Linear regression with cars dataset

Libraries

In [2]:
```python
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import seaborn as sns
sns.set()
```

Loading the raw data

In [3]:
```python
# Load the data
raw_data = pd.read_csv('1.04. Real-life example.csv')

# top 5 rows of the df
raw_data.head()
```

Out[3]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	Model
0	BMW	4200.0	sedan	277	2.0	Petrol	yes	1991	320
1	Mercedes-Benz	7900.0	van	427	2.9	Diesel	yes	1999	Sprinter 212
2	Mercedes-Benz	13300.0	sedan	358	5.0	Gas	yes	2003	S 500
3	Audi	23000.0	crossover	240	4.2	Petrol	yes	2007	Q7
4	Toyota	18300.0	crossover	120	2.0	Petrol	yes	2011	Rav 4

Preprocessing

Exploring the descriptive statistics of the variables

In [4]:
```python
raw_data.describe(include='all')
```

Out[4]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	Model
count	4345	4173.000000	4345	4345.000000	4195.000000	4345	4345	4345.000000	4345
unique	7	NaN	6	NaN	NaN	4	2	NaN	312
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN	E-Class
freq	936	NaN	1649	NaN	NaN	2019	3947	NaN	199
mean	NaN	19418.746935	NaN	161.237284	2.790734	NaN	NaN	2006.550058	NaN
std	NaN	25584.242620	NaN	105.705797	5.066437	NaN	NaN	6.719097	NaN
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	NaN	1969.000000	NaN
25%	NaN	6999.000000	NaN	86.000000	1.800000	NaN	NaN	2003.000000	NaN
50%	NaN	11500.000000	NaN	155.000000	2.200000	NaN	NaN	2008.000000	NaN
75%	NaN	21700.000000	NaN	230.000000	3.000000	NaN	NaN	2012.000000	NaN
max	NaN	300000.000000	NaN	980.000000	99.990000	NaN	NaN	2016.000000	NaN

Determining the variables of interest

In [5]:
```python
data = raw_data.drop(['Model'],axis=1)

# descriptives without 'Model'
data.describe(include='all')
```

Out[5]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
count	4345	4173.000000	4345	4345.000000	4195.000000	4345	4345	4345.000000
unique	7	NaN	6	NaN	NaN	4	2	NaN
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN
freq	936	NaN	1649	NaN	NaN	2019	3947	NaN
mean	NaN	19418.746935	NaN	161.237284	2.790734	NaN	NaN	2006.550058
std	NaN	25584.242620	NaN	105.705797	5.066437	NaN	NaN	6.719097
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	NaN	1969.000000
25%	NaN	6999.000000	NaN	86.000000	1.800000	NaN	NaN	2003.000000
50%	NaN	11500.000000	NaN	155.000000	2.200000	NaN	NaN	2008.000000
75%	NaN	21700.000000	NaN	230.000000	3.000000	NaN	NaN	2012.000000
max	NaN	300000.000000	NaN	980.000000	99.990000	NaN	NaN	2016.000000

Dealing with missing values

In [6]:
```python
data.isnull().sum()
```

Out[6]:
```
Brand             0
Price           172
Body              0
Mileage           0
EngineV         150
Engine Type       0
Registration      0
Year              0
dtype: int64
```

In [7]:
```python
# drop all missing values (<5% so it's ok)
data_no_mv = data.dropna(axis=0)
```

In [8]:
```python
# descriptives without the missing values
data_no_mv.describe(include='all')
```

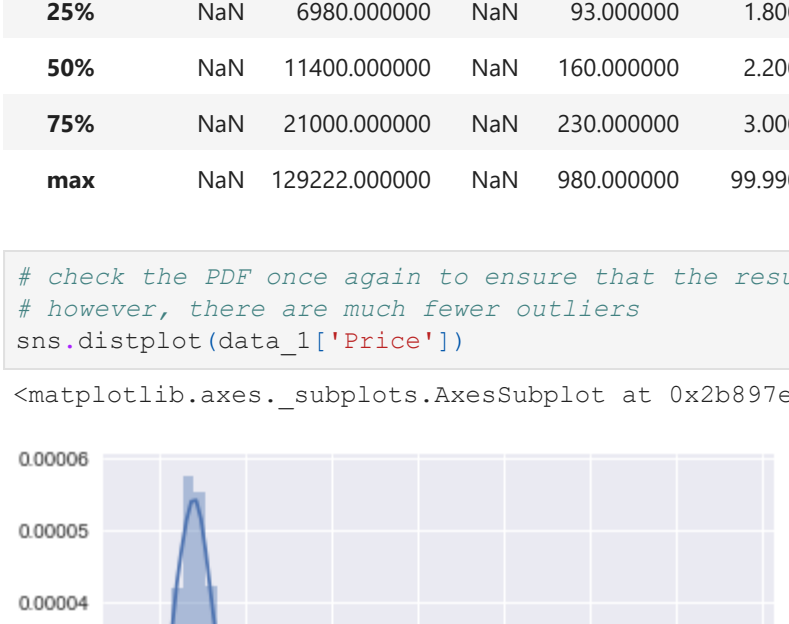
Out[8]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
count	4025	4025.000000	4025	4025.000000	4025.000000	4025	4025	4025.000000
unique	7	NaN	6	NaN	NaN	4	2	NaN
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN
freq	880	NaN	1534	NaN	NaN	1861	3654	NaN
mean	NaN	19552.308065	NaN	163.572174	2.764586	NaN	NaN	2006.379627
std	NaN	25815.734988	NaN	103.394703	4.935941	NaN	NaN	6.695595
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	NaN	1969.000000
25%	NaN	6999.000000	NaN	90.000000	1.800000	NaN	NaN	2003.000000
50%	NaN	11500.000000	NaN	158.000000	2.200000	NaN	NaN	2007.000000
75%	NaN	21900.000000	NaN	230.000000	3.000000	NaN	NaN	2012.000000
max	NaN	300000.000000	NaN	980.000000	99.990000	NaN	NaN	2016.000000

Exploring the PDFs

In [9]:
```python
# probability distribution function (PDF) - how that variable is distributed
sns.distplot(data_no_mv['Price'])
```

Out[9]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b897ab4940>`



Dealing with outliers

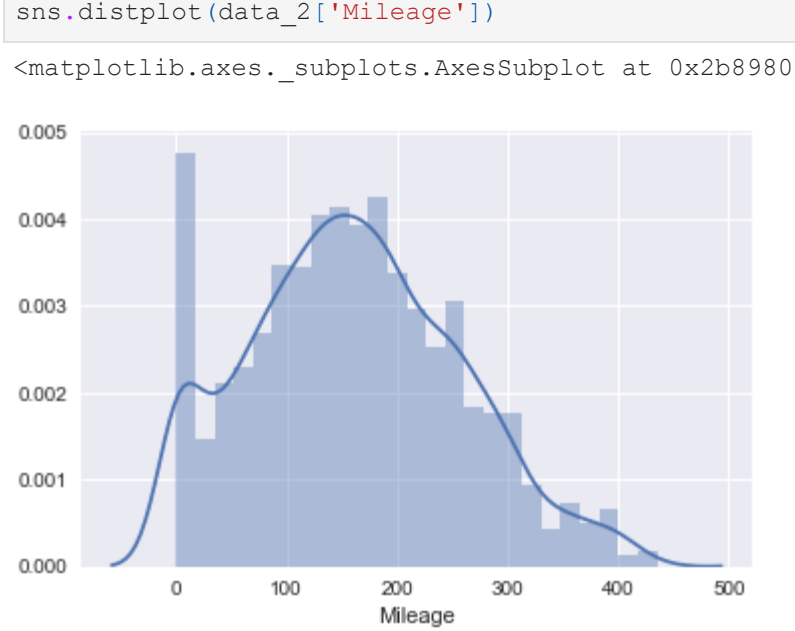
In [10]:
```python
# declare a variable that will be equal to the 99th percentile of the 'Price' variable
q = data_no_mv['Price'].quantile(0.99)
# create a new df, with the condition that all prices must be below the 99 percentile of 'Price'
data_1 = data_no_mv[data_no_mv['Price']<q]
# we have essentially removed the top 1% of the data about 'Price'
data_1.describe(include='all')
```

Out[10]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
count	3984	3984.000000	3984	3984.000000	3984.000000	3984	3984	3984.000000
unique	7	NaN	6	NaN	NaN	4	2	NaN
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN
freq	880	NaN	1528	NaN	NaN	1853	3613	NaN
mean	NaN	17837.117460	NaN	165.116466	2.743770	NaN	NaN	2006.292922
std	NaN	18976.268315	NaN	102.766126	4.956057	NaN	NaN	6.672745
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	NaN	1969.000000
25%	NaN	6980.000000	NaN	93.000000	1.800000	NaN	NaN	2002.750000
50%	NaN	11400.000000	NaN	160.000000	2.200000	NaN	NaN	2007.000000
75%	NaN	21000.000000	NaN	230.000000	3.000000	NaN	NaN	2011.000000
max	NaN	129222.000000	NaN	980.000000	99.990000	NaN	NaN	2016.000000

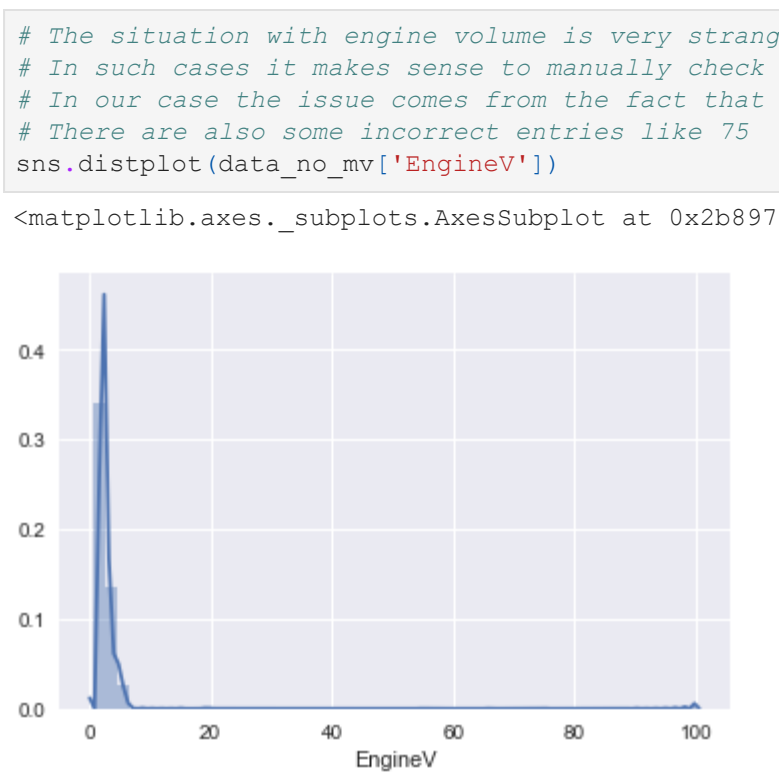
In [11]:
```python
# check the PDF once again to ensure that the result is still distributed in the same way overall
# however, there are much fewer outliers
sns.distplot(data_1['Price'])
```

Out[11]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b897eacfd0>`



In [12]:
```python
# We can treat the other numerical variables in a similar way
sns.distplot(data_no_mv['Mileage'])
```

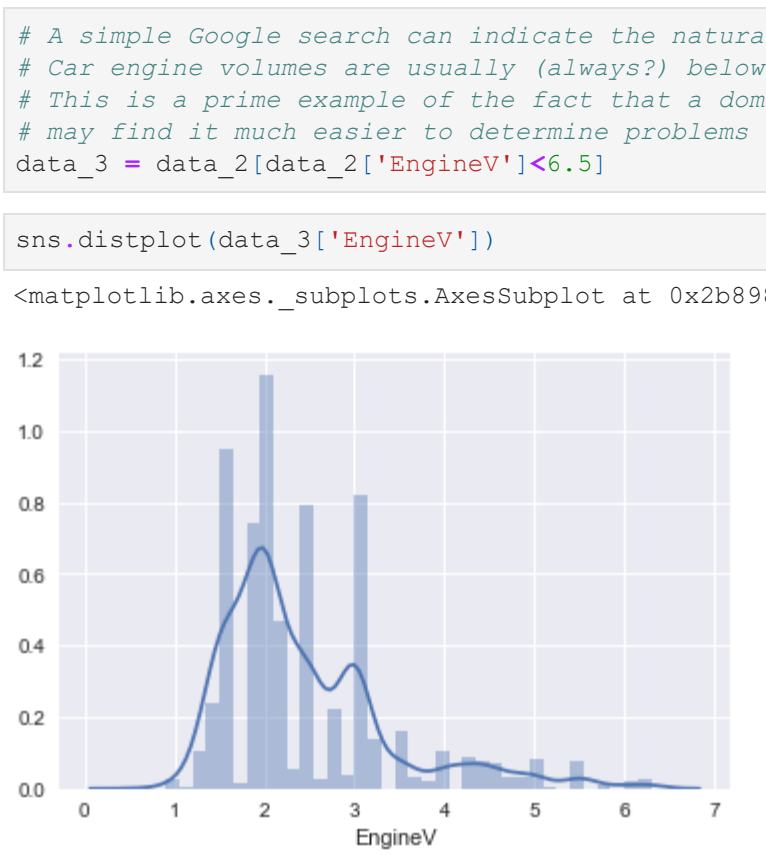
Out[12]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b897e36e80>`



