CoffeeSales

September 11, 2025

These analyses explore the variables that are associated with revenue sold from coffee.

Analysis used: stepwise regression

Created on: August 22, 2025 Created by: Claudia Claudia

Import Libraries

[2]:
```
import pandas as pd
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.stats.outliers_influence import variance_inflation_factor
import matplotlib.pyplot as plt
import itertools
```

Read in the data

[3]:
```
address = '/Users/claudiaclinchard/Desktop/Projects/Coffee_sales/Coffee_sales.
 ↪xlsx'

coffee = pd.read_excel(address, header=int(1))
coffee.columns=['date', 'datetime', 'hour_of_day', 'cash_type', 'card',␣
 ↪'money', 'coffee_name',
                'time_of_day', 'weekday', 'month_name', 'weekdaysort',␣
 ↪'monthsort']

coffee[:5]
```

[3]:
```
        date                datetime  hour_of_day cash_type  \
0 2024-03-01 2024-03-01 12:19:22.539           12      card
1 2024-03-01 2024-03-01 12:20:18.089           12      card
2 2024-03-01 2024-03-01 13:46:33.006           13      card
3 2024-03-01 2024-03-01 13:48:14.626           13      card
4 2024-03-01 2024-03-01 15:39:47.726           15      card

                  card  money        coffee_name time_of_day weekday  \
0  ANON-0000-0000-0002   38.7     Hot Chocolate   Afternoon     Fri
1  ANON-0000-0000-0002   38.7     Hot Chocolate   Afternoon     Fri
2  ANON-0000-0000-0003   28.9         Americano   Afternoon     Fri
3  ANON-0000-0000-0004   38.7             Latte   Afternoon     Fri
```

```
4  ANON-0000-0000-0005   33.8  Americano with Milk   Afternoon     Fri

  month_name  weekdaysort  monthsort
0        Mar            5          3
1        Mar            5          3
2        Mar            5          3
3        Mar            5          3
4        Mar            5          3
```

[4]:

```python
X = coffee[['hour_of_day', 'cash_type', 'coffee_name', 'weekday', 'month_name']]
y = coffee[['money']]
```

[76]:

```python
for col in coffee.select_dtypes(include="object").columns:
    coffee[col] = coffee[col].astype("category")

# Descriptives
print(coffee.head())
print(coffee.describe(include="all"))
print(coffee.dtypes)
print({col: coffee[col].nunique() for col in coffee.
 ↪select_dtypes(include="category").columns})

coffee["hour_of_day"] = coffee["hour_of_day"].astype("category")
```

