

Bitcoin Linear Regression

Introduction

- The USD for example is backed by trust in the US Government and as the world's reserve currency.
 - US Government continues to put more currency into circulation.
 - More currency into circulation devalues the currency over time.
 - USD is not currently backed by anything of physical value other than the US government
- The value of BTC is merely based on the law of supply and demand.
 - BTC has a cap on the amount of coins that can be produced, 21 million.
 - Due to the supply being limited to 21 million, as demand increases the value will likely increase.
- The likelihood of the United States adopting BTC as its universal currency is small
- Some countries that are susceptible to significant currency manipulation, like hyperinflation, may be enticed to use bitcoin.
- Individuals may revert to BTC so that their money holds value

Goal

Identify features around the Bitcoin blockchain that might have an impact on the price of bitcoin, such as, market capitalization, transaction volume, miners revenue, transactions per block, estimated volume, average block size, hash rate, number of orphan blocks...

Proposed Method

A multiple linear regression model where multiple explanatory variables will help us in predicting the price of bitcoin. Several independent variables are explored and analyzed. After the analysis, the most correlated variables with the price of bitcoin are selected. First, the dataset is read and its data is pre-processed. Next, we examine the historical value of bitcoin over time. After that, we will review the correlation between variables to see which one will be included in the linear regression analysis.

In [1]:

```
!pip install requests pandas numpy matplotlib seaborn sklearn  
statsmodels
```

```
Requirement already satisfied: requests in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (2.26.0)  
Requirement already satisfied: pandas in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (1.3.4)  
Requirement already satisfied: numpy in /Users/alvaroserranorivas/.pyenv/version
```

s/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (1.21.4)
 Requirement already satisfied: matplotlib in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (3.4.3)
 Requirement already satisfied: seaborn in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (0.11.2)
 Requirement already satisfied: sklearn in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (0.0)
 Requirement already satisfied: statsmodels in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (0.13.0)
 Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3" in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from requests) (2.0.7)
 Requirement already satisfied: certifi≥2017.4.17 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from requests) (2021.10.8)
 Requirement already satisfied: idna<4, ≥2.5; python_version >= "3" in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from requests) (3.3)
 Requirement already satisfied: urllib3<1.27, ≥1.21.1 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from requests) (1.26.7)
 Requirement already satisfied: python-dateutil≥2.7.3 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from pandas) (2.8.2)
 Requirement already satisfied: pytz≥2017.3 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from pandas) (2021.3)
 Requirement already satisfied: pyparsing≥2.2.1 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from matplotlib) (3.0.4)
 Requirement already satisfied: kiwisolver≥1.0.1 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from matplotlib) (1.3.2)
 Requirement already satisfied: cyclor≥0.10 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from matplotlib) (0.11.0)
 Requirement already satisfied: pillow≥6.2.0 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from matplotlib) (8.4.0)
 Requirement already satisfied: scipy≥1.0 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from seaborn) (1.7.2)
 Requirement already satisfied: scikit-learn in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from sklearn) (1.0.1)
 Requirement already satisfied: patsy≥0.5.2 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from statsmodels) (0.5.2)
 Requirement already satisfied: six≥1.5 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from python-dateutil≥2.7.3→pandas) (1.16.0)
 Requirement already satisfied: threadpoolctl≥2.0.0 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packag

es (from scikit-learn→sklearn) (3.0.0)
Requirement already satisfied: joblib≥0.11 in /Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages (from scikit-learn→sklearn) (1.1.0)
WARNING: You are using pip version 20.2.3; however, version 21.3.1 is available. You should consider upgrading via the '/Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/bin/python3.9 -m pip install --upgrade pip' command.

In [2]:

```
import requests
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from datetime import datetime
import time
import statsmodels.formula.api as smf
import scipy.stats as stats
import statsmodels.api as sm
import matplotlib.cm as cm
from statsmodels.graphics.gofplots import ProbPlot
from sklearn import linear_model
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
sns.set(style="whitegrid")
```

In [3]:

```
USD= 2208000000000 # USD in circulation as of Nov 6, 2021
according to
https://ycharts.com/indicators/us\_currency\_in\_circulation
Bitcoin=21000000 # 21 Million Bitcoin (Most Bitcoin that will
be in Circulation)
Value=USD/Bitcoin # Value of Bitcoin compared to the current
dollar
print(f"USD/BTC in circulation: {Value}")
# Get current USD/BTC price from https://www.coindesk.com/price/
session = requests.Session()
```

```

USD_BTC_rate =
session.get("https://api.coindesk.com/v1/bpi/currentprice.json").
["bpi"]["USD"]["rate_float"]
print(f"Current USD/BTC rate: {USD_BTC_rate}")

```

USD/BTC in circulation: 105142.85714285714

Current USD/BTC rate: 64648.3643

Data set description

In [4]:

```

BTC_data = pd.read_csv("bitcoin_dataset.csv", header=0)
print(BTC_data.head())
print(BTC_data.columns)
print(BTC_data.shape)
BTC_data["Date"] = BTC_data["Date"].apply(lambda x:
datetime.strptime(x, '%Y-%m-%d %H:%M:%S'))
# Create a Days column that is the number of days for each row
BTC_data["Days"] = (BTC_data["Date"] -
BTC_data["Date"].min()).dt.days
# Print subset of data where Median Confirmation Time is greater
than 0
print(BTC_data[BTC_data["btc_median_confirmation_time"] > 0])
# Subset where Median Confirmation Time is greater than 0
BTC_data2 = BTC_data[BTC_data["btc_median_confirmation_time"] >
0]
# Drop NA values
BTC_data2.dropna(inplace=True)

```

	Date	btc_market_price	btc_total_bitcoins	btc_market_cap	\
0	2009-11-10 00:00:00	0.0	1339450.0	0.0	
1	2009-11-11 00:00:00	0.0	1342900.0	0.0	
2	2009-11-12 00:00:00	0.0	1346400.0	0.0	
3	2009-11-13 00:00:00	0.0	1349900.0	0.0	
4	2009-11-14 00:00:00	0.0	1354050.0	0.0	

	btc_trade_volume	btc_blocks_size	btc_avg_block_size	\
0	0.0	0.0	0.000215	
1	0.0	0.0	0.000323	
2	0.0	0.0	0.000215	
3	0.0	0.0	0.000242	
4	0.0	0.0	0.000216	

	btc_n_orphaned_blocks	btc_n_transactions_per_block	\
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0	0.0	1.0
1	0.0	1.0
2	0.0	1.0
3	0.0	1.0
4	0.0	1.0

	btc_median_confirmation_time	...	btc_cost_per_transaction_percent	\
0	0.0	...	0.000000	
1	0.0	...	19.166667	
2	0.0	...	0.000000	
3	0.0	...	673.076923	
4	0.0	...	0.000000	

	btc_cost_per_transaction	btc_n_unique_addresses	btc_n_transactions	\
0	0.0	71.0	71.0	
1	0.0	71.0	78.0	
2	0.0	70.0	70.0	
3	0.0	73.0	73.0	
4	0.0	83.0	83.0	

	btc_n_transactions_total	btc_n_transactions_excluding_popular	\
0	26958.0	71.0	
1	27036.0	78.0	
2	27106.0	70.0	
3	27179.0	73.0	
4	27262.0	83.0	

	btc_n_transactions_excluding_chains_longer_than_100	btc_output_volume	\
0	71.0	3550.0	
1	78.0	93450.0	
2	70.0	3500.0	
3	73.0	4100.0	
4	83.0	4150.0	

	btc_estimated_transaction_volume	btc_estimated_transaction_volume_usd
0	0.0	0.0
1	18000.0	0.0
2	0.0	0.0
3	520.0	0.0
4	0.0	0.0

[5 rows x 24 columns]

```
Index(['Date', 'btc_market_price', 'btc_total_bitcoins', 'btc_market_cap',
      'btc_trade_volume', 'btc_blocks_size', 'btc_avg_block_size',
      'btc_n_orphaned_blocks', 'btc_n_transactions_per_block',
      'btc_median_confirmation_time', 'btc_hash_rate', 'btc_difficulty',
      'btc_miners_revenue', 'btc_transaction_fees',
      'btc_cost_per_transaction_percent', 'btc_cost_per_transaction',
      'btc_n_unique_addresses', 'btc_n_transactions',
      'btc_n_transactions_total', 'btc_n_transactions_excluding_popular',
      'btc_n_transactions_excluding_chains_longer_than_100',
      'btc_output_volume', 'btc_estimated_transaction_volume',
      'btc_estimated_transaction_volume_usd'],
      dtype='object')
```

(2920, 24)

	Date	btc_market_price	btc_total_bitcoins	btc_market_cap	\
752	2011-12-02	3.138000	7787350.0	2.443670e+07	
753	2011-12-03	3.129990	7794850.0	2.439780e+07	
754	2011-12-04	2.990000	7801700.0	2.332708e+07	
755	2011-12-05	2.930000	7809700.0	2.288242e+07	
756	2011-12-06	3.050000	7817650.0	2.384383e+07	
...	
2915	2017-11-03	7197.720060	16662275.0	1.199304e+11	
2916	2017-11-04	7437.543317	16663900.0	1.239385e+11	
2917	2017-11-05	7377.012367	16665662.5	1.229428e+11	
2918	2017-11-06	6989.071667	16667325.0	1.164891e+11	
2919	2017-11-07	7092.127233	16669275.0	1.182206e+11	

	btc_trade_volume	btc_blocks_size	btc_avg_block_size	\
752	1.815046e+05	572.000000	0.017415	
753	3.631256e+05	574.000000	0.016900	
754	2.633752e+05	576.000000	0.015659	
755	9.050023e+04	578.000000	0.017047	
756	1.701647e+05	580.000000	0.018309	
...	
2915	3.748147e+08	139714.873251	1.046606	
2916	5.635740e+08	139848.545492	1.028248	
2917	5.685735e+08	139995.561562	1.042667	
2918	8.328224e+08	140134.487161	1.044553	
2919	5.339933e+08	140294.602454	1.026380	

	btc_n_orphaned_blocks	btc_n_transactions_per_block	\
752	0.0	48.000000	
753	0.0	37.000000	
754	0.0	37.000000	
755	0.0	36.000000	
756	0.0	36.000000	
...	
2915	0.0	2332.756303	
2916	0.0	2262.469231	
2917	0.0	1785.304965	
2918	0.0	2037.812030	
2919	0.0	2151.512821	

	btc_median_confirmation_time	...	btc_cost_per_transaction	\
752	11.066667	...	3.902130	
753	12.783333	...	4.244975	
754	16.016667	...	3.873435	
755	13.366667	...	3.694468	
756	15.183333	...	3.454871	
...	
2915	18.875000	...	45.615461	
2916	15.516667	...	48.001722	
2917	14.900000	...	57.443344	
2918	12.016667	...	49.068810	
2919	10.733333	...	47.419337	

btc_n_unique_addresses	btc_n_transactions	btc_n_transactions_total	\
------------------------	--------------------	--------------------------	---

