanic or Latino, percent, July 1, 2016,  (V2016)',
       'White alone, not Hispanic or Latino, percent, July 1, 2016,  (V201
6)',
       'Veterans, 2011-2015', 'Foreign born persons, percent, 2011-2015',
       'Housing units,  July 1, 2016,  (V2016)',
       'Housing units, April 1, 2010',
       'Owner-occupied housing unit rate, 2011-2015',
       'Median value of owner-occupied housing units, 2011-2015',
       'Median selected monthly owner costs -with a mortgage, 2011-2015',
       'Median selected monthly owner costs -without a mortgage, 2011-201
5',
       'Median gross rent, 2011-2015', 'Building permits, 2016',
       'Households, 2011-2015', 'Persons per household, 2011-2015',
       'Living in same house 1 year ago, percent of persons age 1 year+, 2
011-2015',
       'Language other than English spoken at home, percent of persons age
5 years+, 2011-2015',
       'High school graduate or higher, percent of persons age 25 years+,
2011-2015',
       "Bachelor's degree or higher, percent of persons age 25 years+, 201
1-2015",
       'With a disability, under age 65 years, percent, 2011-2015',
       'Persons  without health insurance, under age 65 years, percent',
       'In civilian labor force, total, percent of population age 16 years
+, 2011-2015',
       'In civilian labor force, female, percent of population age 16 year
s+, 2011-2015',
       'Total accommodation and food services sales, 2012 ($1,000)',
       'Total health care and social assistance receipts/revenue, 2012
($1,000)',
       'Total manufacturers shipments, 2012 ($1,000)',
       'Total merchant wholesaler sales, 2012 ($1,000)',
       'Total retail sales, 2012 ($1,000)',
       'Total retail sales per capita, 2012',
       'Mean travel time to work (minutes), workers age 16 years+, 2011-20
15',
       'Median household income (in 2015 dollars), 2011-2015',
       'Per capita income in past 12 months (in 2015 dollars), 2011-2015',
```

```
       'Persons in poverty, percent',
       'Total employer establishments, 2015', 'Total employment, 2015',
       'Total annual payroll, 2015 ($1,000)',
       'Total employment, percent change, 2014-2015',
       'Total nonemployer establishments, 2015', 'All firms, 2012',
       'Men-owned firms, 2012', 'Women-owned firms, 2012',
       'Minority-owned firms, 2012', 'Nonminority-owned firms, 2012',
       'Veteran-owned firms, 2012', 'Nonveteran-owned firms, 2012',
       'Population per square mile, 2010',
       'Land area in square miles, 2010', 'FIPS Code'], dtype=object)
```

In [13]:

```
# select columns which will be analysed
census = census[['Population, Census, April 1, 2010',
                  'Population estimates, July 1, 2016,  (V2016)',
                  'Population per square mile, 2010',
                  'Land area in square miles, 2010',
                  'White alone, not Hispanic or Latino, percent, July 1, 2016,  (V201
6)',
                  'Hispanic or Latino, percent, July 1, 2016,  (V2016)',
                  'Black or African American alone, percent, July 1, 2016,  (V2016)',
                  'American Indian and Alaska Native alone, percent, July 1, 2016,  (V2
016)',
                  'Native Hawaiian and Other Pacific Islander alone, percent, July 1, 2
016,  (V2016)',
                  'Asian alone, percent, July 1, 2016,  (V2016)',
                  'Foreign born persons, percent, 2011-2015',
                  'Language other than English spoken at home, percent of persons age 5
 years+, 2011-2015',
                  'High school graduate or higher, percent of persons age 25 years+, 20
11-2015',
                  "Bachelor's degree or higher, percent of persons age 25 years+, 2011-
2015",
                  'Veterans, 2011-2015',
                  'With a disability, under age 65 years, percent, 2011-2015',

                  'Persons in poverty, percent',
                  'Persons  without health insurance, under age 65 years, percent',

                  'Persons per household, 2011-2015',
                  'Per capita income in past 12 months (in 2015 dollars), 2011-2015',
                  'Median household income (in 2015 dollars), 2011-2015'
                 ]]

# rename columns
census.columns = ['Population_2010',
                  'Population_2016',
                  'Population_sq_mile_2010',
                  'Land_area_sq_mile_2010',
                  'White_2016',
                  'Hispanic_Latino_2016',
                  'Black_African_American_2016',
                  'American_Indian_Alaska_Native_2016',
                  'Native_Hawaiian_Pacific_Islander_2016',
                  'Asian_2016',
                  'Foreign_born_persons_2011-2015',
                  'Language_not_English_spoken_home_2011-2015',
                  'High_school_or_higher_2011-2015',
                  'Bachelor_or_higher_2011-2015',
                  'Veterans_2011-2015',
                  'With_disability_2011-2015',
                  'Persons_in_poverty',
                  'Persons_no_health_insurance',
                  'Persons_per_household_2011-2015',
                  'Per_capita_income_past_12_months_2011-2015',
                  'Median_household_income_2011-2015']
```

In [14]:

```
int_cols = ['Population_2010',
            'Population_2016',
            'Veterans_2011-2015',
            'Per_capita_income_past_12_months_2011-2015',
            'Median_household_income_2011-2015']

float_cols = ['Population_sq_mile_2010',
              'Land_area_sq_mile_2010',
              'Persons_per_household_2011-2015']

per_cols = ['White_2016',
            'Hispanic_Latino_2016',
            'Black_African_American_2016',
            'American_Indian_Alaska_Native_2016',
            'Native_Hawaiian_Pacific_Islander_2016',
            'Asian_2016',
            'Foreign_born_persons_2011-2015',
            'Language_not_English_spoken_home_2011-2015',
            'High_school_or_higher_2011-2015',
            'Bachelor_or_higher_2011-2015',
            'With_disability_2011-2015',
            'Persons_in_poverty',
            'Persons_no_health_insurance',
            'Persons_per_household_2011-2015'
           ]

# remove commas, percent, dolar and zero signs
for c in census.columns:
    census[c] = census[c].str.replace("Z","0").str.replace(",","").str.replace("%","").
str.replace("$","")

# convert columns from string to int
for c in int_cols:
    census[c] = census[c].astype(int)

# convert columns from string to float
for c in float_cols:
    census[c] = census[c].astype(float)

# convert percent values to floats
for c in per_cols:
    census[c] = census[c].astype(float) / 100
```

In [15]:

```
# display cleaned dataset
census.head()
```

Out[15]:

	Population_2010	Population_2016	Population_sq_mile_2010	Land_area_
Alabama	4779736	4863300	94.4	50645.33
Alaska	710231	741894	1.2	570640.95
Arizona	6392017	6931071	56.3	113594.08
Arkansas	2915918	2988248	56.0	52035.48
California	37253956	39250017	239.1	155779.22

5 rows × 21 columns

In [16]:

```
# display datatypes and non-null counts for cleaned dataset
census.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 21 columns):
Population_2010                              50 non-null int32
Population_2016                              50 non-null int32
Population_sq_mile_2010                      50 non-null float64
Land_area_sq_mile_2010                       50 non-null float64
White_2016                                   50 non-null float64
Hispanic_Latino_2016                         50 non-null float64
Black_African_American_2016                  50 non-null float64
American_Indian_Alaska_Native_2016           50 non-null float64
Native_Hawaiian_Pacific_Islander_2016        50 non-null float64
Asian_2016                                   50 non-null float64
Foreign_born_persons_2011-2015               50 non-null float64
Language_not_English_spoken_home_2011-2015   50 non-null float64
High_school_or_higher_2011-2015              50 non-null float64
Bachelor_or_higher_2011-2015                 50 non-null float64
Veterans_2011-2015                           50 non-null int32
With_disability_2011-2015                    50 non-null float64
Persons_in_poverty                           50 non-null float64
Persons_no_health_insurance                  50 non-null float64
Persons_per_household_2011-2015              50 non-null float64
Per_capita_income_past_12_months_2011-2015   50 non-null int32
Median_household_income_2011-2015            50 non-null int32
dtypes: float64(16), int32(5)
memory usage: 7.6+ KB
```

Gun Dataset

In [17]:

```
# check if all states from gun dataframe exist in the census dataframe
states_drop = gun[~gun['state'].isin(census.index)]['state'].unique()
states_drop
```

Out[17]:

```
array(['District of Columbia', 'Guam', 'Mariana Islands', 'Puerto Rico',
       'Virgin Islands'], dtype=object)
```

In [18]:

```
# drop rows for states which exist only in gun dataframe
gun = gun[~gun['state'].isin(states_drop)].reset_index(drop=True)
```

In [19]:

```
# convert month column to datetime
gun['month'] =  pd.to_datetime(gun['month'])
```

In [20]:

```
# fill blanks with 0.0
gun = gun.fillna(0.0)
```

In [21]:

```
# select columns from gun dataset which will be analysed
gun = gun[['month', 'state', 'permit', 'handgun', 'long_gun', 'other', 'totals']]
```

In [22]:

```
# display cleaned dataset
gun.head(5)
```

Out[22]:

	month	state	permit	handgun	long_gun	other	totals
0	2017-09-01	Alabama	16717.0	5734.0	6320.0	221.0	32019
1	2017-09-01	Alaska	209.0	2320.0	2930.0	219.0	6303
2	2017-09-01	Arizona	5069.0	11063.0	7946.0	920.0	28394
3	2017-09-01	Arkansas	2935.0	4347.0	6063.0	165.0	17747
4	2017-09-01	California	57839.0	37165.0	24581.0	2984.0	123506

In [23]:

```
# display datatypes and non-null counts for cleaned dataset
gun.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11350 entries, 0 to 11349
Data columns (total 7 columns):
month       11350 non-null datetime64[ns]
state       11350 non-null object
permit      11350 non-null float64
handgun     11350 non-null float64
long_gun    11350 non-null float64
other       11350 non-null float64
totals      11350 non-null int64
dtypes: datetime64[ns](1), float64(4), int64(1), object(1)
memory usage: 620.8+ KB
```

Exploratory Data Analysis

What is the overall trend of gun purchases?

These statistics represent the number of firearm background checks initiated through the NICS. They do not represent the number of firearms sold. Based on varying state laws and purchase scenarios, a one-to-one correlation cannot be made between a firearm background check and a firearm sale. Therefore, we will look at the number of firearm background checks.

In [24]:

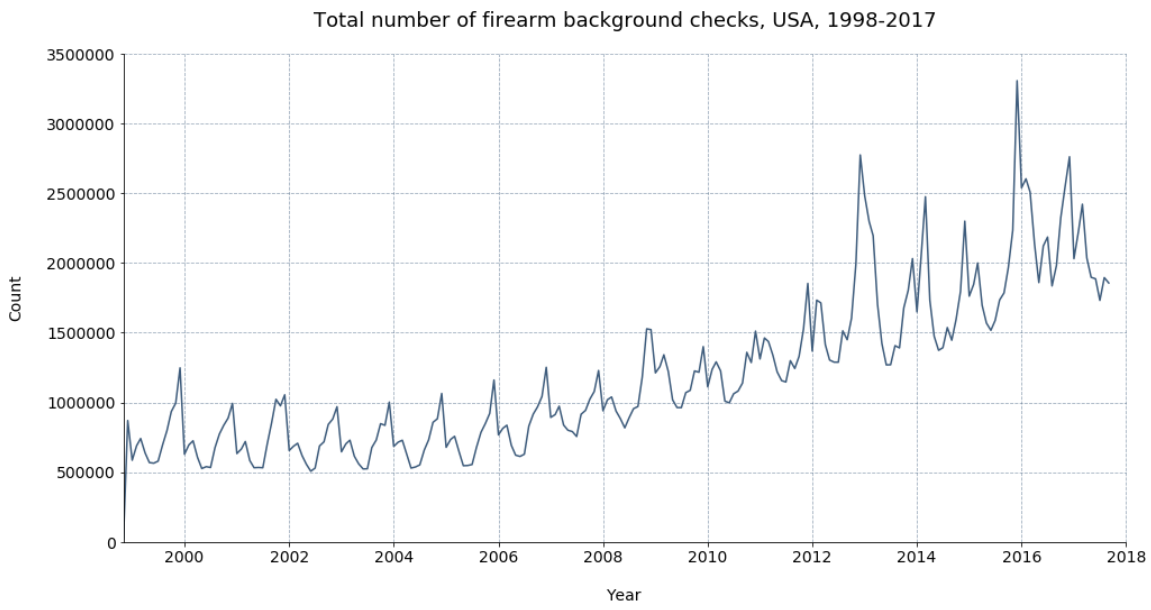
```
# calculate total number of firearm background checks by year
gun_total_year = gun[['month','totals']].groupby(gun['month']).sum()
gun_total_year.head(5)
```

Out[24]:

	totals
month	
1998-11-01	21174
1998-12-01	870202
1999-01-01	585569
1999-02-01	689867
1999-03-01	741234

In [25]:

```
# plot total number of firearm background checks over time
plt.figure(figsize=(16, 8))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='both', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.yticks(fontsize=14)
plt.xticks(fontsize=14)

plt.ylim(0, 3500000)
plt.xlim(datetime.date(1998, 11, 1), datetime.date(2018, 1, 1))

plt.plot(gun_total_year, color="#3F5D7D")

plt.title("Total number of firearm background checks, USA, 1998-2017",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("Year",
           fontsize=14,
           labelpad=20)

plt.ylabel("Count",
           fontsize=14,
           labelpad=20)