In [13]:
```python
q = data_1['Mileage'].quantile(0.99)
data_2 = data_1[data_1['Mileage']<q]
```

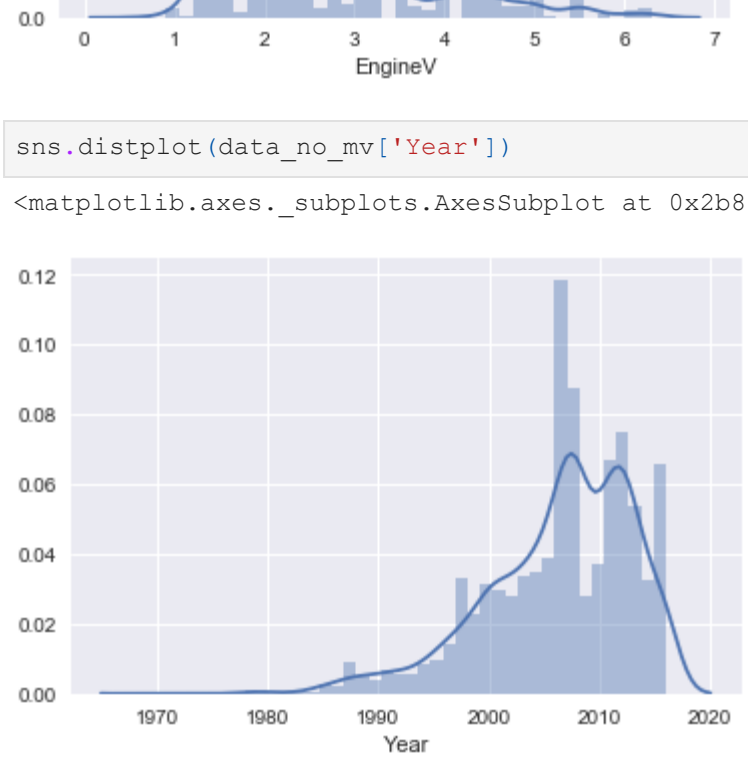
In [14]:
```python
sns.distplot(data_2['Mileage'])
```

Out[14]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b8980359b0>`



In [15]:
```python
# The situation with engine volume is very strange
# In such cases it makes sense to manually check what may be causing the problem
# In our case the issue comes from the fact that most missing values are indicated with 99.99 or 99
# There are also some incorrect entries like 75
sns.distplot(data_no_mv['EngineV'])
```

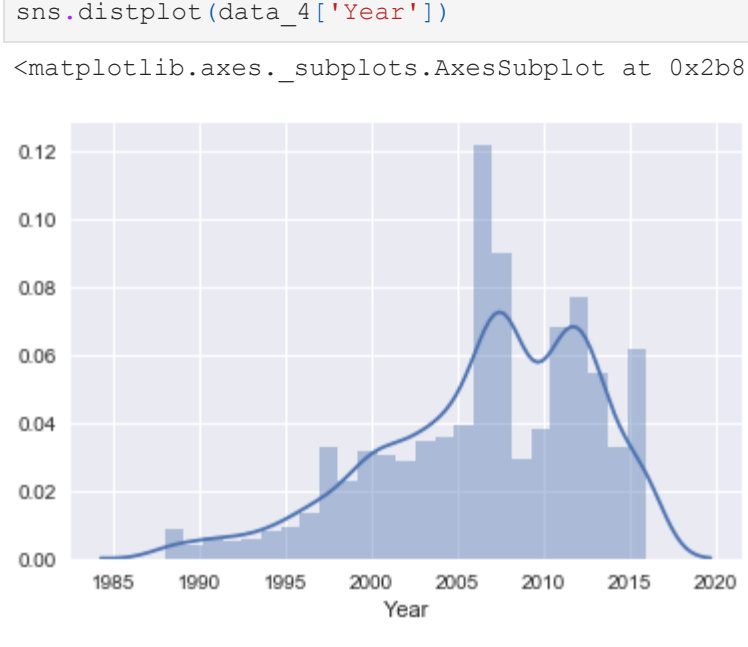
Out[15]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b897f681d0>`



In [16]:
```python
# A simple Google search can indicate the natural domain of this variable
# Car engine volumes are usually (always?) below 6.5l
# This is a prime example of the fact that a domain expert (a person working in the car industry)
# may find it much easier to determine problems with the data than an outsider
data_3 = data_2[data_2['EngineV']<6.5]
```

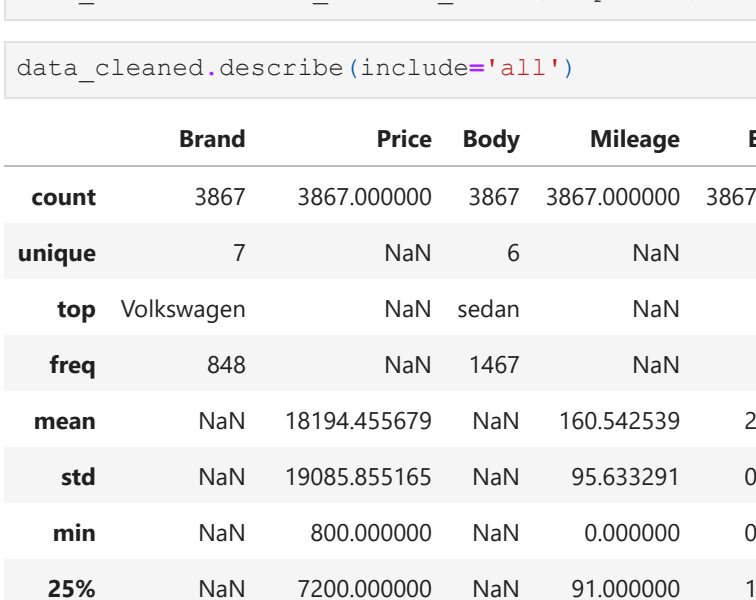
In [17]:
```python
sns.distplot(data_3['EngineV'])
```

Out[17]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b8981a0b00>`



In [18]:
```python
sns.distplot(data_no_mv['Year'])
```

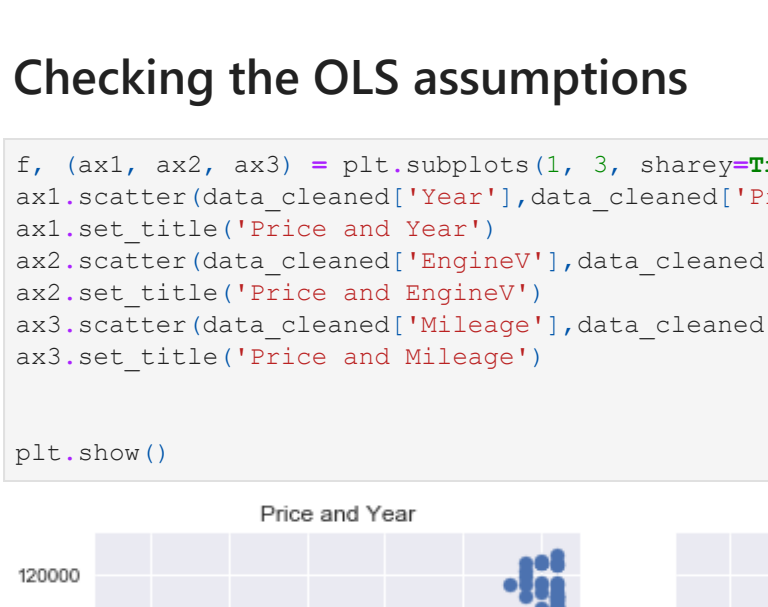
Out[18]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b89825e6a0>`



In [19]:
```python
q = data_3['Year'].quantile(0.01)
data_4 = data_3[data_3['Year']>q]
```

In [20]:
```python
# Here's the new result
sns.distplot(data_4['Year'])
```

Out[20]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b898296d30>`



In [21]:
```python
data_cleaned = data_4.reset_index(drop=True)
```

In [22]:
```python
data_cleaned.describe(include='all')
```

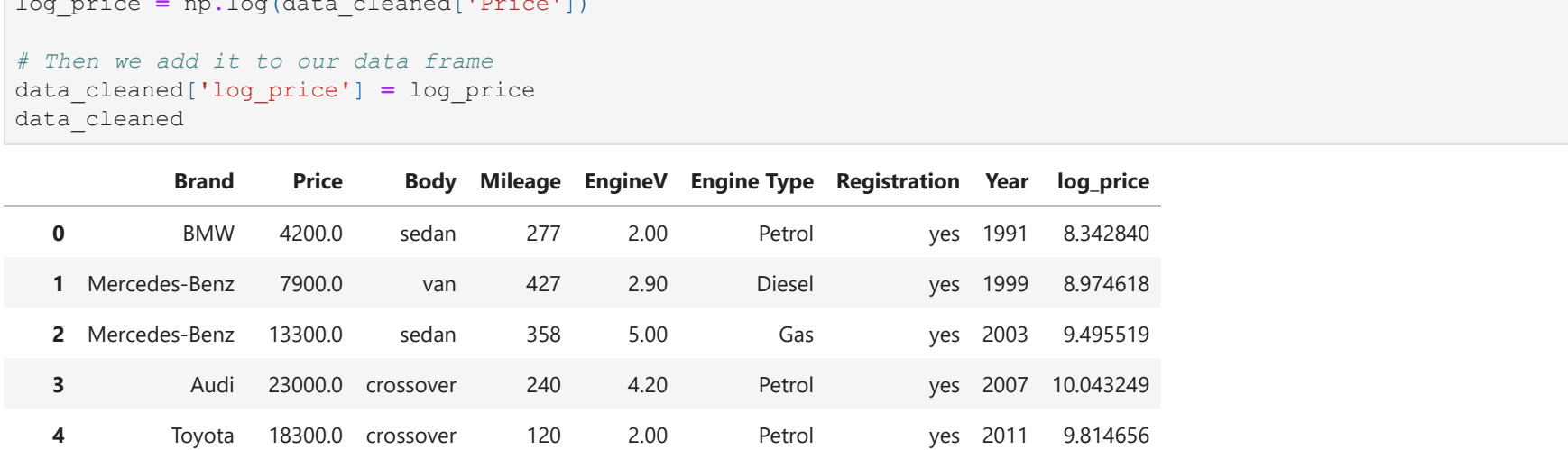
Out[22]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year
count	3867	3867.000000	3867	3867.000000	3867.000000	3867	3867	3867.000000
unique	7	NaN	6	NaN	NaN	4	2	NaN
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	yes	NaN
freq	848	NaN	1467	NaN	NaN	1807	3505	NaN
mean	NaN	18194.455679	NaN	160.542539	2.450440	NaN	NaN	2006.709853
std	NaN	19085.855165	NaN	95.633291	0.949366	NaN	NaN	6.103870
min	NaN	800.000000	NaN	0.000000	0.600000	NaN	NaN	1988.000000
25%	NaN	7200.000000	NaN	91.000000	1.800000	NaN	NaN	2003.000000
50%	NaN	11700.000000	NaN	157.000000	2.200000	NaN	NaN	2008.000000
75%	NaN	21700.000000	NaN	225.000000	3.000000	NaN	NaN	2012.000000
max	NaN	129222.000000	NaN	435.000000	6.300000	NaN	NaN	2016.000000

Checking the OLS assumptions

In [23]:
```python
f, (ax1, ax2, ax3) = plt.subplots(1, 3, sharey=True, figsize =(15,3)) #sharey -> share 'Price' as y
ax1.scatter(data_cleaned['Year'],data_cleaned['Price'])
ax1.set_title('Price and Year')
ax2.scatter(data_cleaned['EngineV'],data_cleaned['Price'])
ax2.set_title('Price and EngineV')
ax3.scatter(data_cleaned['Mileage'],data_cleaned['Price'])
ax3.set_title('Price and Mileage')


plt.show()
```



In [24]:
```python
# From the subplots and the PDF of price, we can easily determine that 'Price' is exponentially distributed
# A good transformation in that case is a log transformation
sns.distplot(data_cleaned['Price'])
```