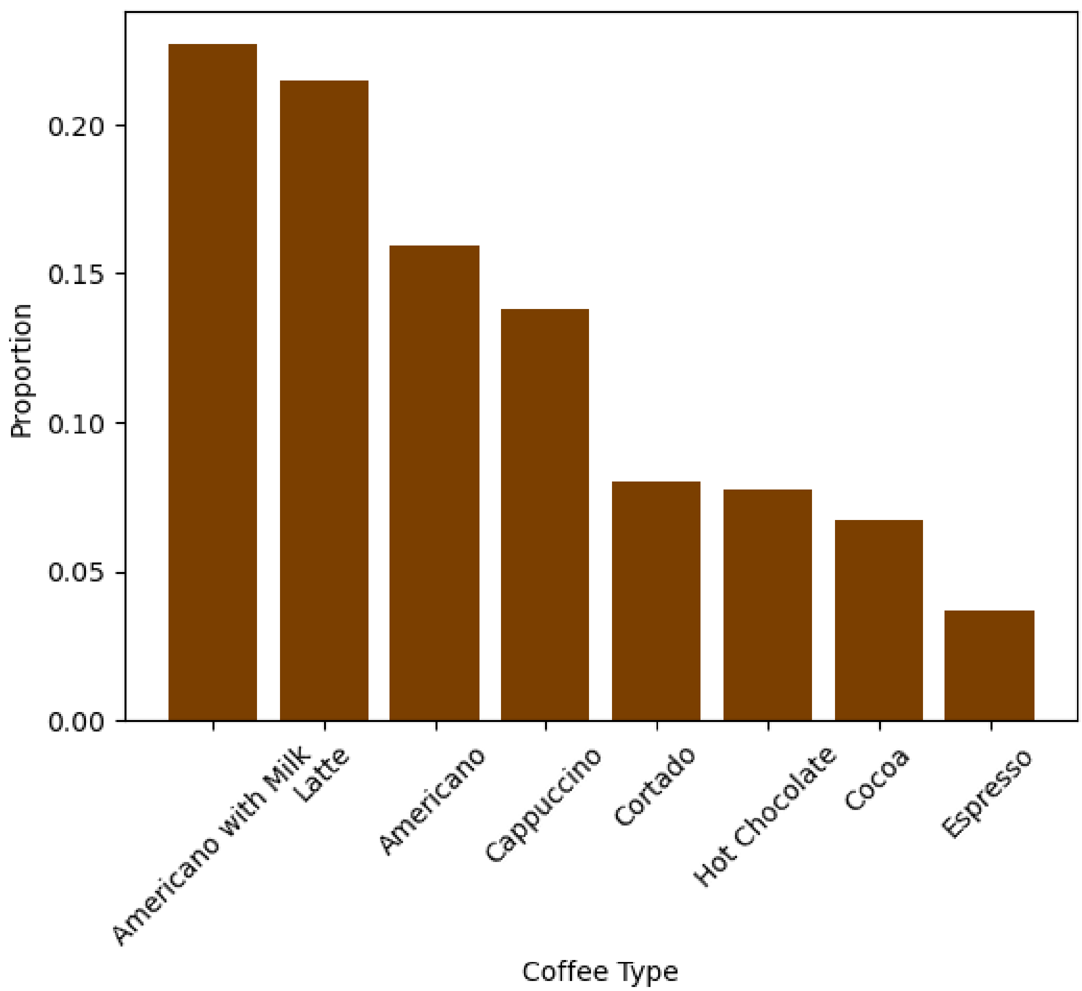
```
         date                 datetime  hour_of_day cash_type  \
0 2024-03-01 2024-03-01 12:19:22.539           12      card
1 2024-03-01 2024-03-01 12:20:18.089           12      card
2 2024-03-01 2024-03-01 13:46:33.006           13      card
3 2024-03-01 2024-03-01 13:48:14.626           13      card
4 2024-03-01 2024-03-01 15:39:47.726           15      card

                  card  money          coffee_name time_of_day weekday  \
0  ANON-0000-0000-0002   38.7        Hot Chocolate   Afternoon     Fri
1  ANON-0000-0000-0002   38.7        Hot Chocolate   Afternoon     Fri
2  ANON-0000-0000-0003   28.9            Americano   Afternoon     Fri
3  ANON-0000-0000-0004   38.7                Latte   Afternoon     Fri
4  ANON-0000-0000-0005   33.8  Americano with Milk   Afternoon     Fri

  month_name  weekdaysort  monthsort
0        Mar            5          3
1        Mar            5          3
2        Mar            5          3
3        Mar            5          3
4        Mar            5          3
                              date                        datetime  \
count                         3635                            3635
unique                         NaN                             NaN
top                            NaN                             NaN
```