plt.show()
```



Overall, we can see an increase in the number of firearm background checks over the time. There seems to be also a seasonal trend. I will have a closer look at it in the next plot.

In [26]:

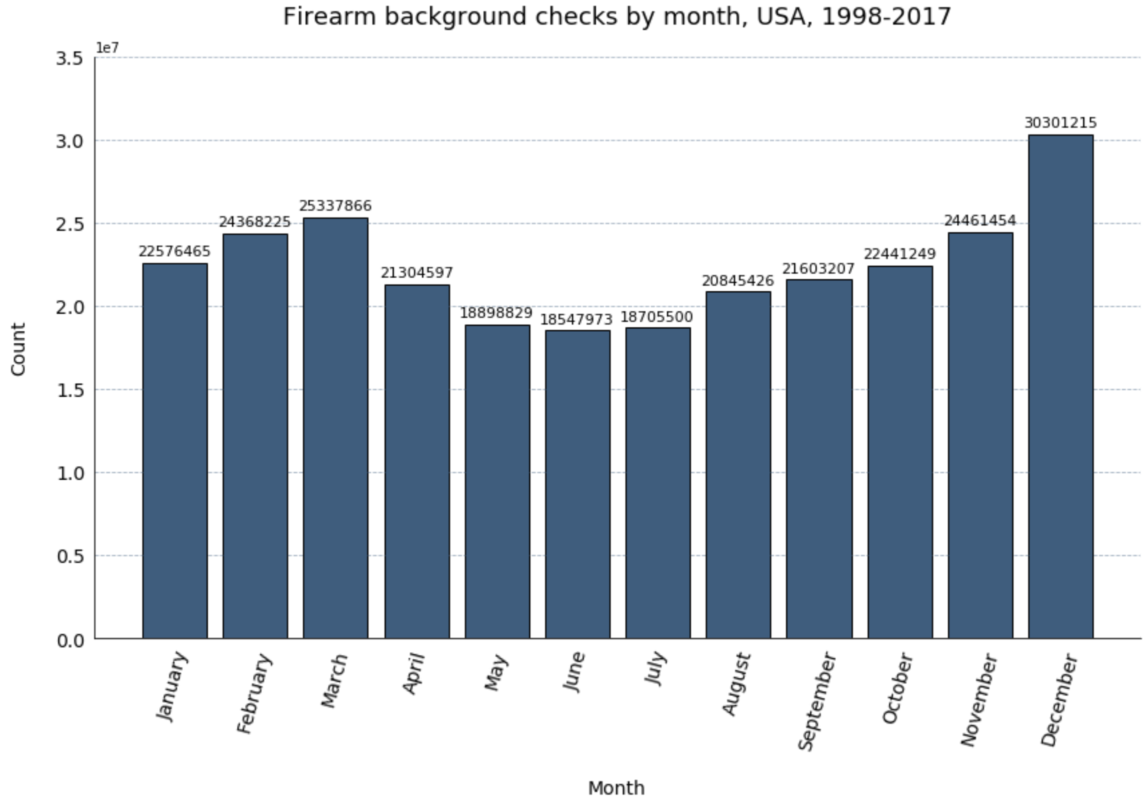
```
# calculate total number of firearm background checks per month
gun_total_month = gun_total_year.reset_index()
gun_total_month = gun_total_month.groupby(gun_total_month['month'].dt.strftime('%B'))[
'totals'].sum().reset_index()

# sort by month - SO https://stackoverflow.com/a/48043319
months = ["January", "February", "March", "April", "May", "June",
          "July", "August", "September", "October", "November", "December"]

gun_total_month['month'] = pd.Categorical(gun_total_month['month'], categories=months,
ordered=True)
gun_total_month.sort_values(by='month',ascending=True,inplace=True)
gun_total_month.reset_index(drop=True, inplace=True)
gun_total_month
```

Out[26]:

	month	totals
0	January	22576465
1	February	24368225
2	March	25337866
3	April	21304597
4	May	18898829
5	June	18547973
6	July	18705500
7	August	20845426
8	September	21603207
9	October	22441249
10	November	24461454
11	December	30301215

In [27]:

```
# plot total number of firearm background checks per month
plt.figure(figsize=(14,8))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14, rotation=75)
plt.yticks(fontsize=14)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

plt.ylim(0, 35000000)

bar_list = plt.bar(gun_total_month['month'], gun_total_month['totals'], color="#3F5D7D"
, edgecolor="k")

for a,b in zip(gun_total_month['month'], gun_total_month['totals']):
    plt.text(a, b + 250000, str(b), ha='center', va='bottom', fontsize=11)

plt.title("Firearm background checks by month, USA, 1998-2017",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("Month",
           fontsize=14,
           labelpad=20)

plt.ylabel("Count",
           fontsize=14,
           labelpad=20)

plt.show()
```



As we can see in the above plot, the number of firearm background checks seems to increase at the end of the year. This might be related to the Black Friday, Christmas and New Years sales, however, we do not have data to prove that suspicion. We can also see a decrease in the number of firearm background checks in the middle of the year - May, June, and July are months with the lowest numbers.

Which states have had the highest number of firearm background checks per capita?

The law on gun purchase can vary significantly between states, which makes it hard to compare states to each other. Nevertheless, it can be interesting to compare the number of firearm background checks in each state against the state's population.

In [28]:

```
# calculate total number of firearm background checks per year by state
gun_total_state = gun[['month','totals','state']]
gun_total_state = gun_total_state.groupby([gun_total_state['state'], gun_total_state['m
onth'].dt.strftime('%Y')])['totals'].sum().reset_index()
gun_total_state.columns = ['state', 'year', 'totals']

# we do not have full year data for 1998 and 2017 in gun dataset
# and population data for 1999 in the census dataset
# we will drop rows for these years
gun_total_state = gun_total_state[(gun_total_state['year'] != '1998') & (gun_total_stat
e['year'] != '1999') & (gun_total_state['year'] != '2017')]
gun_total_state.head()
```

Out[28]:

	state	year	totals
2	Alabama	2000	221911
3	Alabama	2001	230187
4	Alabama	2002	221008
5	Alabama	2003	225479
6	Alabama	2004	229997

In [29]:

```
# copy population data from the census dataset, we have data for 2010 and 2016 only
population = census[['Population_2010', 'Population_2016']].copy()
population.index.name = 'state'
population.head()
```

Out[29]:

	Population_2010	Population_2016
state		
Alabama	4779736	4863300
Alaska	710231	741894
Arizona	6392017	6931071
Arkansas	2915918	2988248
California	37253956	39250017

In [30]:

```
# get gun data for 2010 and 2016
gun_total_state_2010 = gun_total_state[gun_total_state['year'] == '2010'].set_index('st
ate')
gun_total_state_2016 = gun_total_state[gun_total_state['year'] == '2016'].set_index('st
ate')

# merge data into one dataset
gun_total_state_2010_2016 = pd.merge(gun_total_state_2010, gun_total_state_2016, how="l
eft", left_on=gun_total_state_2010.index, right_on=gun_total_state_2016.index, left_ind
ex=True).drop(columns=['key_0', 'year_x', 'year_y'])
gun_total_state_2010_2016.columns = ['totals_2010', 'totals_2016']
gun_total_state_2010_2016.head()
```

Out[30]:

	totals_2010	totals_2016
state		
Alabama	308607	616947
Alaska	65909	87647
Arizona	206050	416279
Arkansas	191448	266014
California	816399	2377167

In [31]:

```
# check if indexes in population and gun datasets are the same
gun_total_state_2010_2016.index.isin(population.index)
```

Out[31]:

```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True])
```

In [32]:

```
# merge population and gun datasets
growth_data_pop = pd.merge(gun_total_state_2010_2016, population, how="left", left_on=g
un_total_state_2010_2016.index, right_on=population.index, left_index=True).drop(column
s=['key_0'])
growth_data_pop.head()
```

Out[32]:

	totals_2010	totals_2016	Population_2010	Population_2016
state				
Alabama	308607	616947	4779736	4863300
Alaska	65909	87647	710231	741894
Arizona	206050	416279	6392017	6931071
Arkansas	191448	266014	2915918	2988248
California	816399	2377167	37253956	39250017

In [33]:

```
# calculate number of firearm background checks per capita for 2010 and 2016
growth_data_pop['checks_per_capita_2010'] = growth_data_pop['totals_2010'] / growth_dat
a_pop['Population_2010']
growth_data_pop['checks_per_capita_2016'] = growth_data_pop['totals_2016'] / growth_dat
a_pop['Population_2016']
growth_data_pop.head()
```

Out[33]:

	totals_2010	totals_2016	Population_2010	Population_2016	checks_pe
state					
Alabama	308607	616947	4779736	4863300	0.064566
Alaska	65909	87647	710231	741894	0.092799
Arizona	206050	416279	6392017	6931071	0.032236
Arkansas	191448	266014	2915918	2988248	0.065656
California	816399	2377167	37253956	39250017	0.021914

Top 10 states with the highest number of firearm background checks per capita for 2010

In [34]:

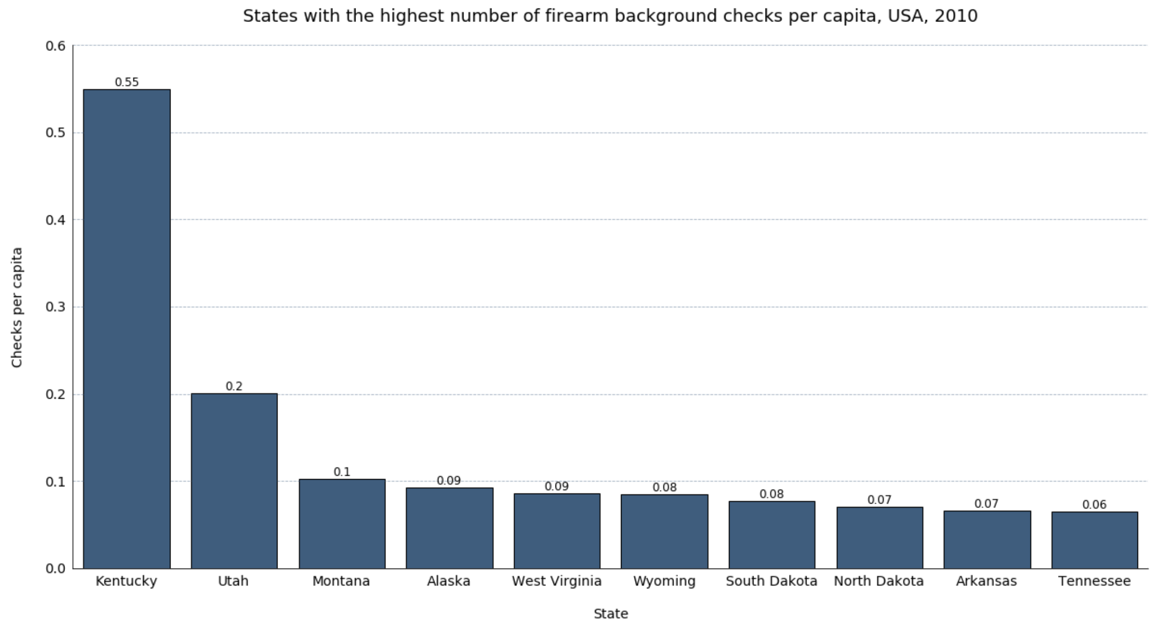
```
# sort dataset by number of firearm background checks per capita for 2010
checks_per_capita_2010 = growth_data_pop.sort_values(by='checks_per_capita_2010', ascen
ding=False).reset_index(drop=False)
top10_checks_per_capita_2010 = checks_per_capita_2010[['state','totals_2010', 'Populati
on_2010', 'checks_per_capita_2010']].head(10)
top10_checks_per_capita_2010
```

Out[34]:

	state	totals_2010	Population_2010	checks_per_capita_2010
0	Kentucky	2385579	4339367	0.549753
1	Utah	553134	2763885	0.200129
2	Montana	101095	989415	0.102177
3	Alaska	65909	710231	0.092799
4	West Virginia	159550	1852994	0.086104
5	Wyoming	47709	563626	0.084647
6	South Dakota	63151	814180	0.077564
7	North Dakota	47083	672591	0.070002
8	Arkansas	191448	2915918	0.065656
9	Tennessee	411024	6346105	0.064768

In [35]:

```
# plot top 10 states with the highest number of firearm background checks per capita in
 2010
plt.figure(figsize=(20,10))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14)
plt.yticks(fontsize=14)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

plt.ylim(0, 0.6)
plt.xlim(-0.5, 9.5)

bar_list = plt.bar(top10_checks_per_capita_2010['state'], top10_checks_per_capita_2010[
'checks_per_capita_2010'], color="#3F5D7D", edgecolor="k")

for a,b in zip(top10_checks_per_capita_2010['state'], top10_checks_per_capita_2010['che
cks_per_capita_2010']):
    plt.text(a, b, str(round(b,2)), ha='center', va='bottom', fontsize=12)

plt.title("States with the highest number of firearm background checks per capita, USA,
 2010",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("State",
           fontsize=14,
           labelpad=20)

plt.ylabel("Checks per capita",
           fontsize=14,
           labelpad=20)