Out[24]: `<matplotlib.axes._subplots.AxesSubplot at 0x2b8994ccdd8>`

Relaxing the assumptions

In [25]:
```python
# transform 'Price' with a log transformation
log_price = np.log(data_cleaned['Price'])

# Then we add it to our data frame
data_cleaned['log_price'] = log_price
data_cleaned
```

Out[25]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Registration	Year	log_price
0	BMW	4200.0	sedan	277	2.00	Petrol	yes	1991	8.342840
1	Mercedes-Benz	7900.0	van	427	2.90	Diesel	yes	1999	8.974618
2	Mercedes-Benz	13300.0	sedan	358	5.00	Gas	yes	2003	9.495519
3	Audi	23000.0	crossover	240	4.20	Petrol	yes	2007	10.043249
4	Toyota	18300.0	crossover	120	2.00	Petrol	yes	2011	9.814656
5	Audi	14200.0	vagon	200	2.70	Diesel	yes	2006	9.560997
6	Renault	10799.0	vagon	193	1.50	Diesel	yes	2012	9.287209
7	Volkswagen	1400.0	other	212	1.80	Gas	no	1999	7.244228
8	Renault	11950.0	vagon	177	1.50	Diesel	yes	2011	9.388487
9	Renault	2500.0	sedan	260	1.79	Petrol	yes	1994	7.824046
10	Audi	9500.0	vagon	165	2.70	Gas	yes	2003	9.159047
11	Volkswagen	10500.0	sedan	100	1.80	Petrol	yes	2008	9.259131
12	Toyota	16000.0	crossover	250	4.70	Gas	yes	2001	9.680344
13	Renault	8600.0	hatch	84	1.50	Diesel	yes	2012	9.059517
14	BMW	2990.0	other	203	2.00	Petrol	no	2001	8.003029
15	Toyota	26500.0	crossover	21	2.00	Petrol	yes	2013	10.184900
16	Audi	3500.0	vagon	250	2.50	Diesel	no	1998	8.160518
17	Toyota	38233.0	other	0	2.40	Diesel	yes	2016	10.551454
18	Volkswagen	7500.0	hatch	132	1.40	Diesel	yes	2006	8.922658
19	Audi	6800.0	sedan	225	2.40	Gas	yes	1998	8.824678
20	Mitsubishi	10500.0	crossover	130	2.40	Gas	yes	2006	9.259131
21	Audi	24900.0	sedan	163	4.20	Diesel	yes	2008	10.122623
22	Volkswagen	20800.0	crossover	151	3.00	Diesel	yes	2008	9.942708
23	Audi	6500.0	sedan	330	2.40	Petrol	yes	1999	8.779557
24	Mercedes-Benz	13566.0	other	171	2.20	Other	no	2011	9.515322
25	Mitsubishi	8500.0	hatch	65	1.30	Petrol	yes	2010	9.047821
26	Audi	2900.0	sedan	1	2.30	Gas	yes	1989	7.972466
27	BMW	21500.0	other	72	3.00	Petrol	yes	2007	9.975808
28	Mitsubishi	17900.0	crossover	87	3.80	Gas	yes	2008	9.792556
29	BMW	28500.0	crossover	160	4.80	Gas	yes	2008	10.257659
...	...	...	...	...	...	...	...	...	...
3837	Mercedes-Benz	11500.0	van	180	2.20	Diesel	yes	2011	9.350102
3838	Mitsubishi	9700.0	van	247	2.40	Gas	yes	2008	9.179881
3839	Renault	10500.0	vagon	185	1.50	Diesel	yes	2011	9.259131
3840	Renault	10900.0	vagon	180	1.50	Diesel	yes	2012	9.296518
3841	Mercedes-Benz	25500.0	crossover	77	3.50	Petrol	yes	2008	10.146434
3842	Volkswagen	15500.0	sedan	80	1.40	Petrol	yes	2013	9.648595
3843	Volkswagen	9750.0	van	159	1.90	Diesel	yes	2009	9.185023
3844	BMW	16100.0	crossover	194	3.00	Diesel	yes	2004	9.686575
3845	Volkswagen	9200.0	vagon	171	1.60	Petrol	yes	2008	9.126959
3846	Volkswagen	5150.0	van	240	2.00	Diesel	yes	2005	8.546752
3847	Toyota	100000.0	crossover	0	4.50	Diesel	yes	2016	11.512925
3848	Renault	8999.0	other	126	2.00	Diesel	yes	2012	9.104869
3849	Mercedes-Benz	16800.0	sedan	125	1.80	Petrol	yes	2008	9.729134
3850	Mercedes-Benz	8200.0	sedan	280	2.40	Gas	yes	1997	9.011889
3851	Mercedes-Benz	24950.0	other	60	1.80	Petrol	yes	2013	10.124629
3852	Audi	80999.0	crossover	0	3.00	Diesel	yes	2016	11.302192
3853	Mercedes-Benz	7300.0	van	207	2.20	Diesel	yes	2003	8.895630
3854	BMW	21335.0	other	105	3.00	Petrol	yes	2008	9.968104
3855	BMW	45000.0	crossover	80	3.00	Petrol	yes	2011	10.714418
3856	Renault	6750.0	van	155	1.50	Diesel	yes	2012	8.817298
3857	Renault	7000.0	van	210	1.50	Diesel	yes	2005	8.853665
3858	BMW	12090.0	hatch	145	1.60	Petrol	yes	2010	9.400134
3859	BMW	27900.0	sedan	38	2.00	Petrol	yes	2013	10.236382
3860	Renault	2100.0	vagon	237	1.90	Diesel	no	2001	7.649693
3861	Renault	6800.0	sedan	152	1.60	Petrol	yes	2007	8.824678
3862	Volkswagen	11500.0	van	163	2.50	Diesel	yes	2008	9.350102
3863	Toyota	17900.0	sedan	35	1.60	Petrol	yes	2014	9.792556
3864	Mercedes-Benz	125000.0	sedan	9	3.00	Diesel	yes	2014	11.736069
3865	BMW	6500.0	sedan	1	3.50	Petrol	yes	1999	8.779557
3866	Volkswagen	13500.0	van	124	2.00	Diesel	yes	2013	9.510445

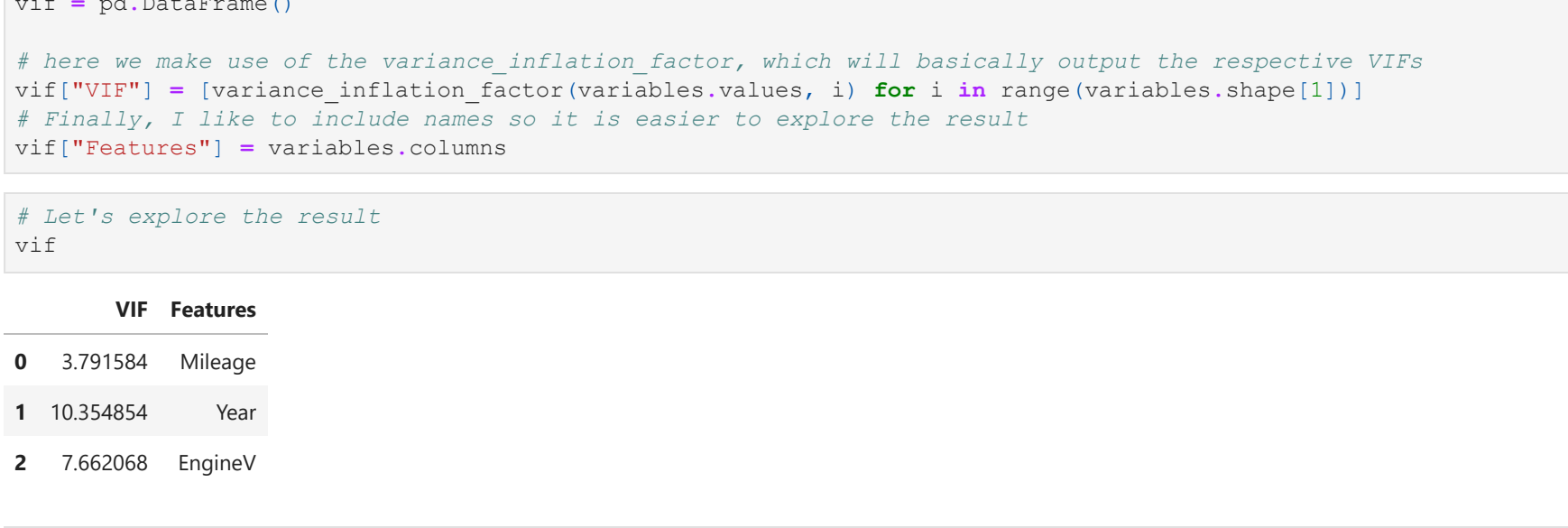
3867 rows × 9 columns

In [26]:
```python
# Let's check the three scatters once again
f, (ax1, ax2, ax3) = plt.subplots(1, 3, sharey=True, figsize =(15,3))
ax1.scatter(data_cleaned['Year'],data_cleaned['log_price'])
ax1.set_title('Log Price and Year')
ax2.scatter(data_cleaned['EngineV'],data_cleaned['log_price'])
ax2.set_title('Log Price and EngineV')
ax3.scatter(data_cleaned['Mileage'],data_cleaned['log_price'])
ax3.set_title('Log Price and Mileage')


plt.show()

# The relationships show a clear linear relationship
# This is some good linear regression material

# Alternatively we could have transformed each of the independent variables
```



In [27]:
```python
# Since we will be using the log price variable, we can drop the old 'Price' one
data_cleaned = data_cleaned.drop(['Price'],axis=1)
```

Multicollinearity

In [28]:
```python
data_cleaned.columns.values
```

Out[28]:
```
array(['Brand', 'Body', 'Mileage', 'EngineV', 'Engine Type',
       'Registration', 'Year', 'log_price'], dtype=object)
```

In [29]:
```python
# sklearn does not have a built-in way to check for multicollinearity
# one of the main reasons is that this is an issue well covered in statistical frameworks and not in ML ones
# surely it is an issue nonetheless, thus we will try to deal with it

# Here's the relevant module
# full documentation: http://www.statsmodels.org/dev/_modules/statsmodels/stats/outliers_influence.html#varianc
from statsmodels.stats.outliers_influence import variance_inflation_factor

# To make this as easy as possible to use, we declare a variable where we put
# all features where we want to check for multicollinearity
# since our categorical data is not yet preprocessed, we will only take the numerical ones
variables = data_cleaned[['Mileage','Year','EngineV']]

# we create a new data frame which will include all the VIFs
# note that each variable has its own variance inflation factor as this measure is variable specific (not model
vif = pd.DataFrame()

# here we make use of the variance_inflation_factor, which will basically output the respective VIFs
vif["VIF"] = [variance_inflation_factor(variables.values, i) for i in range(variables.shape[1])]
# Finally, I like to include names so it is easier to explore the result
vif["Features"] = variables.columns
```

In [30]:
```python
# Let's explore the result
vif
```

Out[30]:

	VIF	Features
0	3.791584	Mileage
1	10.354854	Year
2	7.662068	EngineV

In [31]:
```python
# Since Year has the highest VIF, I will remove it from the model
# This will drive the VIF of other variables down
# So even if EngineV seems with a high VIF, too, once 'Year' is gone that will no longer be the case
data_no_multicollinearity = data_cleaned.drop(['Year'],axis=1)
```

Create dummy variables

In [32]:
```python
# To include the categorical data in the regression, let's create dummies
# There is a very convenient method called: 'get_dummies' which does that seemlessly
# It is extremely important that we drop one of the dummies, alternatively we will introduce multicollinearity
data_with_dummies = pd.get_dummies(data_no_multicollinearity, drop_first=True)
```

In [33]:
```python
data_with_dummies.head()
```

Out[33]:

	Mileage	EngineV	log_price	Brand_BMW	Brand_Mercedes-Benz	Brand_Mitsubishi	Brand_Renault	Brand_Toyota	Brand_Volkswagen	Body_hatcl
0	277	2.0	8.342840	1	0	0	0	0	0	[illegible]
1	427	2.9	8.974618	0	1	0	0	0	0	[illegible]
2	358	5.0	9.495519	0	1	0	0	0	0	[illegible]
3	240	4.2	10.043249	0	0	0	0	0	0	[illegible]
4	120	2.0	9.814656	0	0	0	0	1	0	[illegible]

organizing df

In [34]:
```python
# To make our data frame more organized, we prefer to place the dependent variable in the beginning of the df
# Since each problem is different, that must be done manually
# We can display all possible features and then choose the desired order
data_with_dummies.columns.values
```