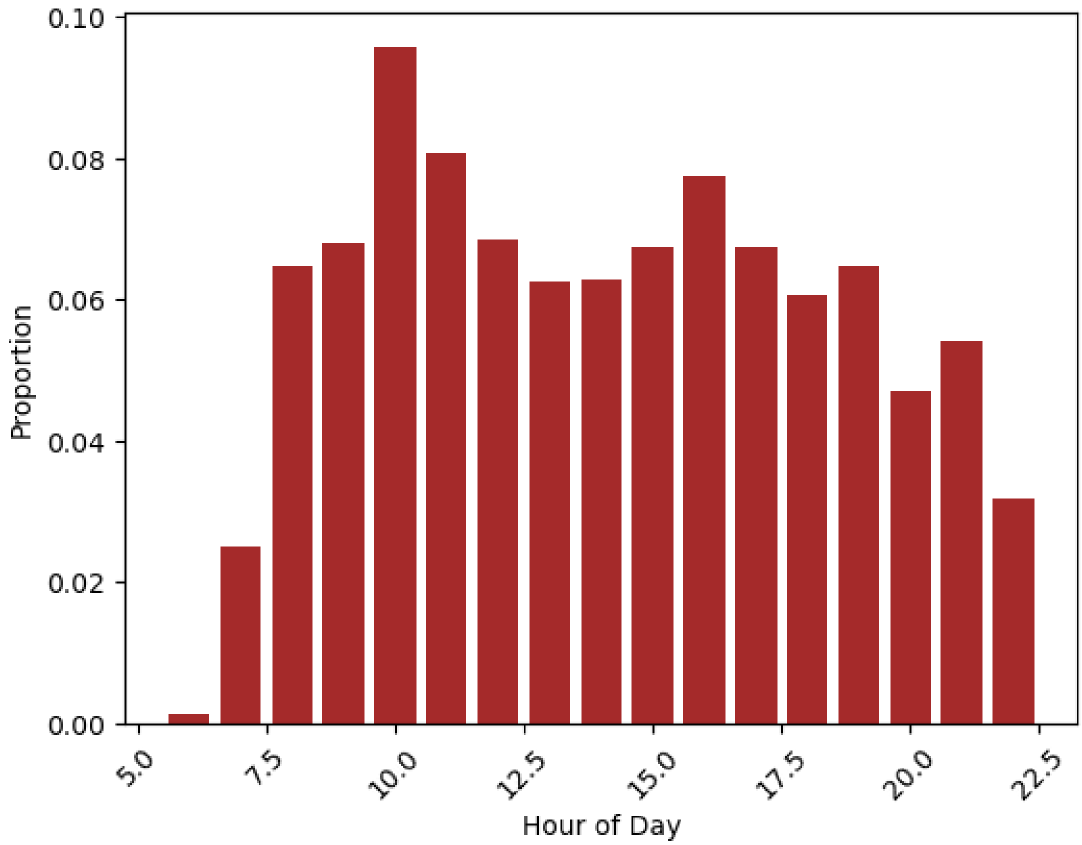
```
freq                               NaN                            NaN
mean    2024-09-30 13:20:36.973865472  2024-10-01 04:00:09.484163584
min               2024-03-01 00:00:00     2024-03-01 12:19:22.539000
25%               2024-07-03 00:00:00  2024-07-03 16:54:57.165000192
50%               2024-10-07 00:00:00  2024-10-07 08:33:36.423000064
75%               2025-01-08 00:00:00  2025-01-08 08:20:38.580500224
max               2025-03-23 00:00:00     2025-03-23 18:11:38.635000
std                               NaN                            NaN

        hour_of_day cash_type                card        money  \
count   3635.000000      3635                3546  3635.000000
unique          NaN         2                1316          NaN
top             NaN      card  ANON-0000-0000-0012          NaN
freq            NaN      3546                 129          NaN
mean      14.168088       NaN                 NaN    31.744946
min        6.000000       NaN                 NaN    18.120000
25%       10.000000       NaN                 NaN    27.920000
50%       14.000000       NaN                 NaN    32.820000
75%       18.000000       NaN                 NaN    35.760000
max       22.000000       NaN                 NaN    40.000000
std        4.227771       NaN                 NaN     4.919250

                coffee_name time_of_day weekday month_name  weekdaysort  \
count                  3635        3635    3635       3635  3635.000000
unique                    8           3       7         12          NaN
top     Americano with Milk   Afternoon     Tue        Mar          NaN
freq                    824        1231     585        524          NaN
mean                    NaN         NaN     NaN        NaN     3.847593
min                     NaN         NaN     NaN        NaN     1.000000
25%                     NaN         NaN     NaN        NaN     2.000000
50%                     NaN         NaN     NaN        NaN     4.000000
75%                     NaN         NaN     NaN        NaN     6.000000
max                     NaN         NaN     NaN        NaN     7.000000
std                     NaN         NaN     NaN        NaN     1.976163

          monthsort
count   3635.000000
unique          NaN
top             NaN
freq            NaN
mean       6.395598
min        1.000000
25%        3.000000
50%        6.000000
75%       10.000000
max       12.000000
std        3.480709
date          datetime64[ns]
```