plt.show()
```



As we can see, Kentucky has a significantly higher number of checks per capita. We do not have enough data to investigate the reason for this difference. It may be caused by legal conditions - more strict control of the sale of weapons, or/and by the higher popularity of gun ownership in this state. However, these are only assumptions that we can not confirm in any way.

Top 10 states with the highest number of firearm background checks per capita for 2016

In [36]:

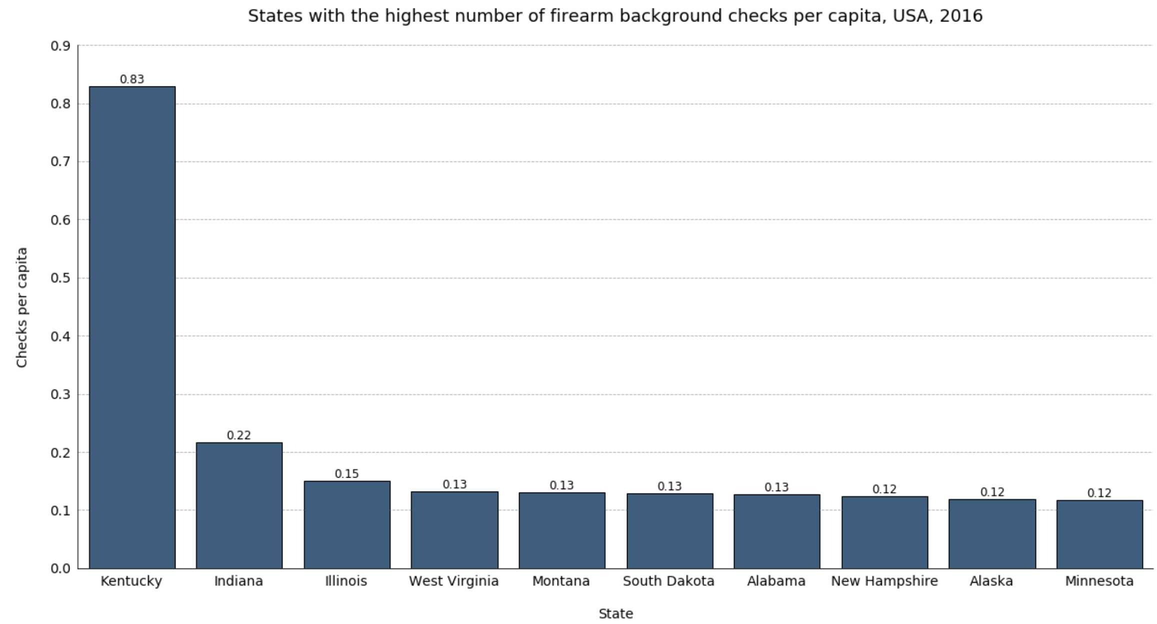
```
# sort dataset by number of firearm background checks per capita for 2016
checks_per_capita_2016= growth_data_pop.sort_values(by='checks_per_capita_2016', ascend
ing=False).reset_index(drop=False)
top10_checks_per_capita_2016 = checks_per_capita_2016[['state','totals_2016', 'Populati
on_2016', 'checks_per_capita_2016']].head(10)
top10_checks_per_capita_2016
```

Out[36]:

	state	totals_2016	Population_2016	checks_per_capita_2016
0	Kentucky	3676847	4436974	0.828683
1	Indiana	1436725	6633053	0.216601
2	Illinois	1924070	12801539	0.150300
3	West Virginia	242350	1831102	0.132352
4	Montana	136337	1042520	0.130776
5	South Dakota	111921	865454	0.129321
6	Alabama	616947	4863300	0.126858
7	New Hampshire	165164	1334795	0.123737
8	Alaska	87647	741894	0.118140
9	Minnesota	651599	5519952	0.118044

In [37]:

```
# plot top 10 states with the highest number of firearm background checks per capita in
 2016
plt.figure(figsize=(20,10))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14)
plt.yticks(fontsize=14)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

plt.ylim(0, 0.9)
plt.xlim(-0.5, 9.5)

bar_list = plt.bar(top10_checks_per_capita_2016['state'], top10_checks_per_capita_2016[
'checks_per_capita_2016'], color="#3F5D7D", edgecolor="k")

for a,b in zip(top10_checks_per_capita_2016['state'], top10_checks_per_capita_2016['che
cks_per_capita_2016']):
    plt.text(a, b, str(round(b,2)), ha='center', va='bottom', fontsize=12)

plt.title("States with the highest number of firearm background checks per capita, USA,
 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("State",
           fontsize=14,
           labelpad=20)

plt.ylabel("Checks per capita",
           fontsize=14,
           labelpad=20)

plt.show()
```



The situation is quite similar for 2016. Again, we can see Kentucky state in the first place, with a significantly higher number of checks per capita than other states. As mentioned already, we do not have enough data to investigate the reason for this difference.

Interestingly, we can see an increase in the number of checks per capita for other states. In 2010, values for most of the states in the top 10 (except for Kentucky) were between `0.2 - 0.06`, while in 2016 values for most of the states (again, excluding Kentucky) are between `10.2 - 0.12`. This increase in the number of checks will become more visible in the further part of the analysis.

Which states have had the highest growth in gun registrations?

Percentage increase by state

In [38]:

```
# for each state, take the total number of firearm background checks form 2000 and 2017
# calculate increase percentage and save to the dataframe and print out

growth = []

for state in gun_total_state['state'].unique():
    first_year = gun_total_state[(gun_total_state['state'] == state) & (gun_total_state
['year'] == '2000')]['totals'].iloc[0]
    last_year = gun_total_state[(gun_total_state['state'] == state) & (gun_total_state[
'year'] == '2016')]['totals'].iloc[0]
    nom_change = last_year - first_year
    per_change = int(round((last_year/first_year) * 100))

    result = pd.DataFrame({
        "state": state,
        "first_year": first_year,
        "last_year": last_year,
        "nom_change": nom_change,
        "per_change": per_change
    }, index=[0])

    growth.append(result)

    print('{} - {}% '.format(state, per_change))
```

```
Alabama - 278%
Alaska - 219%
Arizona - 281%
Arkansas - 157%
California - 299%
Colorado - 176%
Connecticut - 363%
Delaware - 387%
Florida - 540%
Georgia - 174%
Hawaii - 252%
Idaho - 203%
Illinois - 428%
Indiana - 788%
Iowa - 230%
Kansas - 203%
Kentucky - 1599%
Louisiana - 224%
Maine - 248%
Maryland - 196%
Massachusetts - 412%
Michigan - 193%
Minnesota - 352%
Mississippi - 168%
Missouri - 330%
Montana - 192%
Nebraska - 198%
Nevada - 297%
New Hampshire - 412%
New Jersey - 328%
New Mexico - 192%
New York - 247%
North Carolina - 207%
North Dakota - 223%
Ohio - 319%
Oklahoma - 232%
Oregon - 240%
Pennsylvania - 238%
Rhode Island - 295%
South Carolina - 313%
South Dakota - 305%
Tennessee - 305%
Texas - 260%
Utah - 437%
Vermont - 194%
Virginia - 280%
Washington - 532%
West Virginia - 189%
Wisconsin - 311%
Wyoming - 185%
```

In [39]:

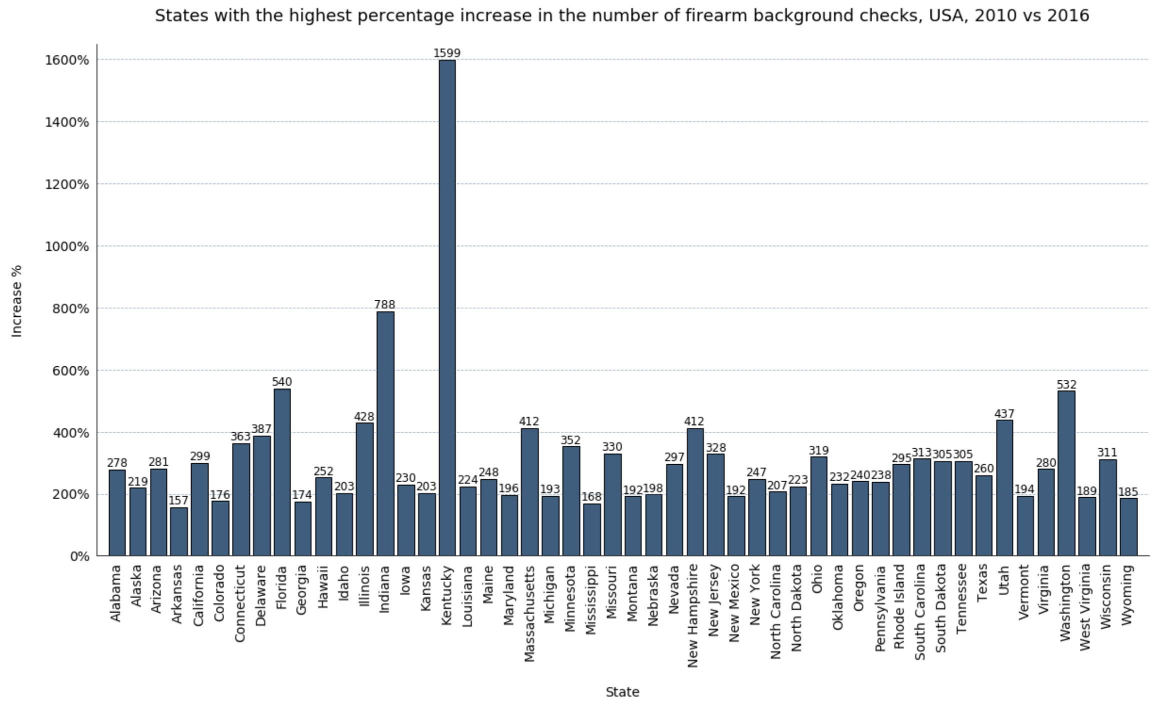
```
# concatenate all dataframes to receive final dataframe with results for all states
growth_data = pd.concat(growth, axis=0, ignore_index=True)
growth_data.columns = ['state', 'totals_2000', 'totals_2016', 'nom_change', 'per_chang
e']
growth_data.set_index('state', inplace=True)
growth_data.head()
```

Out[39]:

	totals_2000	totals_2016	nom_change	per_change
state				
Alabama	221911	616947	395036	278
Alaska	39959	87647	47688	219
Arizona	148263	416279	268016	281
Arkansas	169628	266014	96386	157
California	794506	2377167	1582661	299

In [40]:

```
# plot percentage increase by state
plt.figure(figsize=(20,10))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14, rotation=90)
plt.yticks(range(0, 1601, 200), [str(x) + "%" for x in range(0, 1601, 200)], fontsize=1
4)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

plt.ylim(0, 1650)
plt.xlim(-1, 50)

bar_list = plt.bar(growth_data.index, growth_data['per_change'], color="#3F5D7D", edgec
olor="k")

for a,b in zip(growth_data.index, growth_data['per_change']):
    plt.text(a, b, str(round(b,2)), ha='center', va='bottom', fontsize=12)

plt.title("States with the highest percentage increase in the number of firearm backgro
und checks, USA, 2010 vs 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("State",
           fontsize=14,
           labelpad=20)

plt.ylabel("Increase %",
           fontsize=14,
           labelpad=20)

plt.show()
```



In the above plot, we can see a percentage increase in the number of firearm background checks by state. The comparison is made between the number of background checks in 2010 and 2016.

As we can see, the number of checks has significantly increased for all states. This might be related to the increasing popularity of gun possession or/and more strict control of the sale of weapons. Unfortunately, we do not have enough data to investigate the reason for these increases.

Top 10 states with the highest percentage increase

In [41]:

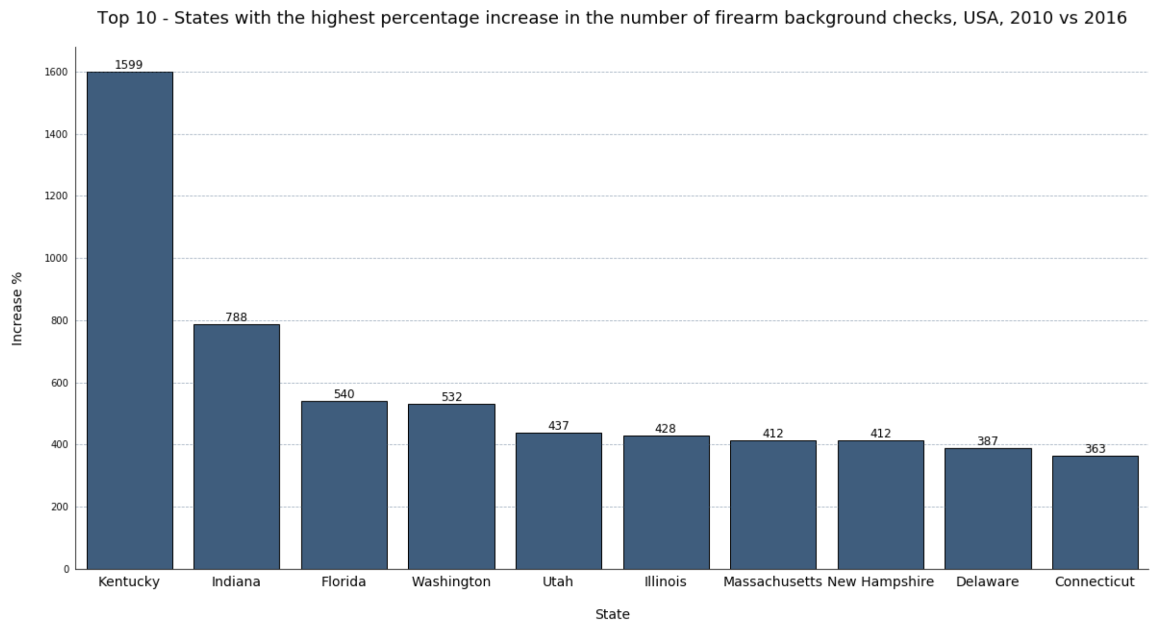
```
# sort dataset by percentage change
growth_data_per = growth_data.sort_values(by='per_change', ascending=False).reset_index
(drop=False)
top10_growth_data_per = growth_data_per.head(10)
top10_growth_data_per
```

Out[41]:

	state	totals_2000	totals_2016	nom_change	per_change
0	Kentucky	229896	3676847	3446951	1599
1	Indiana	182319	1436725	1254406	788
2	Florida	266035	1435340	1169305	540
3	Washington	134255	713996	579741	532
4	Utah	67420	294907	227487	437
5	Illinois	449771	1924070	1474299	428
6	Massachusetts	54843	226212	171369	412
7	New Hampshire	40120	165164	125044	412
8	Delaware	15347	59430	44083	387
9	Connecticut	87586	317692	230106	363

In [42]:

```
# plot top 10 states with percentage increase
plt.figure(figsize=(20,10))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14)
# plt.yticks(range(0, 1601, 200), [str(x) + "%" for x in range(0, 1601, 200)], fontsize
=14)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