Out[34]:
```
array(['Mileage', 'EngineV', 'log_price', 'Brand_BMW',
       'Brand_Mercedes-Benz', 'Brand_Mitsubishi', 'Brand_Renault',
       'Brand_Toyota', 'Brand_Volkswagen', 'Body_hatch', 'Body_other',
       'Body_sedan', 'Body_vagon', 'Body_van', 'Engine Type_Gas',
       'Engine Type_Other', 'Engine Type_Petrol', 'Registration_yes'],
      dtype=object)
```

In [35]:
```python
# To make the code a bit more parametrized, let's declare a new variable that will contain the preferred order
cols = ['log_price', 'Mileage', 'EngineV', 'Brand_BMW',
       'Brand_Mercedes-Benz', 'Brand_Mitsubishi', 'Brand_Renault',
       'Brand_Toyota', 'Brand_Volkswagen', 'Body_hatch', 'Body_other',
       'Body_sedan', 'Body_vagon', 'Body_van', 'Engine Type_Gas',
       'Engine Type_Other', 'Engine Type_Petrol', 'Registration_yes']
```

In [36]:
```python
# To implement the reordering, we will create a new df, which is equal to the old one but with the new order of
data_preprocessed = data_with_dummies[cols]
data_preprocessed.head()
```

Out[36]:

	log_price	Mileage	EngineV	Brand_BMW	Brand_Mercedes-Benz	Brand_Mitsubishi	Brand_Renault	Brand_Toyota	Brand_Volkswagen	Body_hatcl
0	8.342840	277	2.0	1	0	0	0	0	0	[illegible]
1	8.974618	427	2.9	0	1	0	0	0	0	[illegible]
2	9.495519	358	5.0	0	1	0	0	0	0	[illegible]
3	10.043249	240	4.2	0	0	0	0	0	0	[illegible]
4	9.814656	120	2.0	0	0	0	0	1	0	[illegible]

Linear regression model

Declare the inputs and the targets

In [37]:
```python
# The target(s) (dependent variable) is 'log price'
targets = data_preprocessed['log_price']

inputs = data_preprocessed.drop(['log_price'],axis=1)
```

Scale the data

In [38]:
```python
# Import the scaling module
from sklearn.preprocessing import StandardScaler

# Create a scaler object
scaler = StandardScaler()
# Fit the inputs (calculate the mean and standard deviation feature-wise)
scaler.fit(inputs)
```

Out[38]: `StandardScaler(copy=True, with_mean=True, with_std=True)`

In [39]:
```python
# Scale the features and store them in a new variable (the actual scaling procedure)
inputs_scaled = scaler.transform(inputs)
```

Train Test Split

In [40]:
```python
# Import the module for the split
from sklearn.model_selection import train_test_split

# Split the variables with an 80-20 split and some random state
# To have the same split as mine, use random_state = 365
x_train, x_test, y_train, y_test = train_test_split(inputs_scaled, targets, test_size=0.2, random_state=365)
```

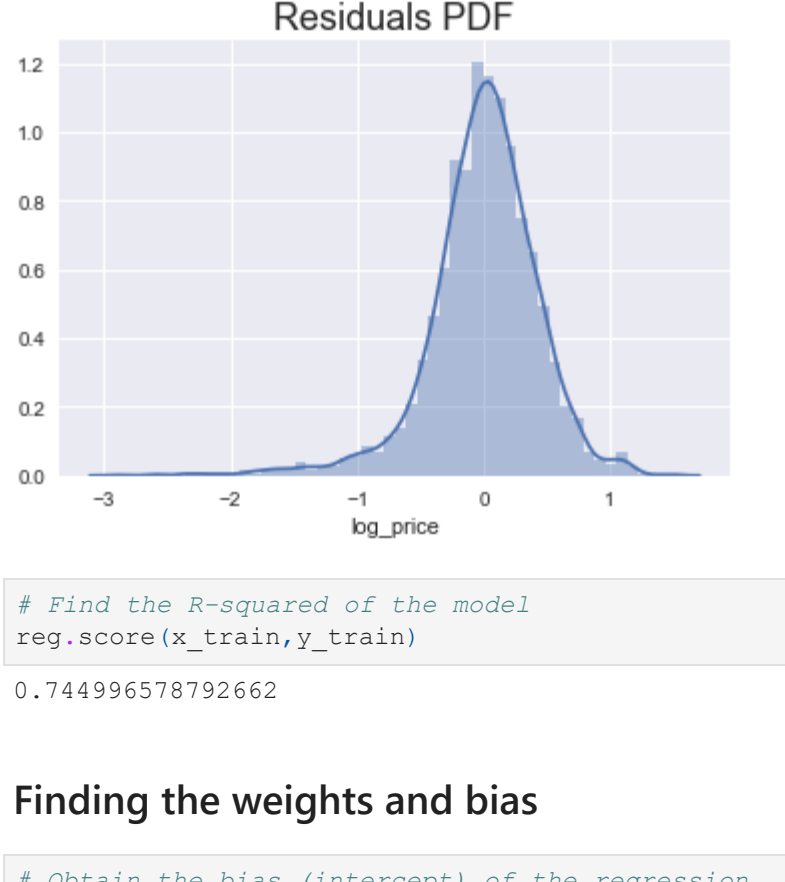
Create the regression

In [41]:
```python
# Create a linear regression object
reg = LinearRegression()
# Fit the regression with the scaled TRAIN inputs and targets
reg.fit(x_train,y_train)
```

Out[41]: `LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)`

In [42]:
```python
# Let's check the outputs of the regression
# I'll store them in y_hat as this is the 'theoretical' name of the predictions
y_hat = reg.predict(x_train)
```

In [43]:
```python
# The simplest way to compare the targets (y_train) and the predictions (y_hat) is to plot them on a scatter pl
# The closer the points to the 45-degree line, the better the prediction
plt.scatter(y_train, y_hat)
# Let's also name the axes
plt.xlabel('Targets (y_train)',size=18)
plt.ylabel('Predictions (y_hat)',size=18)
# Sometimes the plot will have different scales of the x-axis and the y-axis
# This is an issue as we won't be able to interpret the '45-degree line'
# We want the x-axis and the y-axis to be the same
plt.xlim(6,13)
plt.ylim(6,13)
plt.show()
```

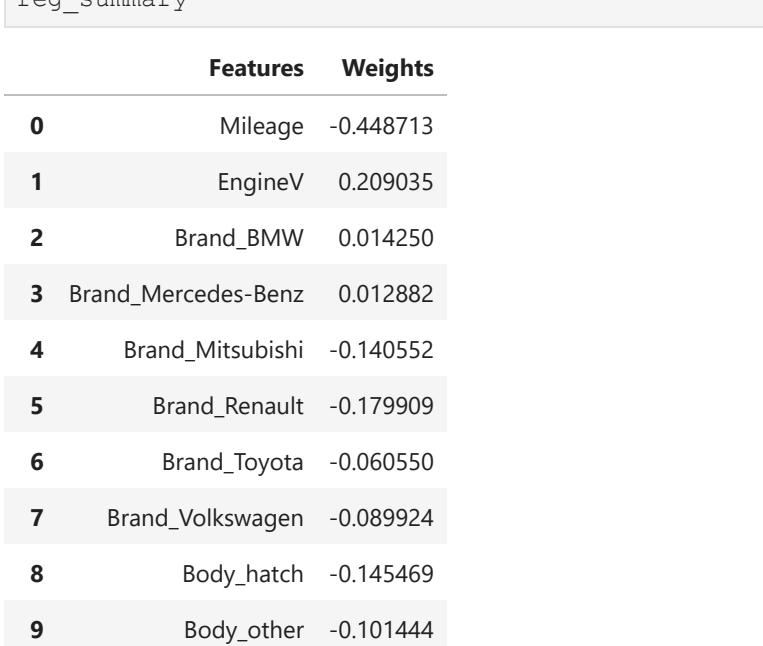


In [44]:
```python
# Another useful check of our model is a residual plot
# We can plot the PDF of the residuals and check for anomalies
sns.distplot(y_train - y_hat)

# Include a title
plt.title("Residuals PDF", size=18)

# In the best case scenario this plot should be normally distributed
# In our case we notice that there are many negative residuals (far away from the mean)
# Given the definition of the residuals (y_train - y_hat), negative values imply
# that y_hat (predictions) are much higher than y_train (the targets)
# This is food for thought to improve our model
```

Out[44]: `Text(0.5,1,'Residuals PDF')`



In [45]:
```python
# Find the R-squared of the model
reg.score(x_train,y_train)
```

Out[45]: `0.744996578792662`

Finding the weights and bias

In [46]:
```python
# Obtain the bias (intercept) of the regression
reg.intercept_
```

Out[46]: `9.415239458021299`

In [47]:
```python
# Obtain the weights (coefficients) of the regression
reg.coef_
```

Out[47]:
```
array([-0.44871341,  0.20903483,  0.0142496 ,  0.01288174, -0.14055166,
       -0.17990912, -0.06054988, -0.08992433, -0.1454692 , -0.10144383,
       -0.20062984, -0.12988747, -0.16859669, -0.12149035, -0.03336798,
       -0.14690868,  0.32047333])
```

In [48]:
```python
# Create a regression summary where we can compare them with one-another
reg_summary = pd.DataFrame(inputs.columns.values, columns=['Features'])
reg_summary['Weights'] = reg.coef_
reg_summary
```

Out[48]:

	Features	Weights
0	Mileage	-0.448713
1	EngineV	0.209035
2	Brand_BMW	0.014250
3	Brand_Mercedes-Benz	0.012882
4	Brand_Mitsubishi	-0.140552
5	Brand_Renault	-0.179909
6	Brand_Toyota	-0.060550
7	Brand_Volkswagen	-0.089924
8	Body_hatch	-0.145469
9	Body_other	-0.101444
10	Body_sedan	-0.200630
11	Body_vagon	-0.129887
12	Body_van	-0.168597
13	Engine Type_Gas	-0.121490
14	Engine Type_Other	-0.033368
15	Engine Type_Petrol	-0.146909
16	Registration_yes	0.320473

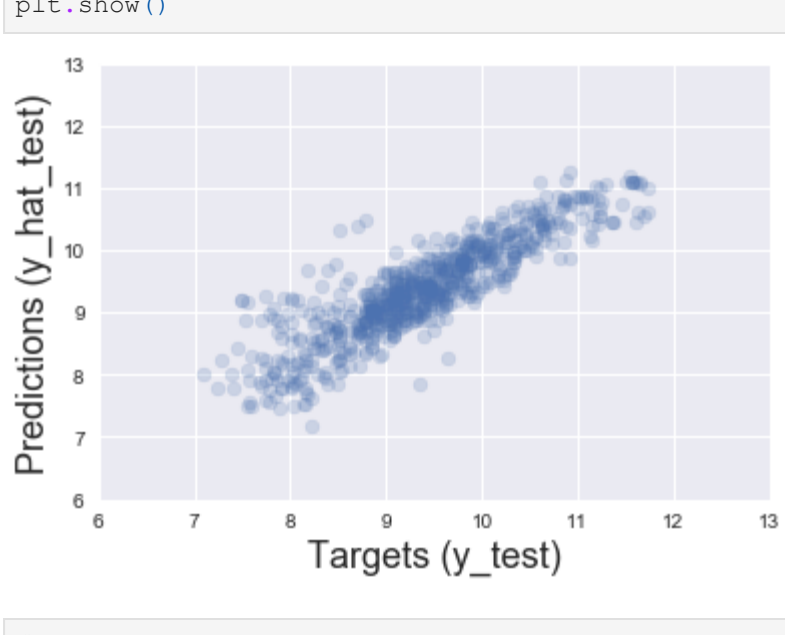
In [49]:
```
# Check the different categories in the 'Brand' variable
data_cleaned['Brand'].unique()

# In this way we can see which 'Brand' is actually the benchmark
```
Out[49]:
```
array(['BMW', 'Mercedes-Benz', 'Audi', 'Toyota', 'Renault', 'Volkswagen',
       'Mitsubishi'], dtype=object)
```

Testing

In [50]:
```
# Once we have trained and fine-tuned our model, we can proceed to testing it
# Testing is done on a dataset that the algorithm has never seen
# Luckily we have prepared such a dataset
# Our test inputs are 'x_test', while the outputs: 'y_test'
# We SHOULD NOT TRAIN THE MODEL ON THEM, we just feed them and find the predictions
# If the predictions are far off, we will know that our model overfitted
y_hat_test = reg.predict(x_test)
```

In [51]:
```
# Create a scatter plot with the test targets and the test predictions
# You can include the argument 'alpha' which will introduce opacity to the graph
plt.scatter(y_test, y_hat_test, alpha=0.2)
plt.xlabel('Targets (y_test)',size=18)
plt.ylabel('Predictions (y_hat_test)',size=18)
plt.xlim(6,13)
plt.ylim(6,13)
plt.show()
```