752	10589.0	6316.0	1958524.0
753	9426.0	5533.0	1964057.0
754	9094.0	5290.0	1969347.0
755	10411.0	6347.0	1975694.0
756	11341.0	7021.0	1982715.0
...
2915	670928.0	277598.0	268308467.0
2916	588058.0	294121.0	268602588.0
2917	555458.0	251728.0	268854316.0
2918	608650.0	271029.0	269125345.0
2919	714349.0	335636.0	269460981.0

btc_n_transactions_excluding_popular \

752	4961.0
753	4169.0
754	3899.0
755	4689.0
756	5580.0
...	...
2915	268570.0
2916	283626.0
2917	243244.0
2918	260465.0
2919	323686.0

btc_n_transactions_excluding_chains_longer_than_100 btc_output_volume \

752	5779.0	4.672087e+06
753	5018.0	4.034196e+06
754	5170.0	3.364466e+06
755	5866.0	2.092724e+06
756	6302.0	7.369513e+06
...
2915	203967.0	3.036930e+06
2916	228764.0	5.765969e+06
2917	180241.0	6.077425e+06
2918	199667.0	2.782649e+06
2919	241986.0	3.523838e+06

btc_estimated_transaction_volume btc_estimated_transaction_volume_usd \

752	3.308930e+06	1.038342e+07
753	3.682124e+06	1.152501e+07
754	3.204551e+06	9.581607e+06
755	1.883357e+06	5.518235e+06
756	5.825066e+06	1.776645e+07
...
2915	2.323145e+05	1.672135e+09
2916	1.915101e+05	1.424365e+09
2917	1.775416e+05	1.309727e+09
2918	2.244207e+05	1.568492e+09
2919	2.574699e+05	1.826009e+09

Days

752	752
753	753

```

754    754
755    755
756    756
...    ...
2915   2915
2916   2916
2917   2917
2918   2918
2919   2919

```

```
[2168 rows x 25 columns]
```

```

/Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages/pandas/util/_decorators.py:311: SettingWithCopyWarning:

```

```
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

return func(*args, **kwargs)

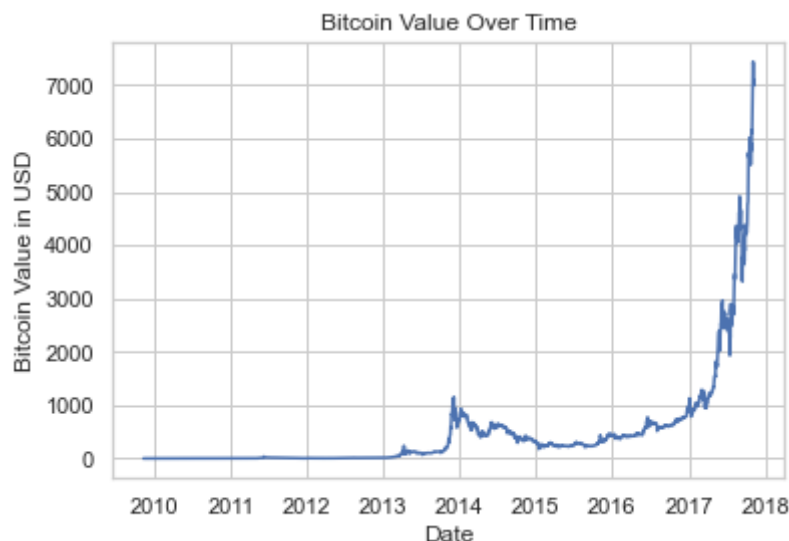
```

In [5]:

```

# Plot btc_market_price vs Date with a scatter plot
plt.plot(BTC_data["Date"], BTC_data["btc_market_price"])
plt.title("Bitcoin Value Over Time")
plt.xlabel("Date")
plt.ylabel("Bitcoin Value in USD")
plt.show()

```



We can see that the value of bitcoin has grown exponentially.

Exploratory data analysis to data set

Since market fluctuations are hard to predict and we can only analyze observational data of the past, and model based on percent change will give an accurate picture of the correlation

between the most significant variables affecting bitcoin's market price. Therefore, as price increases, so will the relative variations of the highest dependent features of Bitcoin's blockchain. This corroborates the initial hypothesis that bitcoin's price is dictated by the law of supply and demand. The reason for that is that eventually the percent change in the count of bitcoin will become irrelevant because of its finite supply of 21 million coins.

Correlation between variables

In [6]:

```
corr = BTC_data.corr()
corr = corr.iloc[1:4, 5:25].corr()
# Plot correlation matrix
sns.heatmap(corr, annot=True, xticklabels=corr.columns,
            yticklabels=corr.columns)
print(corr)
```

	btc_avg_block_size \
btc_avg_block_size	1.000000
btc_n_orphaned_blocks	0.921531
btc_n_transactions_per_block	0.999818
btc_median_confirmation_time	0.979275
btc_hash_rate	-0.756919
btc_difficulty	-0.737205
btc_miners_revenue	-0.791462
btc_transaction_fees	-0.559594
btc_cost_per_transaction_percent	-0.943949
btc_cost_per_transaction	-0.456912
btc_n_unique_addresses	0.996330
btc_n_transactions	0.999945
btc_n_transactions_total	0.749527
btc_n_transactions_excluding_popular	0.999640
btc_n_transactions_excluding_chains_longer_than...	0.986272
btc_output_volume	0.921520
btc_estimated_transaction_volume	0.876795
btc_estimated_transaction_volume_usd	-0.870488
Days	0.987685

	btc_n_orphaned_blocks \
btc_avg_block_size	0.921531
btc_n_orphaned_blocks	1.000000
btc_n_transactions_per_block	0.913945
btc_median_confirmation_time	0.981078
btc_hash_rate	-0.951285
btc_difficulty	-0.941723
btc_miners_revenue	-0.966696
btc_transaction_fees	-0.837498
btc_cost_per_transaction_percent	-0.998054
btc_cost_per_transaction	-0.766460
btc_n_unique_addresses	0.884912
btc_n_transactions	0.925550
btc_n_transactions_total	0.433664

btc_n_transactions_excluding_popular	0.910783
btc_n_transactions_excluding_chains_longer_than...	0.844759
btc_output_volume	1.000000
btc_estimated_transaction_volume	0.994716
btc_estimated_transaction_volume_usd	-0.993301
Days	0.970935

btc_n_transactions_per_block

\	
btc_avg_block_size	0.999818
btc_n_orphaned_blocks	0.913945
btc_n_transactions_per_block	1.000000
btc_median_confirmation_time	0.975227
btc_hash_rate	-0.744296
btc_difficulty	-0.724163
btc_miners_revenue	-0.779641
btc_transaction_fees	-0.543660
btc_cost_per_transaction_percent	-0.937471
btc_cost_per_transaction	-0.439836
btc_n_unique_addresses	0.997783
btc_n_transactions	0.999562
btc_n_transactions_total	0.762036
btc_n_transactions_excluding_popular	0.999970
btc_n_transactions_excluding_chains_longer_than...	0.989246
btc_output_volume	0.913933
btc_estimated_transaction_volume	0.867449
btc_estimated_transaction_volume_usd	-0.860927
Days	0.984516

btc_median_confirmation_time

\	
btc_avg_block_size	0.979275
btc_n_orphaned_blocks	0.981078
btc_n_transactions_per_block	0.975227
btc_median_confirmation_time	1.000000
btc_hash_rate	-0.873590
btc_difficulty	-0.858773
btc_miners_revenue	-0.898852
btc_transaction_fees	-0.715851
btc_cost_per_transaction_percent	-0.991241
btc_cost_per_transaction	-0.627600
btc_n_unique_addresses	0.958345
btc_n_transactions	0.981344
btc_n_transactions_total	0.599919
btc_n_transactions_excluding_popular	0.973490
btc_n_transactions_excluding_chains_longer_than...	0.932387
btc_output_volume	0.981072
btc_estimated_transaction_volume	0.956015
btc_estimated_transaction_volume_usd	-0.952133
Days	0.998903

btc_hash_rate \

btc_avg_block_size	-0.756919
btc_n_orphaned_blocks	-0.951285

btc_n_transactions_per_block	-0.744296
btc_median_confirmation_time	-0.873590
btc_hash_rate	1.000000
btc_difficulty	0.999560
btc_miners_revenue	0.998509
btc_transaction_fees	0.965174
btc_cost_per_transaction_percent	0.930211
btc_cost_per_transaction	0.927149
btc_n_unique_addresses	-0.698203
btc_n_transactions	-0.763726
btc_n_transactions_total	-0.134724
btc_n_transactions_excluding_popular	-0.739116
btc_n_transactions_excluding_chains_longer_than...	-0.638614
btc_output_volume	-0.951294
btc_estimated_transaction_volume	-0.977912
btc_estimated_transaction_volume_usd	0.980539
Days	-0.849842

btc_difficulty \

btc_avg_block_size	-0.737205
btc_n_orphaned_blocks	-0.941723
btc_n_transactions_per_block	-0.724163
btc_median_confirmation_time	-0.858773
btc_hash_rate	0.999560
btc_difficulty	1.000000
btc_miners_revenue	0.996451
btc_transaction_fees	0.972508
btc_cost_per_transaction_percent	0.918917
btc_cost_per_transaction	0.937854
btc_n_unique_addresses	-0.676665
btc_n_transactions	-0.744246
btc_n_transactions_total	-0.105279
btc_n_transactions_excluding_popular	-0.718815
btc_n_transactions_excluding_chains_longer_than...	-0.615511
btc_output_volume	-0.941732
btc_estimated_transaction_volume	-0.971283
btc_estimated_transaction_volume_usd	0.974285
Days	-0.833838

btc_miners_revenue \

btc_avg_block_size	-0.791462
btc_n_orphaned_blocks	-0.966696
btc_n_transactions_per_block	-0.779641
btc_median_confirmation_time	-0.898852
btc_hash_rate	0.998509
btc_difficulty	0.996451
btc_miners_revenue	1.000000
btc_transaction_fees	0.949455
btc_cost_per_transaction_percent	0.948858
btc_cost_per_transaction	0.905315
btc_n_unique_addresses	-0.736239
btc_n_transactions	-0.797824
btc_n_transactions_total	-0.188610
btc_n_transactions_excluding_popular	-0.774781

btc_n_transactions_excluding_chains_longer_than...	-0.679666
btc_output_volume	-0.966703
btc_estimated_transaction_volume	-0.987863
btc_estimated_transaction_volume_usd	0.989793
Days	-0.877344

	btc_transaction_fees \
btc_avg_block_size	-0.559594
btc_n_orphaned_blocks	-0.837498
btc_n_transactions_per_block	-0.543660
btc_median_confirmation_time	-0.715851
btc_hash_rate	0.965174
btc_difficulty	0.972508
btc_miners_revenue	0.949455
btc_transaction_fees	1.000000
btc_cost_per_transaction_percent	0.801798
btc_cost_per_transaction	0.992883
btc_n_unique_addresses	-0.486602
btc_n_transactions	-0.568250
btc_n_transactions_total	0.129191
btc_n_transactions_excluding_popular	-0.537162
btc_n_transactions_excluding_chains_longer_than...	-0.415058
btc_output_volume	-0.837514
btc_estimated_transaction_volume	-0.889174
btc_estimated_transaction_volume_usd	0.895030
Days	-0.682368

	btc_cost_per_transaction_per cent \
btc_avg_block_size	-0.94
3949	
btc_n_orphaned_blocks	-0.99
8054	
btc_n_transactions_per_block	-0.93
7471	
btc_median_confirmation_time	-0.99
1241	
btc_hash_rate	0.93
0211	
btc_difficulty	0.91
8917	
btc_miners_revenue	0.94
8858	
btc_transaction_fees	0.80
1798	
btc_cost_per_transaction_percent	1.00
0000	
btc_cost_per_transaction	0.72
4922	
btc_n_unique_addresses	-0.91
2230	
btc_n_transactions	-0.94
7357	
btc_n_transactions_total	-0.48