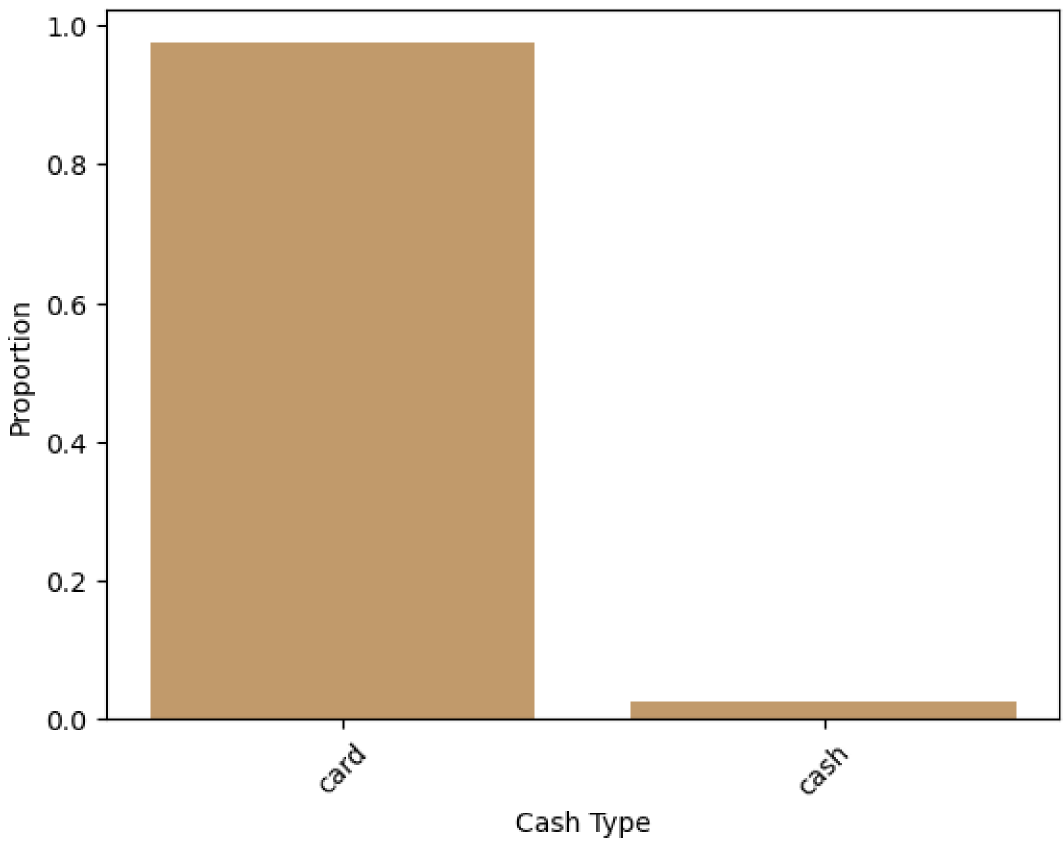
```
datetime       datetime64[ns]
hour_of_day             int64
cash_type            category
card                 category
money                 float64
coffee_name          category
time_of_day          category
weekday              category
month_name           category
weekdaysort             int64
monthsort               int64
dtype: object
{'cash_type': 2, 'card': 1316, 'coffee_name': 8, 'time_of_day': 3, 'weekday': 7,
'month_name': 12}
```