In [52]:
```
# Finally, let's manually check these predictions
# To obtain the actual prices, we take the exponential of the log_price
df_pf = pd.DataFrame(np.exp(y_hat_test), columns=['Prediction'])
df_pf.head()
```

Out[52]:

	Prediction
0	10685.501696
1	3499.255242
2	7553.285218
3	7463.963017
4	11353.490075

In [53]:
```
# We can also include the test targets in that data frame (so we can manually compare them)
df_pf['Target'] = np.exp(y_test)
df_pf

# Note that we have a lot of missing values
# There is no reason to have ANY missing values, though
# This suggests that something is wrong with the data frame / indexing
```

Out[53]:

	Prediction	Target
0	10685.501696	NaN
1	3499.255242	7900.0
2	7553.285218	NaN
3	7463.963017	NaN
4	11353.490075	NaN
5	21289.799394	14200.0
6	20159.189144	NaN
7	20349.617702	NaN
8	11581.537864	11950.0
9	33614.617349	NaN
10	7241.068243	NaN
11	5175.769541	10500.0
12	5484.015362	NaN
13	13292.711243	NaN
14	8248.666686	NaN
15	10621.836767	NaN
16	23721.581637	3500.0
17	11770.636010	NaN
18	37600.146722	7500.0
19	16178.143307	6800.0
20	11876.820988	NaN
21	31557.804999	NaN
22	6102.358118	NaN
23	13111.914144	NaN
24	23650.150725	NaN
25	45272.248411	NaN
26	2178.941672	NaN
27	2555.022542	NaN
28	35991.510539	NaN
29	26062.229419	NaN
...	...	...
744	2379.583414	NaN
745	6421.180201	7777.0
746	13355.106770	NaN
747	8453.281424	10500.0
748	48699.979367	NaN
749	6082.849234	4100.0
750	10381.621436	NaN
751	8493.042746	NaN
752	8591.658845	13999.0
753	6358.547301	NaN
754	17028.451182	NaN
755	15885.658673	NaN
756	3752.540952	NaN
757	12028.905190	NaN
758	9380.459827	16999.0
759	10125.265176	NaN
760	13443.324968	NaN
761	9097.127448	NaN
762	12201.288474	4700.0
763	12383.352887	NaN
764	14049.760996	NaN
765	11034.660068	3750.0
766	18982.148845	NaN
767	24323.483753	NaN
768	38260.361723	NaN
769	29651.726363	6950.0
770	10732.071179	NaN
771	13922.446953	NaN
772	27487.751303	NaN
773	13491.163043	NaN

774 rows × 2 columns

In [54]:
```
# After displaying y_test, we find what the issue is
# The old indexes are preserved (recall earlier in that code we made a note on that)
# The code was: data_cleaned = data_4.reset_index(drop=True)

# Therefore, to get a proper result, we must reset the index and drop the old indexing
y_test = y_test.reset_index(drop=True)

# Check the result
y_test.head()
```

Out[54]:
```
0    7.740664
1    7.937375
2    7.824046
3    8.764053
4    9.121509
Name: log_price, dtype: float64
```

In [55]:
```
# Let's overwrite the 'Target' column with the appropriate values
# Again, we need the exponential of the test log price
df_pf['Target'] = np.exp(y_test)
df_pf
```

Out[55]:

	Prediction	Target
0	10685.501696	2300.0
1	3499.255242	2800.0
2	7553.285218	2500.0
3	7463.963017	6400.0
4	11353.490075	9150.0
5	21289.799394	20000.0
6	20159.189144	38888.0
7	20349.617702	16999.0
8	11581.537864	12500.0
9	33614.617349	41000.0
10	7241.068243	12800.0
11	5175.769541	5000.0
12	5484.015362	7900.0
13	13292.711243	16999.0
14	8248.666686	9200.0
15	10621.836767	11999.0
16	23721.581637	20500.0
17	11770.636010	9700.0
18	37600.146722	39900.0
19	16178.143307	16400.0
20	11876.820988	15200.0
21	31557.804999	24500.0
22	6102.358118	5650.0
23	13111.914144	12900.0
24	23650.150725	20900.0
25	45272.248411	31990.0
26	2178.941672	3600.0
27	2555.022542	11600.0
28	35991.510539	43999.0
29	26062.229419	42500.0
...	...	...
744	2379.583414	3000.0
745	6421.180201	4400.0
746	13355.106770	7500.0
747	8453.281424	10900.0
748	48699.979367	77500.0
749	6082.849234	7450.0
750	10381.621436	3000.0
751	8493.042746	12800.0
752	8591.658845	12000.0
753	6358.547301	4850.0
754	17028.451182	18700.0
755	15885.658673	17300.0
756	3752.540952	2600.0
757	12028.905190	10500.0
758	9380.459827	7950.0
759	10125.265176	6700.0
760	13443.324968	9000.0
761	9097.127448	8000.0
762	12201.288474	12999.0
763	12383.352887	10800.0
764	14049.760996	10700.0
765	11034.660068	9800.0
766	18982.148845	17900.0
767	24323.483753	18800.0
768	38260.361723	75555.0
769	29651.726363	29500.0
770	10732.071179	9600.0
771	13922.446953	18300.0
772	27487.751303	68500.0
773	13491.163043	10800.0

774 rows × 2 columns

In [56]:
```
# Additionally, we can calculate the difference between the targets and the predictions
# Note that this is actually the residual (we already plotted the residuals)
df_pf['Residual'] = df_pf['Target'] - df_pf['Prediction']

# Since OLS is basically an algorithm which minimizes the total sum of squared errors (residuals),
# this comparison makes a lot of sense
```

In [57]:
```
# Finally, it makes sense to see how far off we are from the result percentage-wise
# Here, we take the absolute difference in %, so we can easily order the data frame
df_pf['Difference%'] = np.absolute(df_pf['Residual']/df_pf['Target']*100)
df_pf
```

Out[57]:

	Prediction	Target	Residual	Difference%
0	10685.501696	2300.0	-8385.501696	364.587030
1	3499.255242	2800.0	-699.255242	24.973402
2	7553.285218	2500.0	-5053.285218	202.131409
3	7463.963017	6400.0	-1063.963017	16.624422
4	11353.490075	9150.0	-2203.490075	24.081859
5	21289.799394	20000.0	-1289.799394	6.448997
6	20159.189144	38888.0	18728.810856	48.160900
7	20349.617702	16999.0	-3350.617702	19.710675
8	11581.537864	12500.0	918.462136	7.347697
9	33614.617349	41000.0	7385.382651	18.013128
10	7241.068243	12800.0	5558.931757	43.429154
11	5175.769541	5000.0	-175.769541	3.515391
12	5484.015362	7900.0	2415.984638	30.582084
13	13292.711243	16999.0	3706.288757	21.802981
14	8248.666686	9200.0	951.333314	10.340580
15	10621.836767	11999.0	1377.163233	11.477317
16	23721.581637	20500.0	-3221.581637	15.715032
17	11770.636010	9700.0	-2070.636010	21.346763
18	37600.146722	39900.0	2299.853278	5.764043
19	16178.143307	16400.0	221.856693	1.352785
20	11876.820988	15200.0	3323.179012	21.863020
21	31557.804999	24500.0	-7057.804999	28.807367
22	6102.358118	5650.0	-452.358118	8.006338
23	13111.914144	12900.0	-211.914144	1.642745
24	23650.150725	20900.0	-2750.150725	13.158616
25	45272.248411	31990.0	-13282.248411	41.520001
26	2178.941672	3600.0	1421.058328	39.473842
27	2555.022542	11600.0	9044.977458	77.973944
28	35991.510539	43999.0	8007.489461	18.199253
29	26062.229419	42500.0	16437.770581	38.677107
...	...	...	...	...
744	2379.583414	3000.0	620.416586	20.680553
745	6421.180201	4400.0	-2021.180201	45.935914
746	13355.106770	7500.0	-5855.106770	78.068090
747	8453.281424	10900.0	2446.718576	22.446959
748	48699.979367	77500.0	28800.020633	37.161317
749	6082.849234	7450.0	1367.150766	18.351017
750	10381.621436	3000.0	-7381.621436	246.054048
751	8493.042746	12800.0	4306.957254	33.648104
752	8591.658845	12000.0	3408.341155	28.402843
753	6358.547301	4850.0	-1508.547301	31.104068
754	17028.451182	18700.0	1671.548818	8.938764
755	15885.658673	17300.0	1414.341327	8.175383
756	3752.540952	2600.0	-1152.540952	44.328498
757	12028.905190	10500.0	-1528.905190	14.561002
758	9380.459827	7950.0	-1430.459827	17.993205
759	10125.265176	6700.0	-3425.265176	51.123361
760	13443.324968	9000.0	-4443.324968	49.370277
761	9097.127448	8000.0	-1097.127448	13.714093
762	12201.288474	12999.0	797.711526	6.136715
763	12383.352887	10800.0	-1583.352887	14.660675
764	14049.760996	10700.0	-3349.760996	31.306178
765	11034.660068	9800.0	-1234.660068	12.598572
766	18982.148845	17900.0	-1082.148845	6.045524
767	24323.483753	18800.0	-5523.483753	29.380233
768	38260.361723	75555.0	37294.638277	49.360914
769	29651.726363	29500.0	-151.726363	0.514327
770	10732.071179	9600.0	-1132.071179	11.792408
771	13922.446953	18300.0	4377.553047	23.921055
772	27487.751303	68500.0	41012.248697	59.871896
773	13491.163043	10800.0	-2691.163043	24.918176

774 rows × 4 columns

In [58]:
```
# Exploring the descriptives here gives us additional insights
df_pf.describe()
```

Out[58]:

	Prediction	Target	Residual	Difference%
count	774.000000	774.000000	774.000000	774.000000
mean	15946.760167	18165.817106	2219.056939	36.256693
std	13133.197604	19967.858908	10871.218143	55.066507
min	1320.562768	1200.000000	-29456.498331	0.062794
25%	7413.644234	6900.000000	-2044.191251	12.108022
50%	11568.168859	11600.000000	142.518577	23.467728
75%	20162.408805	20500.000000	3147.343497	39.563570
max	77403.055224	126000.000000	85106.162329	512.688080

In [59]:
```
# Sometimes it is useful to check these outputs manually
# To see all rows, we use the relevant pandas syntax
pd.options.display.max_rows = 999
# Moreover, to make the dataset clear, we can display the result with only 2 digits after the dot
pd.set_option('display.float_format', lambda x: '%.2f' % x)
# Finally, we sort by difference in % and manually check the model
df_pf.sort_values(by=['Difference%'])
```

Out[59]:

	Prediction	Target	Residual	Difference%
698	30480.85	30500.00	19.15	0.06
742	16960.31	16999.00	38.69	0.23
60	12469.21	12500.00	30.79	0.25
110	25614.14	25500.00	-114.14	0.45
367	42703.68	42500.00	-203.68	0.48
369	3084.69	3100.00	15.31	0.49
769	29651.73	29500.00	-151.73	0.51
272	9749.53	9800.00	50.47	0.52
714	23118.07	22999.00	-119.07	0.52
630	8734.58	8800.00	65.42	0.74
380	3473.79	3500.00	26.21	0.75
648	21174.10	21335.00	160.90	0.75
308	8967.74	8900.00	-67.74	0.76
665	17858.02	18000.00	141.98	0.79
379	17654.84	17800.00	145.16	0.82
719	11391.95	11500.00	108.05	0.94
102	28625.56	28900.00	274.44	0.95
94	7724.17	7800.00	75.83	0.97
561	6429.03	6500.00	70.97	1.09
242	7597.39	7500.00	-97.39	1.30
528	18555.09	18800.00	244.91	1.30
61	7396.87	7300.00	-96.87	1.33
19	16178.14	16400.00	221.86	1.35
280	12327.10	12499.00	171.90	1.38
311	51287.19	52055.25	768.06	1.48
723	6009.63	6100.00	90.37	1.48
49	4973.17	4900.00	-73.17	1.49
114	27716.14	27300.00	-416.14	1.52
636	28498.91	28950.00	451.09	1.56
612	2953.17	3000.00	46.83	1.56
47	26425.14	25999.00	-426.14	1.64
23	13111.91	12900.00	-211.91	1.64
31	12858.08	12650.00	-208.08	1.64
91	13421.16	13200.00	-221.16	1.68
329	7327.18	7200.00	-127.18	1.77
549	3816.33	3750.00	-66.33	1.77
252	9721.50	9900.00	178.50	1.80
387	44173.72	44999.00	825.28	1.83
267	40753.58	40000.00	-753.58	1.88
467	22262.80	22711.65	448.85	1.98
556	18231.44	18600.00	368.56	1.98
165	9596.94	9400.00	-196.94	2.10
259	6067.79	6200.00	132.21	2.13
601	35371.16	34600.00	-771.16	2.23
708	11967.39	11700.00	-267.39	2.29
593	17908.00	17500.00	-408.00	2.33
398	8707.13	8500.00	-207.13	2.44
526	29049.27	28350.00	-699.27	2.47
603	14513.46	14900.00	386.54	2.59
53	20453.89	21000.00	546.11	2.60
632	15383.35	14990.00	-393.35	2.62
533	24642.50	24000.00	-642.50	2.68
497	50099.92	51500.00	1400.08	2.72
212	16133.86	15700.00	-433.86	2.76
130	17489.92	18000.00	510.08	2.83
290	1894.40	1950.00	55.60	2.85
78	30810.25	29900.00	-910.25	3.04
642	8721.97	8999.00	277.03	3.08
437	18866.50	18300.00	-566.50	3.10
101	5958.63	6150.00	191.37	3.11
314	5811.74	6000.00	188.26	3.14
150	9800.43	9500.00	-300.43	3.16
565	7324.63	7100.00	-224.63	3.16
574	12583.52	13000.00	416.48	3.20
591	10115.13	9800.00	-315.13	3.22
172	11156.38	10800.00	-356.38	3.30
133	9279.28	9600.00	320.72	3.34
480	31369.37	32500.00	1130.63	3.48
87	2315.71	2400.00	84.29	3.51
11	5175.77	5000.00	-175.77	3.52
43	21611.83	22400.00	788.17	3.52
96	7976.26	7700.00	-276.26	3.59
406	24874.86	23999.00	-875.86	3.65
173	36516.35	37900.00	1383.65	3.65
540	4666.05	4500.00	-166.05	3.69
40	18672.68	18000.00	-672.68	3.74
340	14815.83	15400.00	584.17	3.79
239	10581.62	10999.00	417.38	3.79
109	12663.54	12200.00	-463.54	3.80
256	1825.44	1900.00	74.56	3.92
317	12247.90	12750.00	502.10	3.94
77	5930.73	5700.00	-230.73	4.05
301	9782.47	10200.00	417.53	4.09
333	12452.22	11960.00	-492.22	4.12
570	23163.87	24171.42	1007.55	4.17
581	3246.94	3390.00	143.06	4.22
693	12354.16	12900.00	545.84	4.23
381	33499.44	35000.00	1500.56	4.29
438	16257.03	16999.00	741.97	4.36
368	8415.81	8800.00	384.19	4.37
273	12318.39	12900.00	581.61	4.51
235	2765.14	2900.00	134.86	4.65
168	11420.95	11999.00	578.05	4.82
707	2725.40	2600.00	-125.40	4.82
72	23624.69	22500.00	-1124.69	5.00
559	11377.84	11999.00	621.16	5.18
134	12096.18	11500.00	-596.18	5.18
446	9363.27	8900.00	-463.27	5.21
127	12311.47	11700.00	-611.47	5.23
450	14218.94	13500.00	-718.94	5.33
293	8431.89	7999.00	-432.89	5.41
18	37600.15	39900.00	2299.85	5.76
452	39882.67	37700.00	-2182.67	5.79
195	20588.57	21900.00	1311.43	5.99
676	6861.84	7300.00	438.16	6.00
766	18982.15	17900.00	-1082.15	6.05
328	15067.85	14200.00	-867.85	6.11
762	12201.29	12999.00	797.71	6.14
649	11147.91	10500.00	-647.91	6.17
299	20183.30	18999.00	-1184.30	6.23
641	17334.11	18500.00	1165.89	6.30
5	21289.80	20000.00	-1289.80	6.45
545	6826.78	7300.00	473.22	6.48
622	4472.47	4200.00	-272.47	6.49
422	53294.61	57000.00	3705.39	6.50
740	6658.73	6250.00	-408.73	6.54
85	19001.29	17800.00	-1201.29	6.75
315	4590.49	4300.00	-290.49	6.76
462	43236.92	40500.00	-2736.92	6.76
394	9076.42	8500.00	-576.42	6.78
188	10159.18	10900.00	740.82	6.80
731	16027.02	15000.00	-1027.02	6.85
448	13502.35	14500.00	997.65	6.88
254	6413.26	5999.00	-414.26	6.91
667	49221.63	52999.00	3777.37	7.13
600	21816.43	23500.00	1683.57	7.16
144	11969.66	12900.00	930.34	7.21
270	8263.95	7700.00	-563.95	7.32
8	11581.54	12500.00	918.46	7.35
433	6977.90	6500.00	-477.90	7.35
251	6978.91	6500.00	-478.91	7.37
553	16392.22	17700.00	1307.78	7.39
725	15742.41	16999.00	1256.59	7.39
615	7869.47	8500.00	630.53	7.42
518	21297.65	19800.00	-1497.65	7.56
268	6893.62	6400.00	-493.62	7.71
71	15627.03	14500.00	-1127.03	7.77
579	3411.53	3700.00	288.47	7.80
330	11336.71	12300.00	963.29	7.83
59	8195.34	7600.00	-595.34	7.83
354	16717.08	15500.00	-1217.08	7.85
147	7772.57	7200.00	-572.57	7.95
508	16197.42	15000.00	-1197.42	7.98
22	6102.36	5650.00	-452.36	8.01
103	4488.43	4150.00	-338.43	8.16
755	15885.66	17300.00	1414.34	8.18
198	17983.10	19600.00	1616.90	8.25
470	7045.72	6500.00	-545.72	8.40
710	3795.06	3500.00	-295.06	8.43
185	6130.96	6700.00	569.04	8.49
542	5947.51	6500.00	552.49	8.50
412	7609.28	7000.00	-609.28	8.70
415	8117.44	8900.00	782.56	8.79
200	11098.18	10200.00	-898.18	8.81
754	17028.45	18700.00	1671.55	8.94
65	19847.25	18200.00	-1647.25	9.05
682	5454.34	5000.00	-454.34	9.09
222	20662.46	18900.00	-1762.46	9.33
89	11696.25	12900.00	1203.75	9.33
52	10716.84	9800.00	-916.84	9.36
126	13459.92	12300.00	-1159.92	9.43
598	8767.54	9700.00	932.46	9.61
504	23272.83	25749.75	2476.92	9.62
493	5484.97	4999.00	-485.97	9.72
449	9495.62	8650.00	-845.62	9.78
516	11858.48	10800.00	-1058.48	9.80
261	53312.81	48535.50	-4777.31	9.84
531	47047.70	52300.00	5252.30	10.04
68	6717.17	6100.00	-617.17	10.12
376	5391.77	6000.00	608.23	10.14
538	17591.09	19600.00	2008.91	10.25
419	17591.09	19600.00	2008.91	10.25
595	25576.58	28500.00	2923.42	10.26
472	20367.25	22700.00	2332.75	10.28
386	7267.36	8100.00	832.64	10.28
473	1792.36	1999.00	206.64	10.34
14	8248.67	9200.00	951.33	10.34
123	5643.45	6300.00	656.55	10.42
142	6839.57	7650.00	810.43	10.59
257	41503.90	37500.00	-4003.90	10.68
194	9310.69	8400.00	-910.69	10.84
637	35662.26	40000.00	4337.74	10.84
410	16407.29	14800.00	-1607.29	10.86
395	21303.57	23900.00	2596.43	10.86
213	15872.91	14300.00	-1572.91	11.00
653	10332.54	9300.00	-1032.54	11.10
54	18575.43	20900.00	2324.57	11.12
105	8882.65	10000.00	1117.35	11.17
597	7797.18	6999.00	-798.18	11.40
15	10621.84	11999.00	1377.16	11.48
770	10732.07	9600.00	-1132.07	11.79
674	2381.01	2700.00	318.99	11.81
132	11200.20	9999.00	-1201.20	12.01
525	2373.66	2700.00	326.34	12.09
730	10696.56	12179.00	1482.44	12.17
506	3590.97	3200.00	-390.97	12.22
278	53063.22	60500.00	7436.78	12.29
108	7300.05	6500.00	-800.05	12.31
503	6392.70	7300.00	907.30	12.43
536	6746.43	6000.00	-746.43	12.44
156	9192.06	10500.00	1307.94	12.46
765	11034.66	9800.00	-1234.66	12.60
534	16939.86	19400.00	2460.14	12.68
50	2479.43	2200.00	-279.43	12.70
562	9593.52	11000.00	1406.48	12.79
131	23967.81	27500.00	3532.19	12.84
157	7491.01	8600.00	1108.99	12.90
638	8242.62	7300.00	-942.62	12.91
543	9489.56	10900.00	1410.44	12.94
724	44312.98	50900.00	6587.02	12.94
527	9829.53	8700.00	-1129.53	12.98
610	9269.68	8200.00	-1069.68	13.04
359	4524.77	3999.00	-525.77	13.15
24	23650.15	20900.00	-2750.15	13.16
402	8850.21	10200.00	1349.79	13.23
360	4770.52	5500.00	729.48	13.26
184	29479.97	34000.00	4520.03	13.29
324	8316.92	9600.00	1283.08	13.37
307	24974.57	28900.00	3925.43	13.58
118	14943.75	17300.00	2356.25	13.62
607	28498.91	33000.00	4501.09	13.64
332	14591.35	16900.00	2308.65	13.66
140	10358.58	12000.00	1641.42	13.68
627	13074.74	11500.00	-1574.74	13.69
761	9097.13	8000.00	-1097.13	13.71
207	15010.51	13200.00	-1810.51	13.72
685	12593.00	14600.00	2007.00	13.75
350	20246.04	23500.00	3253.96	13.85
143	8768.29	7700.00	-1068.29	13.87
318	39744.80	34900.00	-4844.80	13.88
377	9909.62	8700.00	-1209.62	13.90
152	44680.77	51900.00	7219.23	13.91
57	21942.05	25500.00	3557.95	13.95
277	12900.31	15000.00	2099.69	14.00
253	18128.32	15900.00	-2228.32	14.01
384	4296.77	5000.00	703.23	14.06
113	6006.27	6999.00	992.73	14.18
287	1972.28	2300.00	327.72	14.25
650	8236.36	7200.00	-1036.36	14.39
319	10612.51	12400.00	1787.49	14.42
430	14197.26	12400.00	-1797.26	14.49
95	47013.28	55000.00	7986.72	14.52
757	12028.91	10500.00	-1528.91	14.56
153	3666.31	3200.00	-466.31	14.57
720	2860.97	3350.00	489.03	14.60
631	7256.86	8500.00	1243.14	14.63
36	10499.60	12300.00	1800.40	14.64
763	12383.35	10800.00	-1583.35	14.66
344	11937.31	13995.00	2057.69	14.70
389	2810.71	2450.00	-360.71	14.72
204	7664.32	9000.00	1335.68	14.84
718	8041.62	6999.00	-1042.62	14.90
484	13334.19	11600.00	-1734.19	14.95
258	13680.48	11900.00	-1780.48	14.96
616	13500.69	15900.00	2399.31	15.09
281	11638.89	13708.50	2069.61	15.10
476	15700.53	18500.00	2799.47	15.13
716	11425.01	13500.00	2074.99	15.37
529	53312.81	63000.00	9687.19	15.38
481	6599.62	7800.00	1200.38	15.39
706	61639.73	72900.00	11260.27	15.45