# plt.ylim(0, 1650)
plt.xlim(-0.5, 9.5)

bar_list = plt.bar(top10_growth_data_per['state'], top10_growth_data_per['per_change'],
 color="#3F5D7D", edgecolor="k")

for a,b in zip(top10_growth_data_per['state'], top10_growth_data_per['per_change']):
    plt.text(a, b, str(round(b,2)), ha='center', va='bottom', fontsize=12)

plt.title("Top 10 - States with the highest percentage increase in the number of firear
m background checks, USA, 2010 vs 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("State",
           fontsize=14,
           labelpad=20)

plt.ylabel("Increase %",
           fontsize=14,
           labelpad=20)

plt.show()
```



This is a bit closer look at the statistics for the top 10 states in terms of the percentage increase in the number of firearm background checks. Again, the comparison is made between the number of background checks in 2010 and 2016. We can observe a significant increase in Kentucky, which would require further analysis, as well as in the other states.

Top 10 states with the highest nominal increase

In [43]:

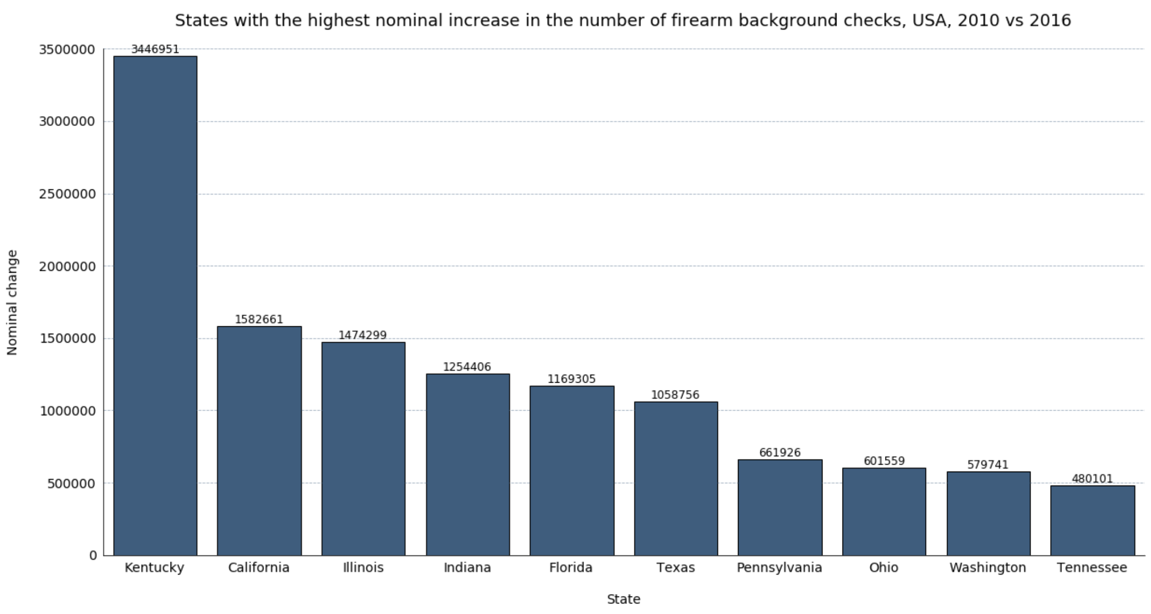
```
# sort dataset by nominal change
growth_data_nom = growth_data.sort_values(by='nom_change', ascending=False).reset_index
(drop=False)
top10_growth_data_nom = growth_data_nom.head(10)
top10_growth_data_nom
```

Out[43]:

	state	totals_2000	totals_2016	nom_change	per_change
0	Kentucky	229896	3676847	3446951	1599
1	California	794506	2377167	1582661	299
2	Illinois	449771	1924070	1474299	428
3	Indiana	182319	1436725	1254406	788
4	Florida	266035	1435340	1169305	540
5	Texas	662970	1721726	1058756	260
6	Pennsylvania	481294	1143220	661926	238
7	Ohio	274165	875724	601559	319
8	Washington	134255	713996	579741	532
9	Tennessee	234673	714774	480101	305

In [44]:

```
# plot top 10 states with the highest nominal increase
plt.figure(figsize=(20,10))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='y', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.xticks(fontsize=14)
plt.yticks(fontsize=14)

plt.tick_params(axis="both", which="both", bottom=False, top=False,
                labelbottom=True, left=False, right=False, labelleft=True)

plt.xlim(-0.5, 9.5)
plt.ylim(0, 3500000)

bar_list = plt.bar(top10_growth_data_nom['state'], top10_growth_data_nom['nom_change'],
 color="#3F5D7D", edgecolor="k")

for a,b in zip(top10_growth_data_nom['state'], top10_growth_data_nom['nom_change']):
    plt.text(a, b, str(round(b,2)), ha='center', va='bottom', fontsize=12)

plt.title("States with the highest nominal increase in the number of firearm background
 checks, USA, 2010 vs 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("State",
           fontsize=14,
           labelpad=20)

plt.ylabel("Nominal change",
           fontsize=14,
           labelpad=20)

plt.show()
```



In the above plot, we can see a nominal increase in the number of firearm background checks by state. The comparison is made between the number of background checks in 2010 and 2016.

As we can see, the number of checks has significantly increased for all states. Again, this might be related to the increasing popularity of gun possession or/and more strict control of the sale of weapons. Unfortunately, we do not have enough data to investigate the reason for these increases.

What census data is most associated with high gunregistration?

In [45]:

```
# get checks per capita
gun_checks_capita = growth_data_pop.drop(['Population_2010','Population_2016'], axis=1)
gun_checks_capita.head()
```

Out[45]:

	totals_2010	totals_2016	checks_per_capita_2010	checks_per_capita_2
state				
Alabama	308607	616947	0.064566	0.126858
Alaska	65909	87647	0.092799	0.118140
Arizona	206050	416279	0.032236	0.060060
Arkansas	191448	266014	0.065656	0.089020
California	816399	2377167	0.021914	0.060565

In [46]:

```
# merge census dateset with checks per capita from the gun dataset
census_gun = pd.merge(census,
                      gun_checks_capita,
                      how="left",
                      left_on=census.index,
                      right_on=gun_checks_capita.index,
                      left_index=True
                     ).drop(columns=['key_0'])
census_gun.head()
```

Out[46]:

	Population_2010	Population_2016	Population_sq_mile_2010	Land_area_
state				
Alabama	4779736	4863300	94.4	50645.33
Alaska	710231	741894	1.2	570640.95
Arizona	6392017	6931071	56.3	113594.08
Arkansas	2915918	2988248	56.0	52035.48
California	37253956	39250017	239.1	155779.22

5 rows × 25 columns

In [47]:

```
# compute the Pearson correlation coefficient
census_gun.corr(method='pearson').style.format("{:.2}").background_gradient(cmap=plt.ge
t_cmap('coolwarm'), axis=1)
```

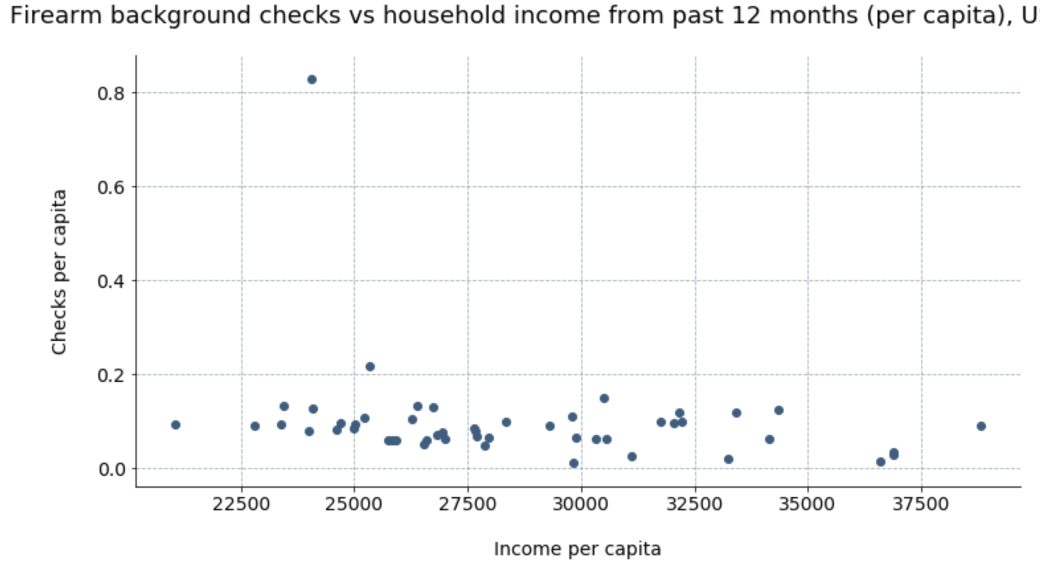
Out[47]:

	Population_2010	Population_2016	Pop
Population_2010	1.0	1.0	0.17
Population_2016	1.0	1.0	0.16
Population_sq_mile_2010	0.17	0.16	1.0
Land_area_sq_mile_2010	0.13	0.14	-0.3
White_2016	-0.22	-0.22	-0.1
Hispanic_Latino_2016	0.56	0.57	0.1
Black_African_American_2016	0.11	0.11	0.17
American_Indian_Alaska_Native_2016	-0.12	-0.12	-0.2
Native_Hawaiian_Pacific_Islander_2016	-0.099	-0.096	-0.0
Asian_2016	0.16	0.16	0.17
Foreign_born_persons_2011-2015	0.48	0.49	0.34
Language_not_English_spoken_home_2011-2015	0.51	0.53	0.26
High_school_or_higher_2011-2015	-0.052	-0.045	-0.0
Bachelor_or_higher_2011-2015	0.014	0.021	0.11
Veterans_2011-2015	0.96	0.96	0.12
With_disability_2011-2015	-0.11	-0.1	-0.1
Persons_in_poverty	0.055	0.062	-0.1
Persons_no_health_insurance	0.12	0.14	-0.2
Persons_per_household_2011-2015	0.37	0.38	0.08
Per_capita_income_past_12_months_2011-2015	0.091	0.084	0.6
Median_household_income_2011-2015	0.064	0.061	0.5
totals_2010	0.43	0.43	-0.0
totals_2016	0.61	0.61	-0.0
checks_per_capita_2010	-0.16	-0.16	-0.2
checks_per_capita_2016	-0.1	-0.1	-0.2

We can see that the strongest correlation is between the checks per capita, household income and the number of veterans. For other columns, correlation is low or negative. Therefore, I will plot the number of checks per capita with household income and the number of veterans.

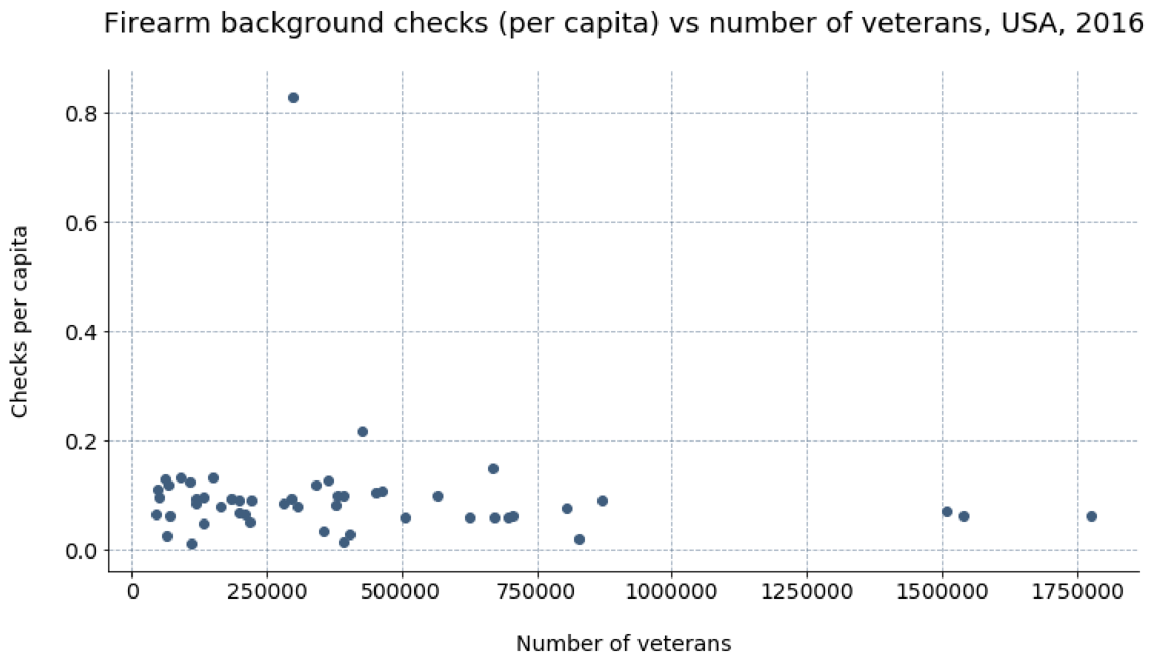
In [48]:

```
# plot firearm background checks in 2016 vs household income (2011-2015) from past 12 m
onths (per capita)
plt.figure(figsize=(12, 6))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='both', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.yticks(fontsize=14)
plt.xticks(fontsize=14)

plt.scatter(census_gun['Per_capita_income_past_12_months_2011-2015'],
            census_gun['checks_per_capita_2016'],
            color="#3F5D7D")

plt.title("Firearm background checks vs household income from past 12 months (per capit
a), USA, 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("Income per capita",
           fontsize=14,
           labelpad=20)

plt.ylabel("Checks per capita",
           fontsize=14,
           labelpad=20)

plt.show()
```



In [49]:

```
# plot firearm background checks in 2016 (per capita) vs number of veterans (2011-2015)
plt.figure(figsize=(12, 6))

ax = plt.subplot(111)
ax.spines["top"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.grid(which='major', axis='both', linestyle='--', alpha=0.5, color="#3F5D7D")

plt.yticks(fontsize=14)
plt.xticks(fontsize=14)

plt.scatter(census_gun['Veterans_2011-2015'],
            census_gun['checks_per_capita_2016'],
            color="#3F5D7D")

plt.title("Firearm background checks (per capita) vs number of veterans, USA, 2016",
          fontsize=18,
          ha="center",
          pad=24)

plt.xlabel("Number of veterans",
           fontsize=14,
           labelpad=20)

plt.ylabel("Checks per capita",
           fontsize=14,
           labelpad=20)

plt.show()
```



Conclusions

In general, we can see that the number of firearm background checks is increasing over time. This increase has been significant over the past 19 years. Further analysis is required to determine the reasons for such a high increase.

Correlation between the number of checks and census data is rather low. Household income and the number of veterans show the highest correlation among all data points but are still rather low.

These datasets have a lot of limitations, which constrain the analysis. Census dataset does not contain information for all the years, and in many cases, provided values represent multiple years.

A further analysis is required.