9002	
btc_n_transactions_excluding_popular	-0.93
4755	
btc_n_transactions_excluding_chains_longer_than...	-0.87
6482	
btc_output_volume	-0.99
8053	
btc_estimated_transaction_volume	-0.98
6379	
btc_estimated_transaction_volume_usd	0.98
4164	
Days	-0.98
3969	

	btc_cost_per_transaction \
btc_avg_block_size	-0.456912
btc_n_orphaned_blocks	-0.766460
btc_n_transactions_per_block	-0.439836
btc_median_confirmation_time	-0.627600
btc_hash_rate	0.927149
btc_difficulty	0.937854
btc_miners_revenue	0.905315
btc_transaction_fees	0.992883
btc_cost_per_transaction_percent	0.724922
btc_cost_per_transaction	1.000000
btc_n_unique_addresses	-0.379096
btc_n_transactions	-0.466210
btc_n_transactions_total	0.246366
btc_n_transactions_excluding_popular	-0.432887
btc_n_transactions_excluding_chains_longer_than...	-0.303754
btc_output_volume	-0.766479
btc_estimated_transaction_volume	-0.828353
btc_estimated_transaction_volume_usd	0.835545
Days	-0.590454

	btc_n_unique_addresses \
btc_avg_block_size	0.996330
btc_n_orphaned_blocks	0.884912
btc_n_transactions_per_block	0.997783
btc_median_confirmation_time	0.958345
btc_hash_rate	-0.698203
btc_difficulty	-0.676665
btc_miners_revenue	-0.736239
btc_transaction_fees	-0.486602
btc_cost_per_transaction_percent	-0.912230
btc_cost_per_transaction	-0.379096
btc_n_unique_addresses	1.000000
btc_n_transactions	0.995378
btc_n_transactions_total	0.803438
btc_n_transactions_excluding_popular	0.998267
btc_n_transactions_excluding_chains_longer_than...	0.996787
btc_output_volume	0.884898
btc_estimated_transaction_volume	0.832417
btc_estimated_transaction_volume_usd	-0.825164

Days

0.970668

	btc_n_transactions \
btc_avg_block_size	0.999945
btc_n_orphaned_blocks	0.925550
btc_n_transactions_per_block	0.999562
btc_median_confirmation_time	0.981344
btc_hash_rate	-0.763726
btc_difficulty	-0.744246
btc_miners_revenue	-0.797824
btc_transaction_fees	-0.568250
btc_cost_per_transaction_percent	-0.947357
btc_cost_per_transaction	-0.466210
btc_n_unique_addresses	0.995378
btc_n_transactions	1.000000
btc_n_transactions_total	0.742547
btc_n_transactions_excluding_popular	0.999304
btc_n_transactions_excluding_chains_longer_than...	0.984487
btc_output_volume	0.925539
btc_estimated_transaction_volume	0.881786
btc_estimated_transaction_volume_usd	-0.875599
Days	0.989270

	btc_n_transactions_total \
btc_avg_block_size	0.749527
btc_n_orphaned_blocks	0.433664
btc_n_transactions_per_block	0.762036
btc_median_confirmation_time	0.599919
btc_hash_rate	-0.134724
btc_difficulty	-0.105279
btc_miners_revenue	-0.188610
btc_transaction_fees	0.129191
btc_cost_per_transaction_percent	-0.489002
btc_cost_per_transaction	0.246366
btc_n_unique_addresses	0.803438
btc_n_transactions	0.742547
btc_n_transactions_total	1.000000
btc_n_transactions_excluding_popular	0.767014
btc_n_transactions_excluding_chains_longer_than...	0.848549
btc_output_volume	0.433638
btc_estimated_transaction_volume	0.338861
btc_estimated_transaction_volume_usd	-0.326637
Days	0.636726

	btc_n_transactions_excluding _popular \
btc_avg_block_size	0.999640
btc_n_orphaned_blocks	0.910783
btc_n_transactions_per_block	0.999970
btc_median_confirmation_time	0.973490

btc_hash_rate	-
0.739116	
btc_difficulty	-
0.718815	
btc_miners_revenue	-
0.774781	
btc_transaction_fees	-
0.537162	
btc_cost_per_transaction_percent	-
0.934755	
btc_cost_per_transaction	-
0.432887	
btc_n_unique_addresses	
0.998267	
btc_n_transactions	
0.999304	
btc_n_transactions_total	
0.767014	
btc_n_transactions_excluding_popular	
1.000000	
btc_n_transactions_excluding_chains_longer_than...	
0.990346	
btc_output_volume	
0.910771	
btc_estimated_transaction_volume	
0.863580	
btc_estimated_transaction_volume_usd	-
0.856972	
Days	
0.983133	

btc_n_transactions_excluding

_chains_longer_than_100 \

btc_avg_block_size	
0.986272	
btc_n_orphaned_blocks	
0.844759	
btc_n_transactions_per_block	
0.989246	
btc_median_confirmation_time	
0.932387	
btc_hash_rate	
-0.638614	
btc_difficulty	
-0.615511	
btc_miners_revenue	
-0.679666	
btc_transaction_fees	
-0.415058	
btc_cost_per_transaction_percent	
-0.876482	
btc_cost_per_transaction	
-0.303754	
btc_n_unique_addresses	

0.996787
 btc_n_transactions
 0.984487
 btc_n_transactions_total
 0.848549
 btc_n_transactions_excluding_popular
 0.990346
 btc_n_transactions_excluding_chains_longer_than...
 1.000000
 btc_output_volume
 0.844744
 btc_estimated_transaction_volume
 0.785353
 btc_estimated_transaction_volume_usd
 -0.777263
 Days
 0.948290

	btc_output_volume \
btc_avg_block_size	0.921520
btc_n_orphaned_blocks	1.000000
btc_n_transactions_per_block	0.913933
btc_median_confirmation_time	0.981072
btc_hash_rate	-0.951294
btc_difficulty	-0.941732
btc_miners_revenue	-0.966703
btc_transaction_fees	-0.837514
btc_cost_per_transaction_percent	-0.998053
btc_cost_per_transaction	-0.766479
btc_n_unique_addresses	0.884898
btc_n_transactions	0.925539
btc_n_transactions_total	0.433638
btc_n_transactions_excluding_popular	0.910771
btc_n_transactions_excluding_chains_longer_than...	0.844744
btc_output_volume	1.000000
btc_estimated_transaction_volume	0.994719
btc_estimated_transaction_volume_usd	-0.993305
Days	0.970928

	btc_estimated_transaction_vo
lume \	
btc_avg_block_size	0.87
6795	
btc_n_orphaned_blocks	0.99
4716	
btc_n_transactions_per_block	0.86
7449	
btc_median_confirmation_time	0.95
6015	
btc_hash_rate	-0.97
7912	
btc_difficulty	-0.97
1283	
btc_miners_revenue	-0.98

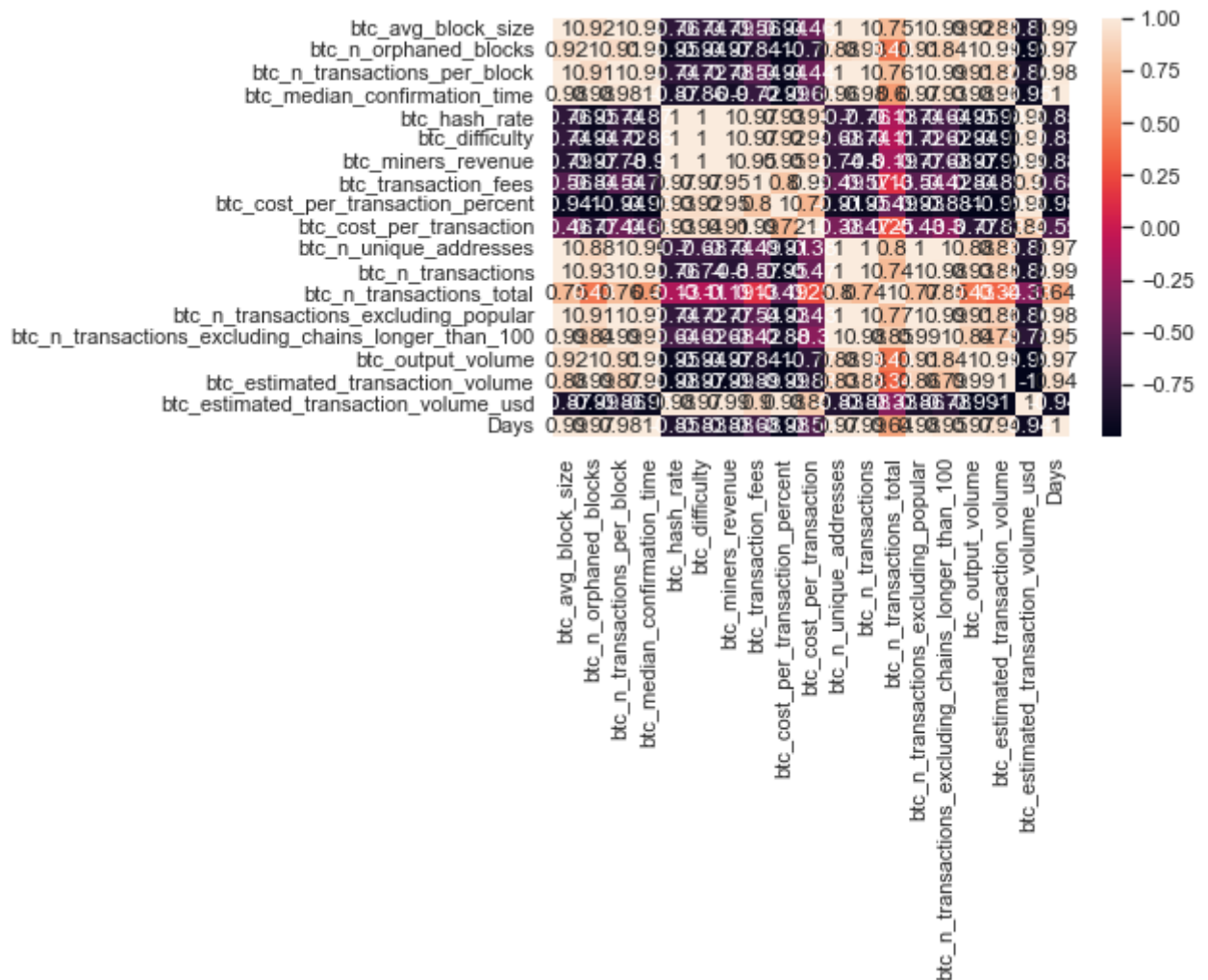
7863	
btc_transaction_fees	-0.88
9174	
btc_cost_per_transaction_percent	-0.98
6379	
btc_cost_per_transaction	-0.82
8353	
btc_n_unique_addresses	0.83
2417	
btc_n_transactions	0.88
1786	
btc_n_transactions_total	0.33
8861	
btc_n_transactions_excluding_popular	0.86
3580	
btc_n_transactions_excluding_chains_longer_than...	0.78
5353	
btc_output_volume	0.99
4719	
btc_estimated_transaction_volume	1.00
0000	
btc_estimated_transaction_volume_usd	-0.99
9916	
Days	0.94
1231	

btc_estimated_transaction_vo

lume_usd \	
btc_avg_block_size	-
0.870488	
btc_n_orphaned_blocks	-
0.993301	
btc_n_transactions_per_block	-
0.860927	
btc_median_confirmation_time	-
0.952133	
btc_hash_rate	
0.980539	
btc_difficulty	
0.974285	
btc_miners_revenue	
0.989793	
btc_transaction_fees	
0.895030	
btc_cost_per_transaction_percent	
0.984164	
btc_cost_per_transaction	
0.835545	
btc_n_unique_addresses	-
0.825164	
btc_n_transactions	-
0.875599	
btc_n_transactions_total	-
0.326637	

btc_n_transactions_excluding_popular	-
0.856972	
btc_n_transactions_excluding_chains_longer_than...	-
0.777263	
btc_output_volume	-
0.993305	
btc_estimated_transaction_volume	-
0.999916	
btc_estimated_transaction_volume_usd	
1.000000	
Days	-
0.936774	