558	7098.53	8400.00	1301.47	15.49
151	10889.39	12900.00	2010.61	15.59
663	2613.97	3099.00	485.03	15.65
16	23721.58	20500.00	-3221.58	15.72
356	10133.68	8750.00	-1383.68	15.81
297	22261.50	19200.00	-3061.50	15.95
119	10448.50	8999.00	-1449.50	16.11
390	24271.90	20900.00	-3371.90	16.13
439	14926.69	17800.00	2873.31	16.14
441	11619.16	10000.00	-1619.16	16.19
548	46465.02	39900.00	-6565.02	16.45
460	50954.68	61000.00	10045.32	16.47
211	6848.88	8200.00	1351.12	16.48
106	16547.03	14200.00	-2347.03	16.53
599	4590.16	5500.00	909.84	16.54
220	13348.91	15999.00	2650.09	16.56
226	11191.05	9600.00	-1591.05	16.57
197	2126.49	2550.00	423.51	16.61
3	7463.96	6400.00	-1063.96	16.62
378	2749.08	3300.00	550.92	16.69
507	18282.75	21950.00	3667.25	16.71
186	19071.43	22900.00	3828.57	16.72
100	32886.86	39500.00	6613.14	16.74
620	25752.19	30990.00	5237.81	16.90
229	7719.69	9300.00	1580.31	16.99
400	25986.31	31310.00	5323.69	17.00
336	8250.47	9950.00	1699.53	17.08
483	28937.50	34900.00	5962.50	17.08
171	8392.42	7150.00	-1242.42	17.38
421	8033.61	9750.00	1716.39	17.60
643	8156.11	9900.00	1743.89	17.62
696	2470.61	3000.00	529.39	17.65
286	19659.97	16700.00	-2959.97	17.72
496	17540.72	14899.00	-2641.72	17.73
655	7814.16	9500.00	1685.84	17.75
407	21097.66	17900.00	-3197.66	17.86
464	4266.27	5200.00	933.73	17.96
758	9380.46	7950.00	-1430.46	17.99
670	33614.62	41000.00	7385.38	18.01
9	33614.62	41000.00	7385.38	18.01
263	9089.35	7700.00	-1389.35	18.04
521	27740.81	23500.00	-4240.81	18.05
46	3542.72	3000.00	-542.72	18.09
237	25037.87	21200.00	-3837.87	18.10
28	35991.51	43999.00	8007.49	18.20
125	13733.33	16800.00	3066.67	18.25
721	11431.35	13999.00	2567.65	18.34
749	6082.85	7450.00	1367.15	18.35
55	12674.57	10700.00	-1974.57	18.45
466	25975.12	21900.00	-4075.12	18.61
651	3026.25	2550.00	-476.25	18.68
560	33172.20	40800.00	7627.80	18.70
247	13159.16	16200.00	3040.84	18.77
738	20216.67	24900.00	4683.33	18.81
715	10220.74	8600.00	-1620.74	18.85
608	29127.72	24500.00	-4627.72	18.89
509	5839.08	7200.00	1360.92	18.90
435	53063.22	65500.00	12436.78	18.99
187	28256.79	34900.00	6643.21	19.03
689	4524.77	3800.00	-724.77	19.07
51	2543.57	3149.25	605.68	19.23
501	60493.51	75000.00	14506.49	19.34
292	8962.29	7500.00	-1462.29	19.50
193	14832.32	12400.00	-2432.32	19.62
711	19676.51	24500.00	4823.49	19.69
7	20349.62	16999.00	-3350.62	19.71
569	1926.60	2400.00	473.40	19.72
453	8381.60	6999.00	-1382.60	19.75
444	38334.67	32000.00	-6334.67	19.80
454	20972.54	17500.00	-3472.54	19.84
176	6732.97	8400.00	1667.03	19.85
240	10419.20	13000.00	2580.80	19.85
688	24572.28	20500.00	-4072.28	19.86
313	10014.71	12500.00	2485.29	19.88
471	4209.17	3500.00	-709.17	20.26
535	34678.95	43500.00	8821.05	20.28
79	18893.76	15700.00	-3193.76	20.34
409	8121.22	10200.00	2078.78	20.38
154	11443.85	9499.00	-1944.85	20.47
494	33392.40	42000.00	8607.60	20.49
98	6746.48	8500.00	1753.52	20.63
227	17251.60	14300.00	-2951.60	20.64
115	6981.34	8800.00	1818.66	20.67
744	2379.58	3000.00	620.42	20.68
474	10932.17	13800.00	2867.83	20.78
459	2779.04	2300.00	-479.04	20.83
331	11002.01	13900.00	2897.99	20.85
76	5144.02	6500.00	1355.98	20.86
244	7110.32	8990.00	1879.68	20.91
644	53312.81	67431.00	14118.19	20.94
174	7745.02	6400.00	-1345.02	21.02
358	63921.33	80999.00	17077.67	21.08
425	3940.49	4999.00	1058.51	21.17
321	23630.85	19500.00	-4130.85	21.18
312	14792.29	18800.00	4007.71	21.32
17	11770.64	9700.00	-2070.64	21.35
517	9424.34	12000.00	2575.66	21.46
392	8139.48	6700.00	-1439.48	21.48
416	22367.52	28500.00	6132.48	21.52
335	13004.34	10700.00	-2304.34	21.54
45	8512.03	7000.00	-1512.03	21.60
515	32121.20	41000.00	8878.80	21.66
557	12523.73	16000.00	3476.27	21.73
41	19845.36	16300.00	-3545.36	21.75
13	13292.71	16999.00	3706.29	21.80
691	8467.17	6950.00	-1517.17	21.83
20	11876.82	15200.00	3323.18	21.86
275	22547.55	18500.00	-4047.55	21.88
120	50728.89	65000.00	14271.11	21.96
647	2625.10	2150.00	-475.10	22.10
524	5863.41	4800.00	-1063.41	22.15
547	9175.06	7499.00	-1676.06	22.35
747	8453.28	10900.00	2446.72	22.45
295	5350.91	6900.00	1549.09	22.45
80	6819.44	8800.00	1980.56	22.51
661	10303.21	13300.00	2996.79	22.53
537	9139.04	11800.00	2660.96	22.55
626	18621.12	24100.00	5478.88	22.73
576	15954.72	12999.00	-2955.72	22.74
499	12270.01	15900.00	3629.99	22.83
218	11490.44	14900.00	3409.56	22.88
458	14136.01	11500.00	-2636.01	22.92
138	11095.57	8999.00	-2096.57	23.30
320	10350.25	13500.00	3149.75	23.33
606	20680.40	27000.00	6319.60	23.41
709	34446.96	27900.00	-6546.96	23.47
75	4209.17	5500.00	1290.83	23.47
155	3086.38	2499.00	-587.38	23.50
602	16427.12	13300.00	-3127.12	23.51
736	53312.81	43163.25	-10149.56	23.51
495	3747.21	4900.00	1152.79	23.53
399	14410.15	18932.55	4522.40	23.89
771	13922.45	18300.00	4377.55	23.92
662	9232.79	7450.00	-1782.79	23.93
634	18165.16	23900.00	5734.84	24.00
4	11353.49	9150.00	-2203.49	24.08
580	6205.48	5000.00	-1205.48	24.11
687	11004.05	14500.00	3495.95	24.11
305	10505.98	13900.00	3394.02	24.42
206	19920.63	16000.00	-3920.63	24.50
659	3621.08	4799.00	1177.92	24.55
178	17316.59	13900.00	-3416.59	24.58
692	8471.55	6799.00	-1672.55	24.60
479	36883.77	49000.00	12116.23	24.73
209	8242.62	6600.00	-1642.62	24.89
773	13491.16	10800.00	-2691.16	24.92
594	3001.37	4000.00	998.63	24.97
1	3499.26	2800.00	-699.26	24.97
625	23485.45	18777.00	-4708.45	25.08
370	10835.95	14500.00	3664.05	25.27
83	6013.05	4800.00	-1213.05	25.27
443	3735.04	4999.00	1263.96	25.28
158	15623.39	20999.00	5375.61	25.60
519	8667.12	6900.00	-1767.12	25.61
177	8916.19	11999.00	3082.81	25.69
361	8688.92	11700.00	3011.08	25.74
482	12027.56	16200.00	4172.44	25.76
705	12976.15	17500.00	4523.85	25.85
135	44407.14	59999.00	15591.86	25.99
264	31059.18	42000.00	10940.82	26.05
372	8110.06	10990.00	2879.94	26.21
672	5679.39	4500.00	-1179.39	26.21
699	4255.62	5800.00	1544.38	26.63
306	3164.66	2499.00	-665.66	26.64
279	3154.48	4300.00	1145.52	26.64
145	4307.68	3400.00	-907.68	26.70
681	5195.69	4100.00	-1095.69	26.72
175	34863.53	47600.00	12736.47	26.76
440	8638.63	11800.00	3161.37	26.79
683	32771.45	44800.00	12028.55	26.85
592	28154.84	38500.00	10345.16	26.87
429	67952.07	53500.00	-14452.07	27.01
294	13471.84	10600.00	-2871.84	27.09
623	23227.15	31900.00	8672.85	27.19
107	7131.92	9800.00	2668.08	27.23
86	8071.70	11100.00	3028.30	27.28
37	26478.15	20800.00	-5678.15	27.30
92	7116.68	9800.00	2683.32	27.38
231	9312.21	7300.00	-2012.21	27.56
62	10848.85	8500.00	-2348.85	27.63
572	10597.72	8300.00	-2297.72	27.68
568	7940.44	11000.00	3059.56	27.81
202	5040.46	7000.00	1959.54	27.99
327	10716.00	14900.00	4184.00	28.08
310	9205.10	12800.00	3594.90	28.09
461	31656.01	24700.00	-6956.01	28.16
613	13853.36	10800.00	-3053.36	28.27
323	7098.53	9900.00	2801.47	28.30
752	8591.66	12000.00	3408.34	28.40
348	12201.29	9500.00	-2701.29	28.43
424	50074.56	69990.00	19915.44	28.45
584	11432.63	8900.00	-2532.63	28.46
99	6437.21	8999.00	2561.79	28.47
149	8351.34	6500.00	-1851.34	28.48
58	35336.33	49500.00	14163.67	28.61
423	74232.55	103999.00	29766.45	28.62
726	45664.45	35500.00	-10164.45	28.63
614	19298.61	14999.00	-4299.61	28.67
129	11580.54	9000.00	-2580.54	28.67
303	23496.36	33000.00	9503.64	28.80
21	31557.80	24500.00	-7057.80	28.81
767	24323.48	18800.00	-5523.48	29.38
192	18285.07	25900.00	7614.93	29.40
700	25640.67	19800.00	-5840.67	29.50
552	5983.44	8500.00	2516.56	29.61
500	8973.16	12750.00	3776.84	29.62
734	23336.06	33200.00	9863.94	29.71
233	6110.94	8700.00	2589.06	29.76
582	7724.17	11000.00	3275.83	29.78
201	10094.58	7777.00	-2317.58	29.80
296	21690.99	30900.00	9209.01	29.80
523	10809.48	15400.00	4590.52	29.81
357	11018.79	15700.00	4681.21	29.82
190	13377.99	10300.00	-3077.99	29.88
234	12731.26	9800.00	-2931.26	29.91
695	11178.46	8600.00	-2578.46	29.98
364	21681.00	30999.00	9318.00	30.06
362	27293.13	39040.00	11746.87	30.09
309	6510.80	5000.00	-1510.80	30.22
146	8298.32	11900.00	3601.68	30.27
373	10821.19	8299.00	-2522.19	30.39
513	5346.97	4100.00	-1246.97	30.41
12	5484.02	7900.00	2415.98	30.58
352	5238.05	4000.00	-1238.05	30.95
181	17597.10	25500.00	7902.90	30.99
128	7727.53	11200.00	3472.47	31.00
753	6358.55	4850.00	-1508.55	31.10
671	2886.35	4200.00	1313.65	31.28
764	14049.76	10700.00	-3349.76	31.31
216	12974.89	18900.00	5925.11	31.35
260	6858.89	9999.00	3140.11	31.40
124	15691.29	22900.00	7208.71	31.48
214	2393.34	3500.00	1106.66	31.62
405	6425.00	9400.00	2975.00	31.65
70	50206.83	73500.00	23293.17	31.69
596	25685.67	19500.00	-6185.67	31.72
351	25951.31	19692.08	-6259.23	31.79
489	28910.96	42500.00	13589.04	31.97
38	9919.19	14600.00	4680.81	32.06
274	9113.05	6900.00	-2213.05	32.07
374	24427.14	36000.00	11572.86	32.15
302	4738.89	7000.00	2261.11	32.30
148	25040.42	37000.00	11959.58	32.32
164	18403.35	13893.75	-4509.60	32.46
420	14576.33	11000.00	-3576.33	32.51
555	6610.04	9800.00	3189.96	32.55
505	10105.70	15000.00	4894.30	32.63
250	5041.20	3800.00	-1241.20	32.66
491	6503.62	4900.00	-1603.62	32.73
426	13542.79	10200.00	-3342.79	32.77
84	4364.08	6500.00	2135.92	32.86
136	12006.66	17900.00	5893.34	32.92