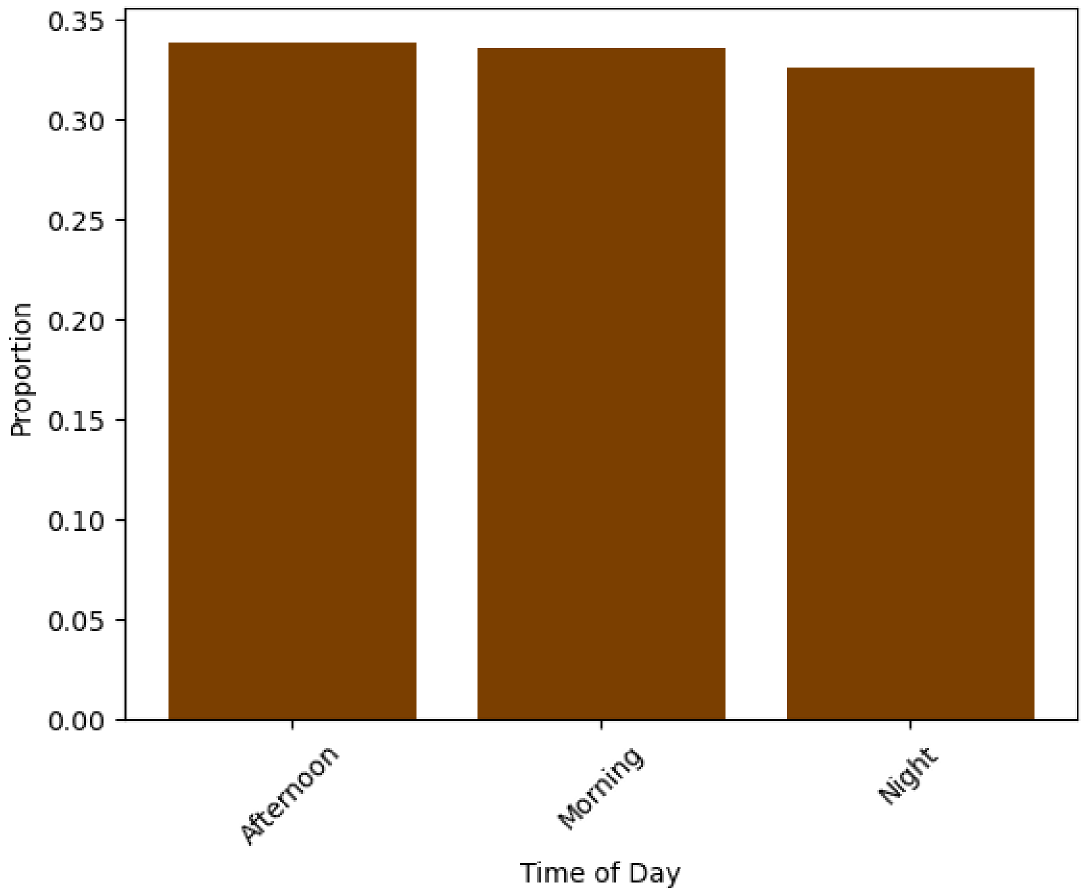
[77]:
```python
# Barplots of proportions

#Coffee Type
counts = coffee['coffee_name'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#7B3F00")
plt.ylabel("Proportion")
plt.xlabel("Coffee Type")
plt.xticks(rotation=45)
plt.show()

#Hour of Day
counts = coffee['hour_of_day'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#A52A2A")
plt.ylabel("Proportion")
plt.xlabel("Hour of Day")
plt.xticks(rotation=45)
plt.show()

#Cash Type
counts = coffee['cash_type'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#C19A6B")
plt.ylabel("Proportion")
plt.xlabel("Cash Type")
plt.xticks(rotation=45)
plt.show()

#Time of Day
counts = coffee['time_of_day'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#7B3F00")
plt.ylabel("Proportion")
plt.xlabel("Time of Day")
plt.xticks(rotation=45)
```