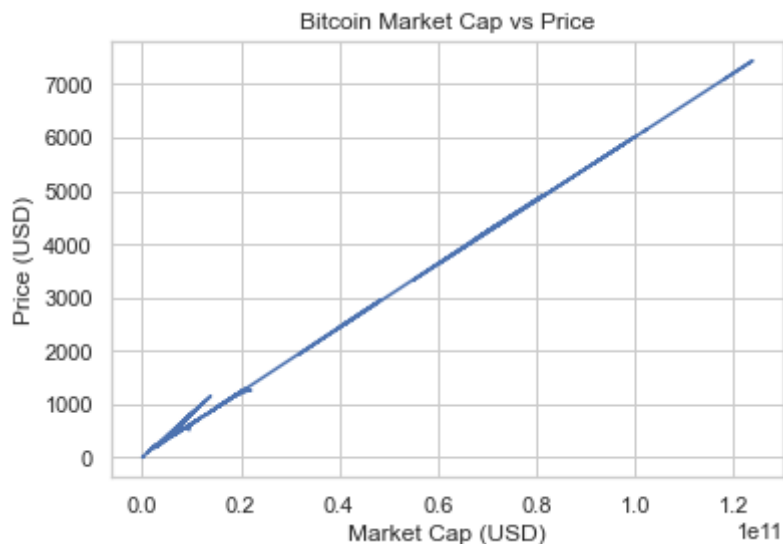
	Days
btc_avg_block_size	0.987685
btc_n_orphaned_blocks	0.970935
btc_n_transactions_per_block	0.984516
btc_median_confirmation_time	0.998903
btc_hash_rate	-0.849842
btc_difficulty	-0.833838
btc_miners_revenue	-0.877344
btc_transaction_fees	-0.682368
btc_cost_per_transaction_percent	-0.983969
btc_cost_per_transaction	-0.590454
btc_n_unique_addresses	0.970668
btc_n_transactions	0.989270
btc_n_transactions_total	0.636726
btc_n_transactions_excluding_popular	0.983133
btc_n_transactions_excluding_chains_longer_than...	0.948290
btc_output_volume	0.970928
btc_estimated_transaction_volume	0.941231
btc_estimated_transaction_volume_usd	-0.936774
Days	1.000000



The most correlated variables to Market Price are Market Cap, Hash Rate, Difficulty, Miner Revenue, and Estimated USD Transaction Volume

Market Cap and Market Price

```
In [7]: # Plot btc_market_cap vs btc_market_price with a scatter plot
plt.plot(BTC_data2["btc_market_cap"],
BTC_data2["btc_market_price"])
# Market Cap vs Price
plt.title("Bitcoin Market Cap vs Price")
plt.xlabel("Market Cap (USD)")
plt.ylabel("Price (USD)")
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()
```



In [8]:

```
# Create a linear regression object
fit1 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
# Train the model using the training sets
fit1.fit(BTC_data2[["btc_market_cap"]],
BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions = fit1.predict(BTC_data2[["btc_market_cap"]])
# Residuals
residuals = BTC_data2["btc_market_price"] - predictions
# The coefficients
print(f'Coefficients: {fit1.coef_}')
# Intercept
print(f'Intercept: {fit1.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions -
BTC_data2["btc_market_price"]) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
fit1.score(BTC_data2[["btc_market_cap"]],
BTC_data2["btc_market_price"]))
# Plot outputs
plt.scatter(BTC_data2["btc_market_cap"],
BTC_data2["btc_market_price"], color='blue')
```

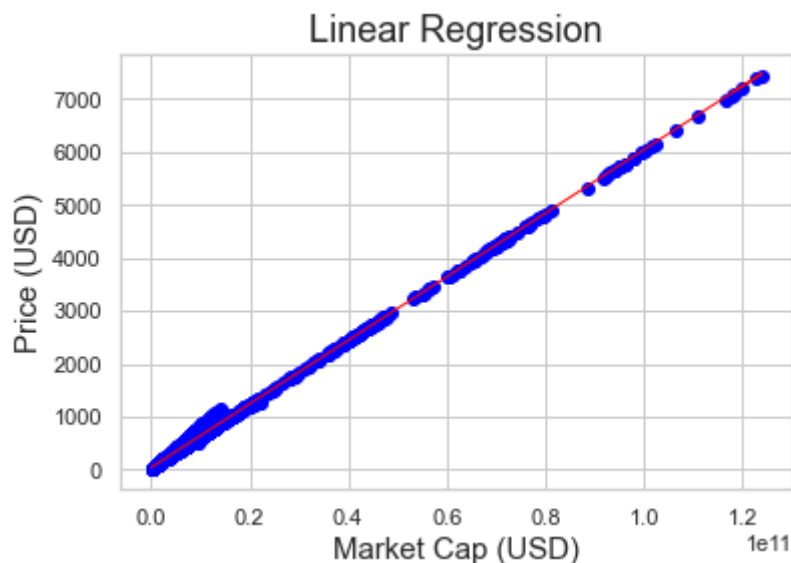
```
plt.plot(BTC_data2["btc_market_cap"], predictions, color='red',
linewidth=1)
plt.title('Linear Regression')
plt.xlabel('Market Cap (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=15)
plt.rc('axes', titlesize=18)
plt.show()
```

Coefficients: [5.99422357e-08]

Intercept: 46.039960391727504

Mean squared error: 2447.80

Variance score: 1.00

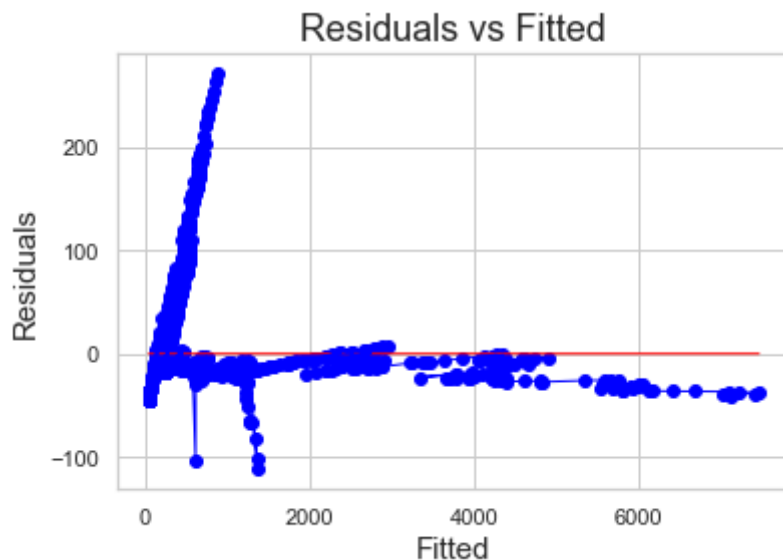


Since R-Squared is very close to 1, Market Capitalization is significant to Market Price.

In [9]:

```
# Residuals vs fitted plot
plt.scatter(predictions, residuals, color='blue')
plt.xticks(np.arange(0, max(predictions), step=2000))
plt.yticks(np.arange(-100, 300, step=100))
plt.plot(np.unique(predictions),
np.poly1d(np.polyfit(predictions, residuals, 1))
(np.unique(predictions)), color='red', linewidth=1)
plt.plot(predictions, residuals, color='blue', linewidth=1)
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
```

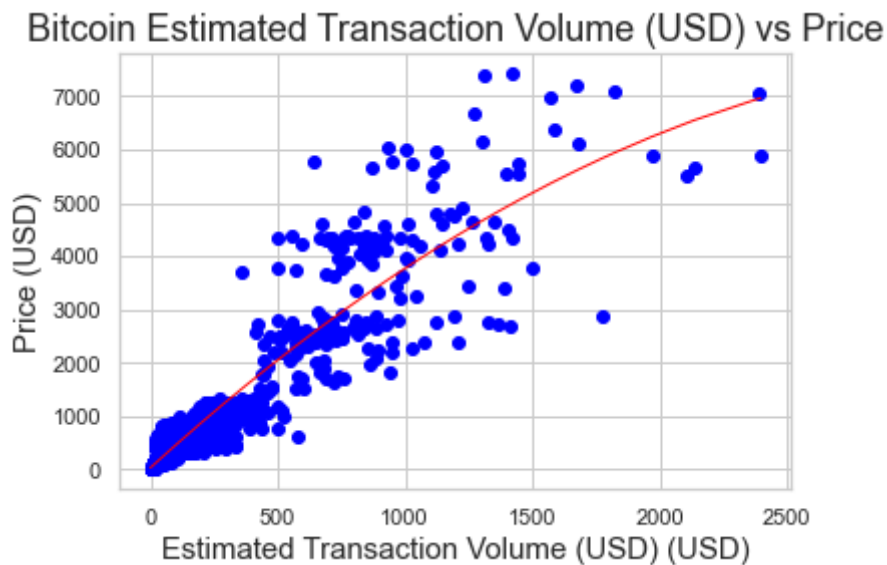
```
plt.ylabel('Residuals')
plt.show()
```



Estimated USD Transaction Volume vs. Market Price

In [10]:

```
# Plot btc_estimated_transaction_volume_usd vs btc_market_price
with a scatter plot
plt.plot(BTC_data2["btc_estimated_transaction_volume_usd"]/100000,
         BTC_data2["btc_market_price"], 'o', color='blue', linewidth=1)
plt.plot(np.unique(BTC_data2["btc_estimated_transaction_volume_usd"])/100000,
         np.poly1d(np.polyfit(BTC_data2["btc_estimated_transaction_volume_usd"],
                              BTC_data2["btc_market_price"], 2))
         color='red', linewidth=1)
# Estimated Transaction Volume (USD) vs Price
plt.title("Bitcoin Estimated Transaction Volume (USD) vs Price")
plt.xlabel("Estimated Transaction Volume (USD) (USD)")
plt.ylabel("Price (USD)")
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()
```