139	7712.65	11500.00	3787.35	32.93
618	31251.89	23500.00	-7751.89	32.99
702	7011.74	10500.00	3488.26	33.22
728	5792.10	8700.00	2907.90	33.42
751	8493.04	12800.00	4306.96	33.65
498	7950.27	12000.00	4049.73	33.75
605	8940.39	13500.00	4559.61	33.77
678	4569.15	6900.00	2330.85	33.78
205	13041.39	19700.00	6658.61	33.80
265	20163.48	30500.00	10336.52	33.89
403	2839.03	4300.00	1460.97	33.98
291	20433.23	30999.00	10565.77	34.08
74	1746.19	2650.00	903.81	34.11
741	19855.31	14800.00	-5055.31	34.16
170	19741.65	29999.00	10257.35	34.19
203	65613.31	99999.00	34385.69	34.39
289	7178.20	10950.00	3771.80	34.45
90	9143.17	6800.00	-2343.17	34.46
563	2285.24	3500.00	1214.76	34.71
112	22835.48	16950.00	-5885.48	34.72
189	10786.38	8000.00	-2786.38	34.83
669	11477.47	17650.00	6172.53	34.97
163	23972.56	36900.00	12927.44	35.03
97	3648.96	2700.00	-948.96	35.15
690	11706.93	18100.00	6393.07	35.32
117	7178.20	11100.00	3921.80	35.33
673	22213.53	34500.00	12286.47	35.61
739	22213.53	34500.00	12286.47	35.61
341	12897.92	9500.00	-3397.92	35.77
159	12904.68	9500.00	-3404.68	35.84
64	9611.80	15000.00	5388.20	35.92
300	20236.85	31600.00	11363.15	35.96
269	4151.02	6500.00	2348.98	36.14
345	28951.20	45500.00	16548.80	36.37
442	25951.31	18988.13	-6963.18	36.67
475	5570.46	8800.00	3229.54	36.70
355	22454.74	35500.00	13045.26	36.75
246	41711.18	30500.00	-11211.18	36.76
111	3152.62	4999.00	1846.38	36.93
490	8902.52	6500.00	-2402.52	36.96
748	48699.98	77500.00	28800.02	37.16
457	16821.54	26800.00	9978.46	37.23
104	5521.28	8800.00	3278.72	37.26
743	5268.17	8400.00	3131.83	37.28
469	65825.25	104999.00	39173.75	37.31
32	12459.85	19900.00	7440.15	37.39
666	65723.62	104999.00	39275.38	37.41
401	9070.23	14500.00	5429.77	37.45
586	9348.90	6800.00	-2548.90	37.48
541	9369.66	15000.00	5630.34	37.54
160	32954.19	52777.00	19822.81	37.56
652	17195.57	12500.00	-4695.57	37.56
583	3425.23	5500.00	2074.77	37.72
589	3173.48	5100.00	1926.52	37.77
735	10337.11	7500.00	-2837.11	37.83
375	65742.57	105999.00	40256.43	37.98
217	8661.95	13999.00	5337.05	38.12
29	26062.23	42500.00	16437.77	38.68
283	7630.64	5500.00	-2130.64	38.74
418	11378.43	18600.00	7221.57	38.83
137	66032.76	107999.00	41966.24	38.86
567	7279.97	11950.00	4670.03	39.08
73	18577.88	30500.00	11922.12	39.09
488	4043.74	2900.00	-1143.74	39.44
26	2178.94	3600.00	1421.06	39.47
42	23286.27	38500.00	15213.73	39.52
468	12558.90	8999.00	-3559.90	39.56
241	18432.63	30500.00	12067.37	39.57
325	9057.77	14999.00	5941.23	39.61
675	13476.90	22500.00	9023.10	40.10
737	37704.71	26900.00	-10804.71	40.17
346	32945.80	23500.00	-9445.80	40.19
445	7712.65	5500.00	-2212.65	40.23
266	65742.57	109999.00	44256.43	40.23
478	36764.38	62000.00	25235.62	40.70
48	77403.06	55000.00	-22403.06	40.73
712	8530.54	14500.00	5969.46	41.17
587	15259.81	26000.00	10740.19	41.31
431	16253.48	11500.00	-4753.48	41.33
141	1815.28	3100.00	1284.72	41.44
363	44193.38	75500.00	31306.62	41.47
25	45272.25	31990.00	-13282.25	41.52
230	9198.08	15800.00	6601.92	41.78
34	19854.79	14000.00	-5854.79	41.82
697	10031.96	17300.00	7268.04	42.01
371	9661.78	6800.00	-2861.78	42.09
628	2539.57	4400.00	1860.43	42.28
388	11474.22	19999.00	8524.78	42.63
316	65887.51	114999.00	49111.49	42.71
199	2784.46	1950.00	-834.46	42.79
514	15015.22	10500.00	-4515.22	43.00
210	31216.83	55000.00	23783.17	43.24
337	5374.74	3750.00	-1624.74	43.33
10	7241.07	12800.00	5558.93	43.43
646	3450.69	6100.00	2649.31	43.43
39	16724.45	29600.00	12875.55	43.50
322	65210.35	115800.00	50589.65	43.69
645	10740.09	19100.00	8359.91	43.77
413	12234.68	8500.00	-3734.68	43.94
640	14402.34	10000.00	-4402.34	44.02
88	10807.78	7500.00	-3307.78	44.10
585	39074.36	69999.00	30924.64	44.18
590	14512.61	25999.00	11486.39	44.18
66	3316.44	2300.00	-1016.44	44.19
588	12255.45	22000.00	9744.55	44.29
539	6781.86	4700.00	-2081.86	44.29
756	3752.54	2600.00	-1152.54	44.33
428	2389.14	1650.00	-739.14	44.80
285	34761.74	24000.00	-10761.74	44.84
566	11881.05	8200.00	-3681.05	44.89
510	1873.03	3400.00	1526.97	44.91
167	13212.52	23999.00	10786.48	44.95
511	17282.06	11900.00	-5382.06	45.23
522	17011.43	11700.00	-5311.43	45.40
349	2020.25	3700.00	1679.75	45.40
684	18942.34	12999.00	-5943.34	45.72
35	11337.51	20900.00	9562.49	45.75
365	10547.82	19500.00	8952.18	45.91
745	6421.18	4400.00	-2021.18	45.94
334	12414.72	23000.00	10585.28	46.02
255	24796.09	46000.00	21203.91	46.10
717	4172.84	7750.00	3577.16	46.16
191	15956.95	29999.00	14042.05	46.81
575	1858.34	3500.00	1641.66	46.90
169	8522.39	5800.00	-2722.39	46.94
385	13235.55	8999.00	-4236.55	47.08
393	13600.39	25800.00	12199.61	47.29
654	4032.10	7650.00	3617.90	47.29
262	12414.41	8420.00	-3994.41	47.44
617	2573.48	4900.00	2326.52	47.48
342	14572.70	27900.00	13327.30	47.77
512	15144.28	29000.00	13855.72	47.78
6	20159.19	38888.00	18728.81	48.16
44	7241.07	14000.00	6758.93	48.28
564	25682.58	17300.00	-8382.58	48.45
658	10563.39	20500.00	9936.61	48.47
304	6546.81	4400.00	-2146.81	48.79
768	38260.36	75555.00	37294.64	49.36
338	38260.36	75555.00	37294.64	49.36
760	13443.32	9000.00	-4443.32	49.37
179	14933.54	29500.00	14566.46	49.38
486	13884.26	27800.00	13915.74	50.06
604	31373.47	20859.15	-10514.32	50.41
183	47014.52	95000.00	47985.48	50.51
121	41075.73	27200.00	-13875.73	51.01
759	10125.27	6700.00	-3425.27	51.12
343	60603.06	124000.00	63396.94	51.13
414	14363.76	9500.00	-4863.76	51.20
391	25302.43	52000.00	26697.57	51.34
249	7391.67	15200.00	7808.33	51.37
353	9753.44	20400.00	10646.56	52.19
243	32925.60	69500.00	36574.40	52.63
33	22941.80	15000.00	-7941.80	52.95
223	6199.59	13200.00	7000.41	53.03
703	5597.06	11999.00	6401.94	53.35
411	13409.47	8700.00	-4709.47	54.13
288	6635.73	4300.00	-2335.73	54.32
573	33707.27	73900.00	40192.73	54.39
732	19309.90	12500.00	-6809.90	54.48
456	19624.73	12700.00	-6924.73	54.53
383	13757.58	8900.00	-4857.58	54.58
544	12354.92	27500.00	15145.08	55.07
530	17714.62	11400.00	-6314.62	55.39
551	11555.80	7400.00	-4155.80	56.16
248	22011.47	13999.00	-8012.47	57.24
245	15457.91	9800.00	-5657.91	57.73
339	11099.09	6999.00	-4100.09	58.58
656	35039.40	85555.00	50515.60	59.04
219	34376.16	85000.00	50623.84	59.56
520	16773.62	10500.00	-6273.62	59.75
772	27487.75	68500.00	41012.25	59.87
701	7996.00	4999.00	-2997.00	59.95
215	5284.06	3300.00	-1984.06	60.12
447	34863.53	87777.00	52913.47	60.28
180	19701.70	49999.00	30297.30	60.60
722	30409.09	18900.00	-11509.09	60.89
577	14486.38	9000.00	-5486.38	60.96
733	11601.33	7200.00	-4401.33	61.13
487	10824.89	6700.00	-4124.89	61.57
408	65448.37	40500.00	-24948.37	61.60
63	5351.86	3300.00	-2051.86	62.18
679	25864.65	69990.00	44125.35	63.05
228	15682.82	9600.00	-6082.82	63.36
284	40765.33	112000.00	71234.67	63.60
232	1320.56	3700.00	2379.44	64.31
417	3795.06	2300.00	-1495.06	65.00
122	19335.34	55555.00	36219.66	65.20
238	26736.21	16100.00	-10636.21	66.06
347	26441.03	15900.00	-10541.03	66.30
276	5002.39	2999.00	-2003.39	66.80
93	18317.20	10974.21	-7342.99	66.91
436	40893.84	126000.00	85106.16	67.54
621	38473.71	119000.00	80526.29	67.67
221	34863.53	109999.00	75135.47	68.31
455	10946.44	6500.00	-4446.44	68.41
578	3205.38	1900.00	-1305.38	68.70
624	16924.74	9999.00	-6925.74	69.26
326	9356.43	5500.00	-3856.43	70.12
477	15374.08	8900.00	-6474.08	72.74
633	11056.52	6400.00	-4656.52	72.76
69	2440.90	1400.00	-1040.90	74.35
224	3939.91	15500.00	11560.09	74.58
56	15380.04	8800.00	-6580.04	74.77
463	35093.27	19990.00	-15103.27	75.55
668	8270.38	4700.00	-3570.38	75.97
225	6916.13	3900.00	-3016.13	77.34
546	6746.48	3799.00	-2947.48	77.59
27	2555.02	11600.00	9044.98	77.97
746	13355.11	7500.00	-5855.11	78.07
271	3948.74	2200.00	-1748.74	79.49
236	9024.05	4900.00	-4124.05	84.16
166	15292.10	8300.00	-6992.10	84.24
67	7621.25	4100.00	-3521.25	85.88
432	2975.40	1600.00	-1375.40	85.96
550	14915.98	7900.00	-7015.98	88.81
208	5716.14	3000.00	-2716.14	90.54
116	15819.50	8300.00	-7519.50	90.60
366	13420.15	6999.00	-6421.15	91.74
686	23576.99	12000.00	-11576.99	96.47
404	8648.80	4400.00	-4248.80	96.56
30	15559.43	7900.00	-7659.43	96.95
713	4004.65	2000.00	-2004.65	100.23
611	27225.34	13500.00	-13725.34	101.67
427	5462.52	2700.00	-2762.52	102.32
694	8131.92	3999.00	-4132.92	103.35
727	10810.62	5000.00	-5810.62	116.21
397	7973.87	3650.00	-4323.87	118.46
196	5948.04	2600.00	-3348.04	128.77
704	6891.99	3000.00	-3891.99	129.73
571	26331.41	11200.00	-15131.41	135.10
680	21493.44	9000.00	-12493.44	138.82
465	6537.82	2700.00	-3837.82	142.14
81	12891.96	5300.00	-7591.96	143.24
554	8340.94	3350.00	-4990.94	148.98
609	3040.77	1200.00	-1840.77	153.40
677	9631.08	3799.00	-5832.08	153.52
161	13967.55	5500.00	-8467.55	153.96
635	3818.71	1450.00	-2368.71	163.36
660	7809.13	2899.00	-4910.13	169.37
664	4590.49	1700.00	-2890.49	170.03
82	7320.42	2600.00	-4720.42	181.55
282	12261.19	4100.00	-8161.19	199.05
2	7553.29	2500.00	-5053.29	202.13
729	9817.06	3200.00	-6617.06	206.78
492	7161.67	2200.00	-4961.67	225.53
382	7918.89	2400.00	-5518.89	229.95
502	9984.87	3000.00	-6984.87	232.83
750	10381.62	3000.00	-7381.62	246.05
434	8843.22	2500.00	-6343.22	253.73
182	10123.04	2800.00	-7323.04	261.54
396	16165.79	4400.00	-11765.79	267.40
298	17937.36	4800.00	-13137.36	273.69
629	7319.77	1850.00	-5469.77	295.66
619	16095.32	3600.00	-12495.32	347.09
0	10685.50	2300.00	-8385.50	364.59
485	9664.46	1900.00	-7764.46	408.66
657	32481.05	6000.00	-26481.05	441.35
162	9954.42	1800.00	-8154.42	453.02
451	35956.50	6500.00	-29456.50	453.18
532	10019.90	1800.00	-8219.90	456.66
639	30628.28	4999.00	-25629.28	512.69