In [11]:

```
# Fit polynomial regression to
btc_estimated_transaction_volume_usd squared vs btc_market_price
poly_btc_estimated_transaction_volume =
PolynomialFeatures(degree=2).fit_transform(BTC_data2[["btc_estima

fit2 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit2.fit(poly_btc_estimated_transaction_volume,
BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions2 =
fit2.predict(poly_btc_estimated_transaction_volume)
# Residuals
residuals2 = BTC_data2["btc_market_price"] - predictions2
# The coefficients
print(f'Coefficients: {fit2.coef_}')
# Intercept
print(f'Intercept: {fit2.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions2 -
BTC_data2["btc_market_price"]) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
```

```

fit2.score(poly_btc_estimated_transaction_volume,
BTC_data2["btc_market_price"]))
# Plot outputs
plt.scatter(BTC_data2["btc_estimated_transaction_volume_usd"]/1000,
            BTC_data2["btc_market_price"], color='blue')
plt.plot(np.unique(BTC_data2["btc_estimated_transaction_volume_usd"]/1000),
         np.poly1d(np.polyfit(BTC_data2["btc_estimated_transaction_volume_usd"]/1000,
                              BTC_data2["btc_market_price"], 2))
         (np.unique(BTC_data2["btc_estimated_transaction_volume_usd"]/1000),
          color='red', linewidth=1)
plt.title('Polynomial Regression')
plt.xlabel('Estimated Transaction Volume (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=15)
plt.rc('axes', titlesize=18)
plt.show()

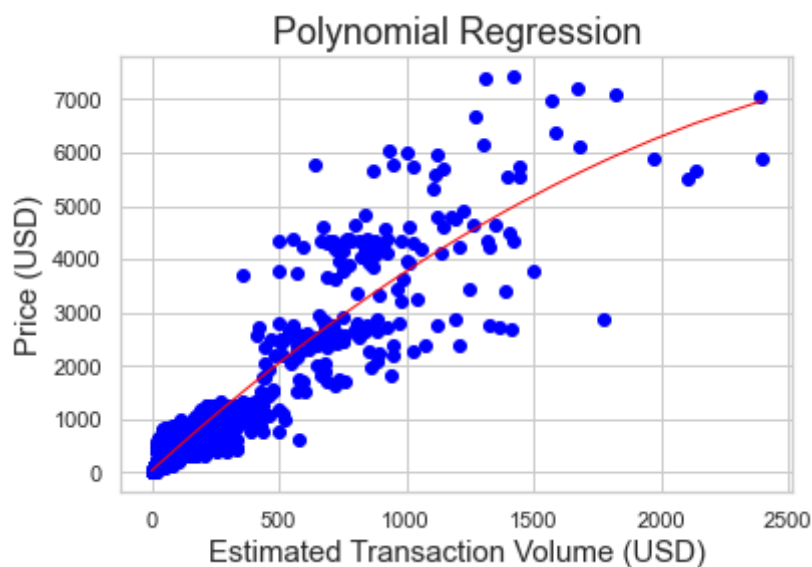
```

Coefficients: [0.00000000e+00 4.34114978e-06 -6.04679033e-16]

Intercept: 34.44178114396766

Mean squared error: 142605.89

Variance score: 0.87



Transaction Volume is significant to Market Price due to $R^2 = 0.86$

In [12]:

```
# Residuals vs fitted plot for transaction volume
```



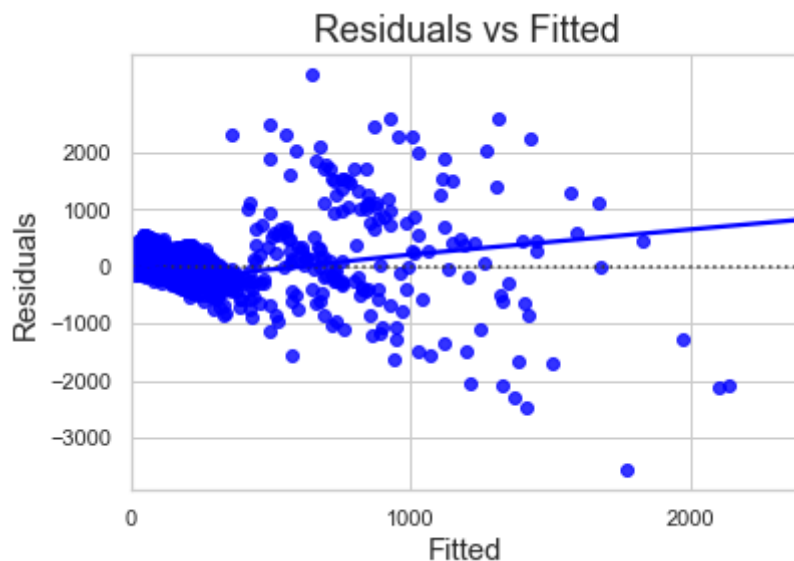
```

sns.residplot(BTC_data2["btc_estimated_transaction_volume_usd"] / 1
BTC_data2["btc_market_price"], lowess=True, color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.xticks(np.arange(0,
max(BTC_data2["btc_estimated_transaction_volume_usd"] / 1000000),
step=1000))
plt.yticks(np.arange(-3000, 3000, step=1000))
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=15)
plt.rc('axes', titlesize=18)
plt.show()

```

/Users/alvaroserranorivas/.pyenv/versions/3.9.2/envs/bitcoin_linear_regression/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

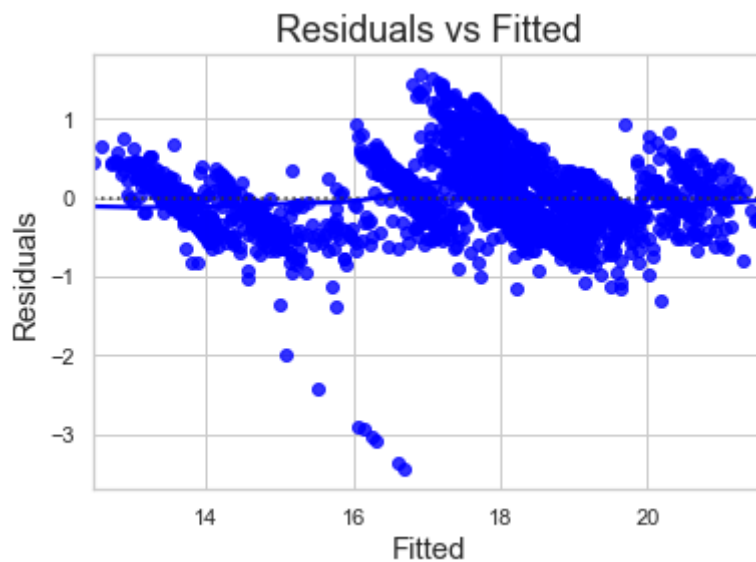


- Heteroscedasticity in the residuals plot is not ideal.
 - We can see that the residuals variance increases as the prediction values increase. As the price increases the variability increases. Therefore, a transformation of a variable in the model might be required.
 - Since most of the load appears to be in bottom, a log transformation will be attempted first.

Second iteration of Estimated Transaction Volume (USD) and market price

In [13]:

```
# Residuals vs fitted plot for linear model fit2b
sns.residplot(x=np.log(BTC_data2["btc_estimated_transaction_volume_usd"]),
              y=np.log(BTC_data2["btc_market_price"]), lowess=True,
              color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



In [14]:

```
# Fit linear model for log transformed
# btc_estimated_transaction_volume_usd vs log transformed
# btc_market_price
fit2b = linear_model.LinearRegression(fit_intercept=True,
                                     copy_X=True, n_jobs=1)
fit2b.fit(np.log(BTC_data2[["btc_estimated_transaction_volume_usd",
                           "btc_market_price"]]))
# Make predictions using the testing set
predictions2b =
```

```

fit2b.predict(np.log(BTC_data2[["btc_estimated_transaction_volume_usd"]]))

# Residuals
residuals2b = np.log(BTC_data2["btc_market_price"]) -
np.log(predictions2b)
# The coefficients
print(f'Coefficients: {fit2b.coef_}')
# Intercept
print(f'Intercept: {fit2b.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions2b -
np.log(BTC_data2["btc_market_price"]))) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
fit2b.score(np.log(BTC_data2[["btc_estimated_transaction_volume_usd"]]),
np.log(BTC_data2["btc_market_price"])))
# Plot outputs
plt.scatter(np.log(BTC_data2["btc_estimated_transaction_volume_usd"]),
np.log(BTC_data2["btc_market_price"]), color='blue')
plt.plot(np.unique(np.log(BTC_data2["btc_estimated_transaction_volume_usd"])),
np.poly1d(np.polyfit(np.log(BTC_data2["btc_estimated_transaction_volume_usd"]),
np.log(BTC_data2["btc_market_price"]), 1))
color='red', linewidth=1)
plt.title('Polynomial Regression')
plt.xlabel('Estimated Transaction Volume (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()

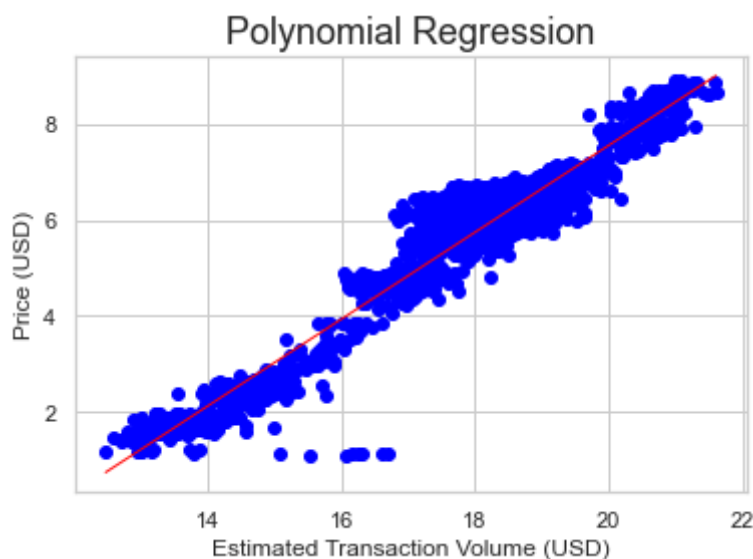
```

Coefficients: [0.90880364]

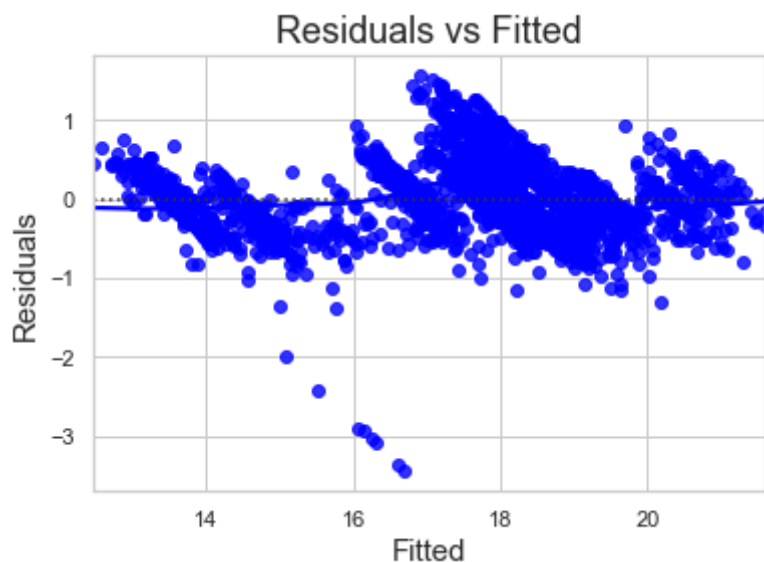
Intercept: -10.605824739229279

Mean squared error: 0.23

Variance score: 0.93



```
In [15]: sns.residplot(x=np.log(BTC_data2["btc_estimated_transaction_volume_usd"],
y=np.log(BTC_data2["btc_market_price"])), lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



- The log transformation improves the heteroscedasticity issue significantly in the x direction
- The dispersion on the y-axis is not ideal but less of pattern

Miners Revenue and market price

In [16]:

```
# Fit polynomial regression for btc_miners_revenue vs
btc_market_price
poly_btc_miners_revenue =
PolynomialFeatures(degree=2).fit_transform(BTC_data2[["btc_miners_revenue",
btc_market_price]])

fit3 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit3.fit(poly_btc_miners_revenue,
BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions3 = fit3.predict(poly_btc_miners_revenue)
# Residuals
residuals3 = BTC_data2["btc_market_price"] - predictions3
# The coefficients
print(f'Coefficients: {fit3.coef_}')
# Intercept
print(f'Intercept: {fit3.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions3 -
BTC_data2["btc_market_price"]) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
fit3.score(poly_btc_miners_revenue,
BTC_data2["btc_market_price"]))
# Plot outputs
plt.scatter(BTC_data2["btc_miners_revenue"]/1000000,
BTC_data2["btc_market_price"], color='blue')
plt.plot(np.unique(BTC_data2["btc_miners_revenue"]/1000000),
np.poly1d(np.polyfit(BTC_data2["btc_miners_revenue"]/1000000,
BTC_data2["btc_market_price"], 2))
(np.unique(BTC_data2["btc_miners_revenue"]/1000000)),
```

```

color='red', linewidth=1)
plt.title('Polynomial Regression')
plt.xlabel('Estimated Transaction Volume (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()

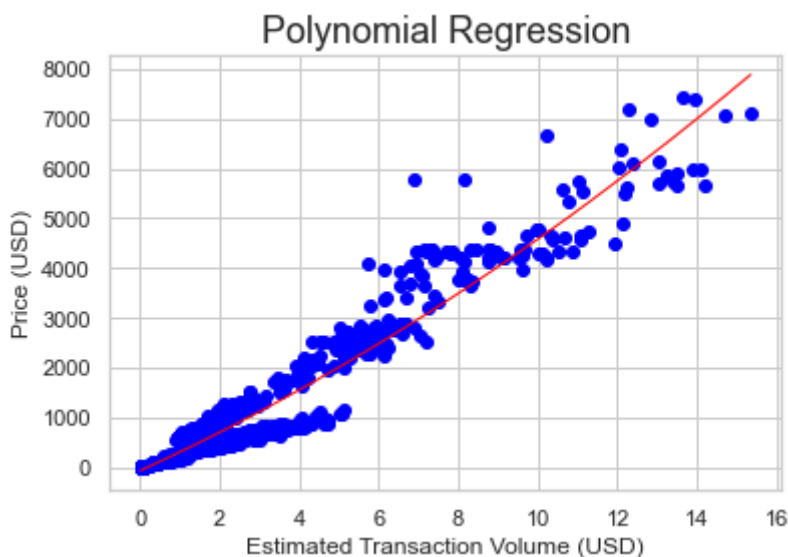
```

Coefficients: [0.00000000e+00 3.65309044e-04 9.94627427e-12]

Intercept: -67.27876218906135

Mean squared error: 75171.20

Variance score: 0.93

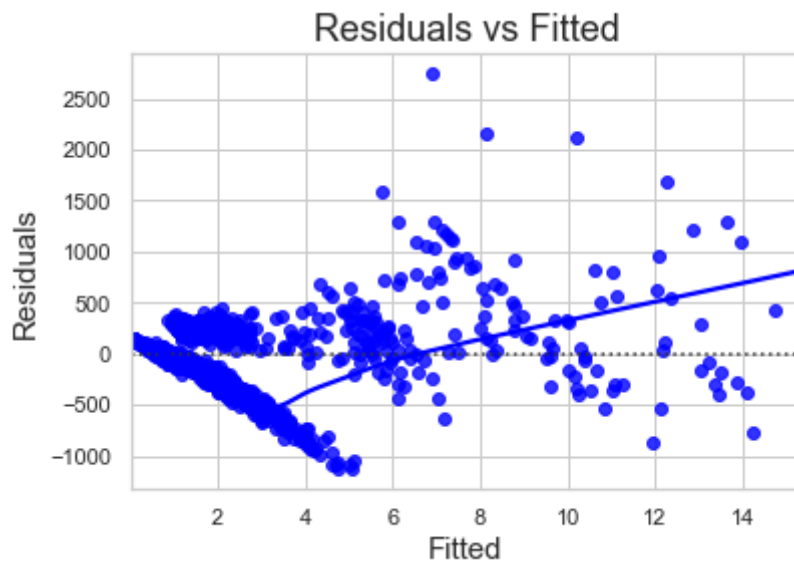


In [17]:

```

# Residuals vs Fitted
sns.residplot(x=BTC_data2["btc_miners_revenue"]/1000000,
y=BTC_data2["btc_market_price"], lowess=True, color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=12)
plt.rc('axes', titlesize=18)
plt.show()

```



We can see that residuals are clustered in a certain area and do not show the best dispersion in terms of heteroscedasticity

Difficulty and Market Price

In [18]:

```
# Fit polynomial regression for btc_difficulty vs
btc_market_price
poly_btc_difficulty =
PolynomialFeatures(degree=2).fit_transform(BTC_data2[["btc_diffic

fit4 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit4.fit(poly_btc_difficulty, BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions4 = fit4.predict(poly_btc_difficulty)
# Residuals
residuals4 = BTC_data2["btc_market_price"] - predictions4
# The coefficients
print(f'Coefficients: {fit4.coef_}')
# Intercept
print(f'Intercept: {fit4.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions4 -
BTC_data2["btc_market_price"]) ** 2))
# Explained variance score: 1 is perfect prediction
```

```

print('Variance score: %.2f' % fit4.score(poly_btc_difficulty,
BTC_data2["btc_market_price"]))
# Plot outputs
plt.scatter(BTC_data2["btc_difficulty"]/1000000,
BTC_data2["btc_market_price"], color='blue')
plt.plot(np.unique(BTC_data2["btc_difficulty"]/1000000),
np.poly1d(np.polyfit(BTC_data2["btc_difficulty"]/1000000,
BTC_data2["btc_market_price"], 2))
(np.unique(BTC_data2["btc_difficulty"]/1000000)), color='red',
linewidth=1)
plt.title('Polynomial Regression')
plt.xlabel('Estimated Transaction Volume (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()

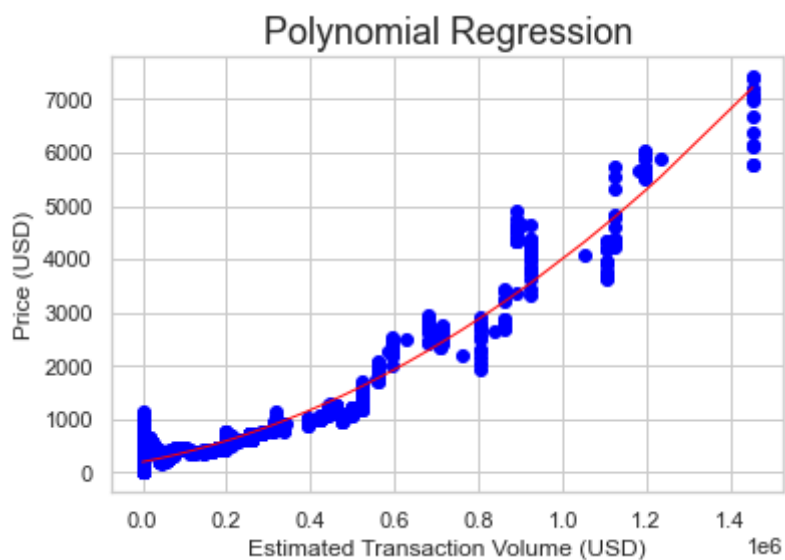
```

Coefficients: [0.00000000e+00 1.52149420e-09 2.27722823e-21]

Intercept: 199.6913915205463

Mean squared error: 69117.55

Variance score: 0.94



In [19]:

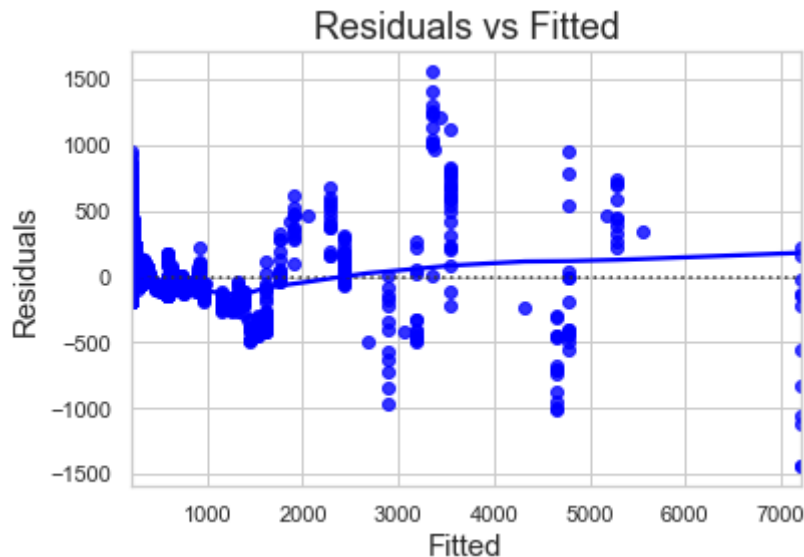
```

# Plot predictions4 vs residuals4 with sns
sns.residplot(x=predictions4, y=residuals4, lowess=True,
color='blue')

```



```
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



We can see some patterns, and therefore, reject a random dispersion

Hash Rate and Market Price

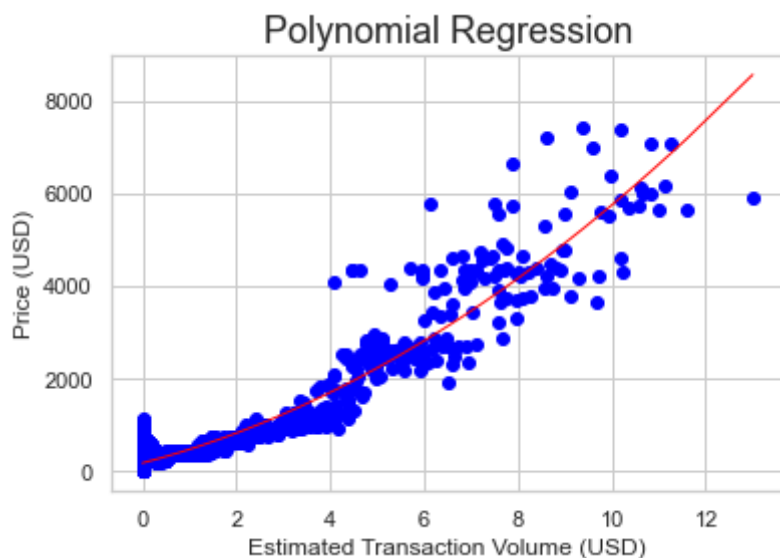
In [20]:

```
# Fit polynomial regression for btc_hash_rate vs
btc_market_price
poly_btc_hash_rate =
PolynomialFeatures(degree=2).fit_transform(BTC_data2[["btc_hash_r

fit5 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit5.fit(poly_btc_hash_rate, BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions5 = fit5.predict(poly_btc_hash_rate)
# Residuals
residuals5 = BTC_data2["btc_market_price"] - predictions5
# The coefficients
```

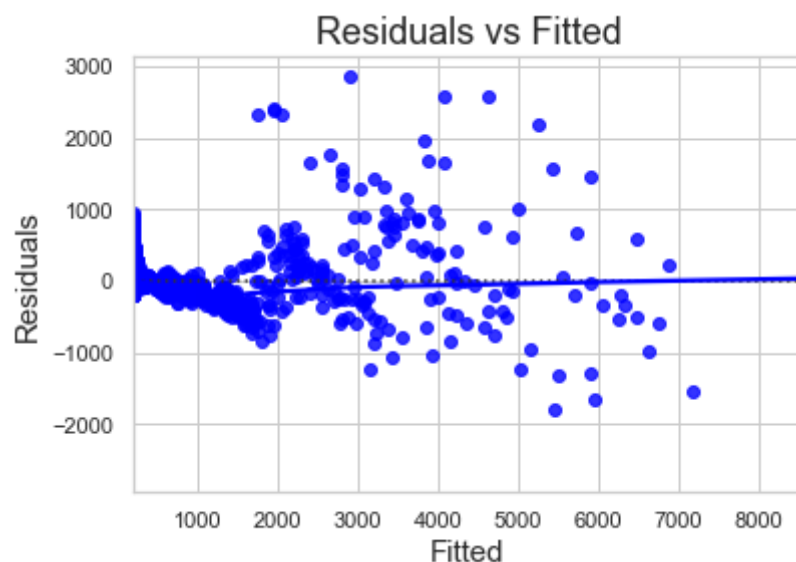
```
print(f'Coefficients: {fit5.coef_}')
# Intercept
print(f'Intercept: {fit5.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions5 -
BTC_data2["btc_market_price"])) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % fit5.score(poly_btc_hash_rate,
BTC_data2["btc_market_price"]))
# Plot outputs
plt.scatter(BTC_data2["btc_hash_rate"]/1000000,
BTC_data2["btc_market_price"], color='blue')
plt.plot(np.unique(BTC_data2["btc_hash_rate"]/1000000),
np.poly1d(np.polyfit(BTC_data2["btc_hash_rate"]/1000000,
BTC_data2["btc_market_price"], 2))
(np.unique(BTC_data2["btc_hash_rate"]/1000000)), color='red',
linewidth=1)
plt.title('Polynomial Regression')
plt.xlabel('Estimated Transaction Volume (USD)')
plt.ylabel('Price (USD)')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=15)
plt.rc('axes', titlesize=18)
plt.show()
```

Coefficients: [0.00000000e+00 2.63592983e-04 2.93199784e-11]
Intercept: 184.0088987538802
Mean squared error: 110833.67
Variance score: 0.90



In [21]:

```
# Residuals vs Fitted
sns.residplot(x=predictions5, y=residuals5, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



Despite some heteroscedasticity the residuals mostly follow a flat line

Significance Analysis of All Variables to Market Price

In [22]:

```
print(BTC_data2.columns.values)
```

```
['Date' 'btc_market_price' 'btc_total_bitcoins' 'btc_market_cap'
 'btc_trade_volume' 'btc_blocks_size' 'btc_avg_block_size'
 'btc_n_orphaned_blocks' 'btc_n_transactions_per_block'
 'btc_median_confirmation_time' 'btc_hash_rate' 'btc_difficulty'
 'btc_miners_revenue' 'btc_transaction_fees'
 'btc_cost_per_transaction_percent' 'btc_cost_per_transaction'
 'btc_n_unique_addresses' 'btc_n_transactions' 'btc_n_transactions_total'
 'btc_n_transactions_excluding_popular'
 'btc_n_transactions_excluding_chains_longer_than_100' 'btc_output_volume'
 'btc_estimated_transaction_volume' 'btc_estimated_transaction_volume_usd'
 'Days']
```

In [23]:

```
# Run linear regression on all variables vs btc_market_price
fit6 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit6.fit(BTC_data2[["btc_difficulty", "btc_hash_rate",
"btc_market_cap", "btc_estimated_transaction_volume_usd",
"btc_output_volume", "btc_n_transactions_total"
, "btc_trade_volume"]], BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions6 = fit6.predict(BTC_data2[["btc_difficulty",
"btc_hash_rate", "btc_market_cap",
"btc_estimated_transaction_volume_usd",
"btc_output_volume", "btc_n_transactions_total"
, "btc_trade_volume"]])
# Residuals
residuals6 = BTC_data2["btc_market_price"] - predictions6
# The coefficients
print(f'Coefficients: {fit6.coef_}')
# Intercept
print(f'Intercept: {fit6.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions6 -
BTC_data2["btc_market_price"])) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
```

```
fit6.score(BTC_data2[["btc_difficulty", "btc_hash_rate",
"btc_market_cap", "btc_estimated_transaction_volume_usd",
"btc_output_volume", "btc_n_transactions_total",
"btc_trade_volume"]], BTC_data2["btc_market_price"])))
```

Coefficients: [-6.09934168e-10 -7.11124066e-06 6.73424241e-08 1.78257397e-09
-1.47371627e-06 7.09254435e-07 -4.21248993e-08]

Intercept: 19.050210647484846

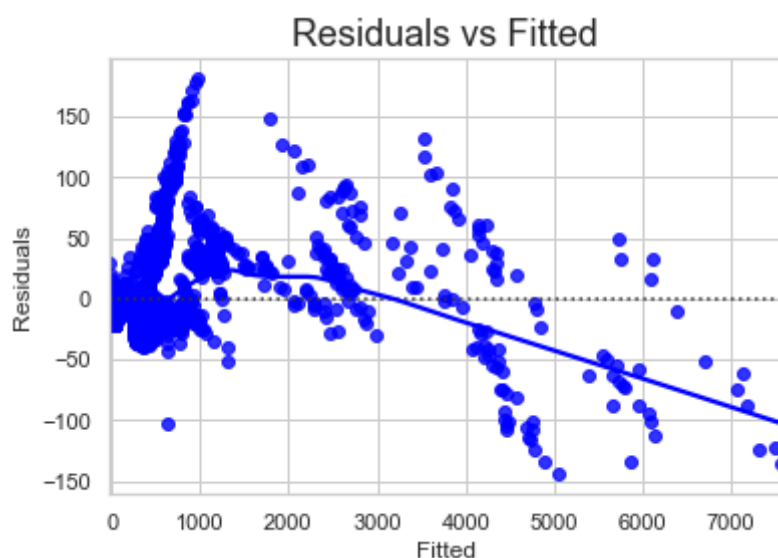
Mean squared error: 1319.51

Variance score: 1.00

R^2 score is very close to 1

In [24]:

```
# Residuals vs Fitted
sns.residplot(x=predictions6, y=residuals6, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



Even though most of the volume is closer to small values on the x-axis, most of the trend line is relatively flat.

Highly Correlated Variable vs Market Price

In [25]:

```
# Linear model of Highly correlated variables vs Market Price
fit7 = linear_model.LinearRegression(fit_intercept=True,
copy_X=True, n_jobs=1)
fit7.fit(BTC_data2[["btc_difficulty", "btc_hash_rate",
"btc_market_cap", "btc_estimated_transaction_volume_usd",
"btc_miners_revenue"]], BTC_data2["btc_market_price"])
# Make predictions using the testing set
predictions7 = fit7.predict(BTC_data2[["btc_difficulty",
"btc_hash_rate", "btc_market_cap",
"btc_estimated_transaction_volume_usd", "btc_miners_revenue"]])
# Residuals
residuals7 = BTC_data2["btc_market_price"] - predictions7
# The coefficients
print(f'Coefficients: {fit7.coef_}')
# Intercept
print(f'Intercept: {fit7.intercept_}')
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((predictions7 -
BTC_data2["btc_market_price"]) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' %
fit7.score(BTC_data2[["btc_difficulty", "btc_hash_rate",
"btc_market_cap", "btc_estimated_transaction_volume_usd",
"btc_miners_revenue"]], BTC_data2["btc_market_price"]))
```

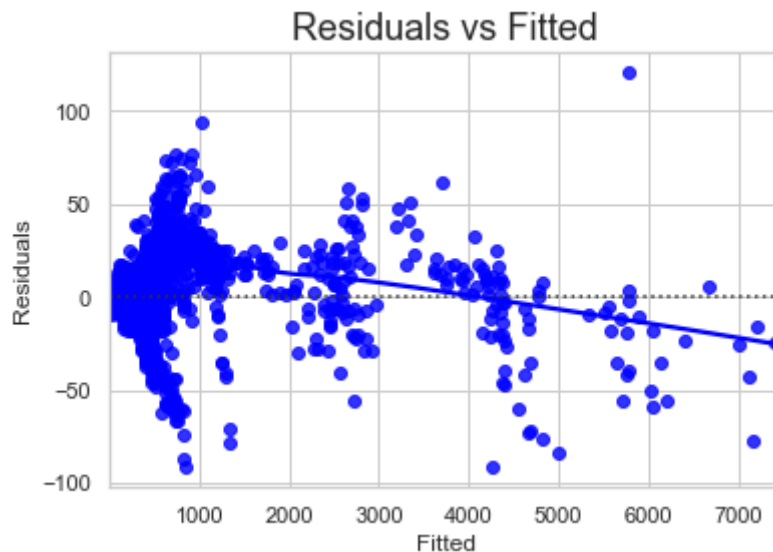
```
Coefficients: [ 4.62077875e-10 -6.36732046e-05  5.21760429e-08 -3.07034342e-08
 7.14661614e-05]
Intercept: 7.08707499472996
Mean squared error: 470.90
Variance score: 1.00
```

It appears that all of the highly correlated variables to Market Price (Market Cap, Hash Rate, BTC Difficulty, Miners Revenue, and Estimated Transaction Volume USD) are significant.

In [26]:

```
# Residuals vs Fitted
sns.residplot(x=predictions7, y=residuals7, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
```

```
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



We do not see neither a dispersion nor a trend line, so a better adjustment is needed

Narrow down variables

- Market Capitalization and Estimated Transaction Volume are highly correlated, only one will be included in the model.
- Difficulty and Hash Rate are highly correlated, only one will be included in the model.

In [27]:

```
highly_correlated_variables = ["btc_difficulty",
                               "btc_miners_revenue", "btc_estimated_transaction_volume_usd"]
highly_correlated_variables_with_market_price =
["btc_market_price", "btc_difficulty", "btc_miners_revenue",
 "btc_estimated_transaction_volume_usd"]
# Multiple Linear Regression
# Create a new dataframe with the highly correlated variables
BTC_data3 =
BTC_data2[highly_correlated_variables_with_market_price]
# Run a multiple linear regression model using sm.OLS
BTC_data3 = sm.add_constant(BTC_data3)
fit8 = sm.OLS(BTC_data3["btc_market_price"],
```

```
BTC_data3[highly_correlated_variables]).fit()
# Print the summary
print(fit8.summary())
print(fit8)
```

OLS Regression Results

```
=====
=====
Dep. Variable:          btc_market_price    R-squared (uncentered):
0.980
Model:                  OLS    Adj. R-squared (uncentered):
0.980
Method:                 Least Squares    F-statistic:                3.
537e+04
Date:                  Thu, 11 Nov 2021    Prob (F-statistic):
0.00
Time:                  09:21:23    Log-Likelihood:
-14135.
No. Observations:      2153    AIC:                2.
828e+04
Df Residuals:          2150    BIC:                2.
829e+04
Df Model:              3
Covariance Type:       nonrobust
=====
=====
```

	coef	std err	t	P> t
[0.025 0.975]				

btc_difficulty	1.721e-09	3.45e-11	49.899	0.000
1.65e-09 1.79e-09				
btc_miners_revenue	0.0002	3.4e-06	68.173	0.000
0.000 0.000				
btc_estimated_transaction_volume_usd	2.595e-07	3.85e-08	6.749	0.000
1.84e-07 3.35e-07				
=====				
Omnibus:	1616.641	Durbin-Watson:	0.346	
Prob(Omnibus):	0.000	Jarque-Bera (JB):	57441.829	
Skew:	3.162	Prob(JB):	0.00	
Kurtosis:	27.502	Cond. No.	2.79e+05	
=====				

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

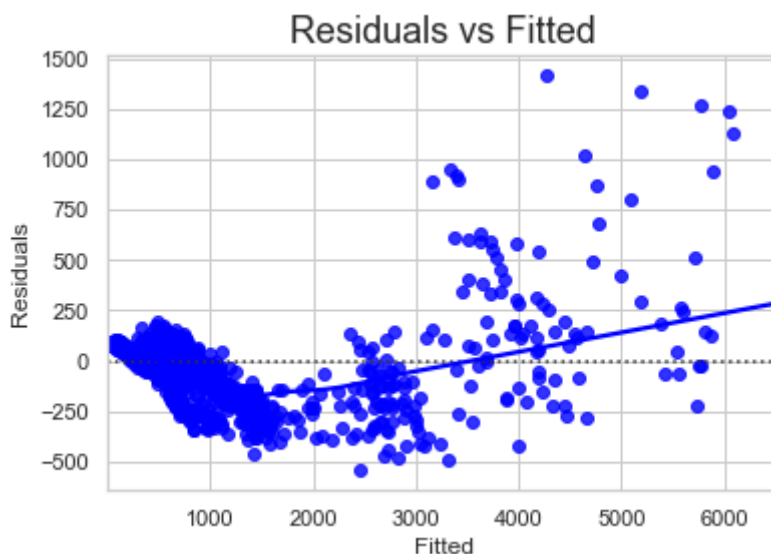
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[3] The condition number is large, 2.79e+05. This might indicate that there are strong multicollinearity or other numerical problems.

<statsmodels.regression.linear_model.RegressionResultsWrapper object at 0x13547d3a0>

In [28]:

```
# Residuals vs fit plot
sns.residplot(x=fit8.fittedvalues, y=fit8.resid, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



Narrow down variables some more

- Difficulty, Hash Rate and Miners revenue are highly correlated, only one will be included in the model.

In [29]:

```
highly_correlated_variables_excluding_volume =
["btc_miners_revenue", "btc_estimated_transaction_volume_usd"]
highly_correlated_variables_excluding_volume_with_market_price
= ["btc_market_price", "btc_miners_revenue",
"btc_estimated_transaction_volume_usd"]
# Multiple Linear Regression
# Create a new dataframe with the highly correlated variables
BTC_data4 =
BTC_data2[highly_correlated_variables_excluding_volume_with_marke
```

```
# Run a multiple linear regression model using sm.OLS
BTC_data4 = sm.add_constant(BTC_data4)
fit9 = sm.OLS(BTC_data4["btc_market_price"],
BTC_data4[highly_correlated_variables_excluding_volume]).fit()
# Print the summary
print(fit9.summary())
print(fit9)
```

OLS Regression Results

```
=====
=====
Dep. Variable:          btc_market_price    R-squared (uncentered):
0.957
Model:                  OLS                Adj. R-squared (uncentered):
0.957
Method:                 Least Squares       F-statistic:                2.
402e+04
Date:                  Thu, 11 Nov 2021     Prob (F-statistic):
0.00
Time:                  09:21:23            Log-Likelihood:
-14963.
No. Observations:      2153                AIC:                    2.
993e+04
Df Residuals:          2151                BIC:                    2.
994e+04
Df Model:              2
Covariance Type:       nonrobust
=====
=====
```

	coef	std err	t	P> t
[0.025 0.975]				

btc_miners_revenue	0.0003	4.84e-06	56.597	0.000
0.000 0.000				
btc_estimated_transaction_volume_usd	1.491e-06	4.33e-08	34.423	0.000
1.41e-06 1.58e-06				
=====				
Omnibus:	1510.442	Durbin-Watson:	0.588	
Prob(Omnibus):	0.000	Jarque-Bera (JB):	58848.695	
Skew:	2.811	Prob(JB):	0.00	
Kurtosis:	27.988	Cond. No.	275.	
=====				

Notes:

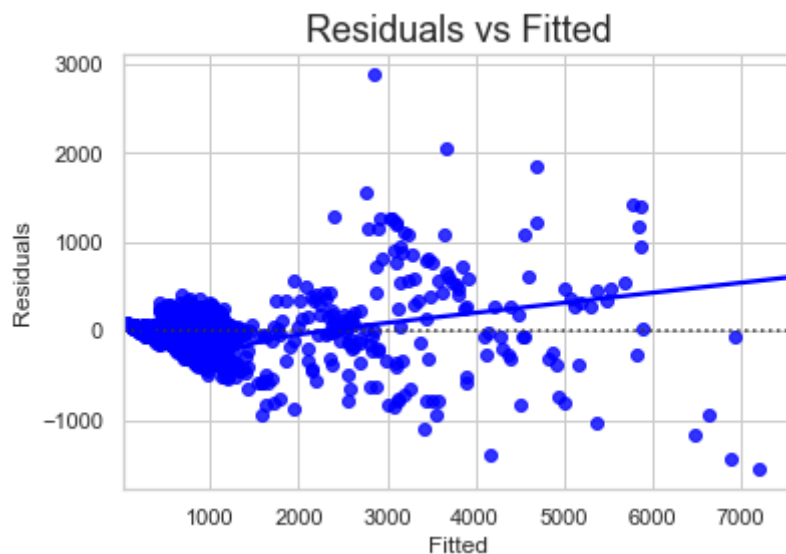
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

<statsmodels.regression.linear_model.RegressionResultsWrapper object at 0x1350b85b0>

In [30]:

```
# Residuals vs fit plot
sns.residplot(x=fit9.fittedvalues, y=fit9.resid, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
plt.show()
```



Despite some heteroscedasticity this is the best model so far

In [31]:

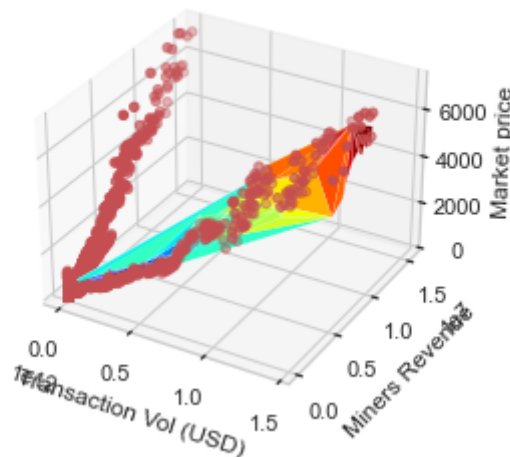
```
# Draw a 3D plot of the regression line
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
# Plot the surface.
ax.scatter(BTC_data2["btc_difficulty"],
BTC_data2["btc_hash_rate"], BTC_data2["btc_market_price"],
c='r', marker='o')
ax.plot_trisurf(BTC_data2["btc_difficulty"],
BTC_data2["btc_hash_rate"], fit8.fittedvalues, cmap='jet',
```

```

linewidth=0.1)
ax.scatter(BTC_data2["btc_estimated_transaction_volume_usd"],
BTC_data2["btc_miners_revenue"], BTC_data2["btc_market_price"],
c='r', marker='o')
plt.title('Market price ~ Trans. Vol + Miners Revenue')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsiz=12)
plt.rc('axes', titlesize=18)
ax.set_xlabel('Transaction Vol (USD)')
ax.set_ylabel('Miners Revenue')
ax.set_zlabel('Market price')
ax.set_zlim(0, BTC_data2["btc_market_price"].max())
plt.show()

```

Market price ~ Trans. Vol + Miners Revenue



Polynomial Multilinear Regression

Linear Model: Market Price ~ Miners Revenue Squared + Count of Transactions Squared

In [32]:

```

# Create a dataframe with the highly correlated variables
BTC_data5 = BTC_data2[[ "btc_market_price",
"btc_estimated_transaction_volume_usd", "btc_miners_revenue",
"Date" ]]
# Convert BTC_data5["btc_miners_revenue"] to a degree-2
polynomial
BTC_data5 = BTC_data5.loc[:,
BTC_data5["btc_miners_revenue_squared"] = BTC_data5.loc[:,

```

```

"btc_miners_revenue"].apply(lambda x: np.power(x, 2))
# Convert BTC_data5["btc_estimated_transaction_volume_usd"] to a
degree-2 polynomial
BTC_data5["btc_estimated_transaction_volume_usd_squared"] =
BTC_data5.loc[:,
"btc_estimated_transaction_volume_usd"].apply(lambda x:
np.power(x, 2))
# Run a multiple linear regression model using sm.OLS
BTC_data5 = sm.add_constant(BTC_data5)
fit10 = sm.OLS(BTC_data5["btc_market_price"],
BTC_data5[["btc_estimated_transaction_volume_usd",
"btc_miners_revenue"]]).fit()
# Print the summary
print(fit10.summary())
print(fit10)

```

OLS Regression Results

```

=====
=====
Dep. Variable:          btc_market_price    R-squared (uncentered):
0.957
Model:                  OLS    Adj. R-squared (uncentered):
0.957
Method:                Least Squares    F-statistic:                2.
402e+04
Date:                  Thu, 11 Nov 2021    Prob (F-statistic):
0.00
Time:                  09:21:24    Log-Likelihood:
-14963.
No. Observations:      2153    AIC:                2.
993e+04
Df Residuals:          2151    BIC:                2.
994e+04
Df Model:              2
Covariance Type:       nonrobust
=====
=====

```

	coef	std err	t	P> t
[0.025 0.975]				

btc_estimated_transaction_volume_usd	1.491e-06	4.33e-08	34.423	0.000
1.41e-06 1.58e-06				
btc_miners_revenue	0.0003	4.84e-06	56.597	0.000
0.000 0.000				
=====				
Omnibus:	1510.442	Durbin-Watson:	0.588	

Prob(Omnibus):	0.000	Jarque-Bera (JB):	58848.695
Skew:	2.811	Prob(JB):	0.00
Kurtosis:	27.988	Cond. No.	275.

=====

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

<statsmodels.regression.linear_model.RegressionResultsWrapper object at 0x137798e80>

In [33]:

```
# Residuals vs fit plot
sns.residplot(x=fit10.fittedvalues, y=fit10.resid, lowess=True,
color='blue')
plt.title('Residuals vs Fitted')
plt.xlabel('Fitted')
plt.ylabel('Residuals')
plt.rc('font', size=14)
plt.rc('figure', titlesize=18)
plt.rc('axes', labelsz=12)
plt.rc('axes', titlesize=18)
plt.show()
```