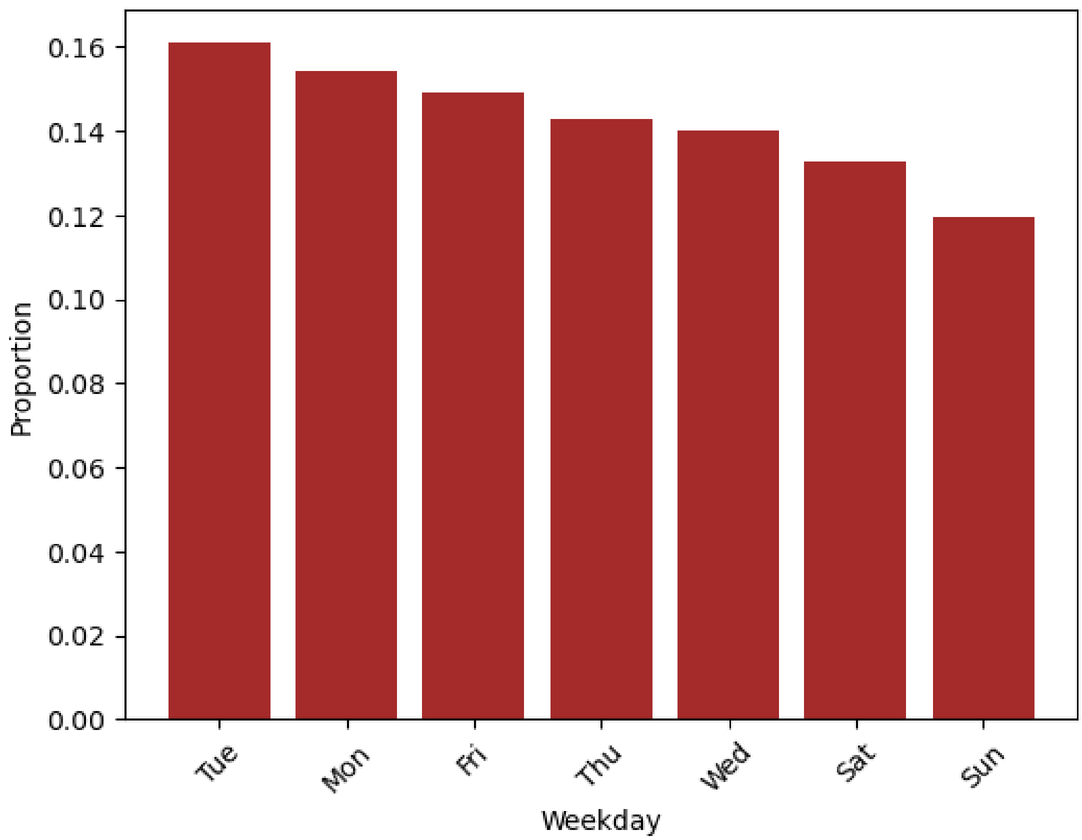
```
plt.show()

#Weekday
counts = coffee['weekday'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#A52A2A")
plt.ylabel("Proportion")
plt.xlabel("Weekday")
plt.xticks(rotation=45)
plt.show()

#Month
counts = coffee['month_name'].value_counts(normalize=True)
plt.bar(counts.index, counts.values, color = "#A52A2A")
plt.ylabel("Proportion")
plt.xlabel("Month")
plt.xticks(rotation=45)
plt.show()
```

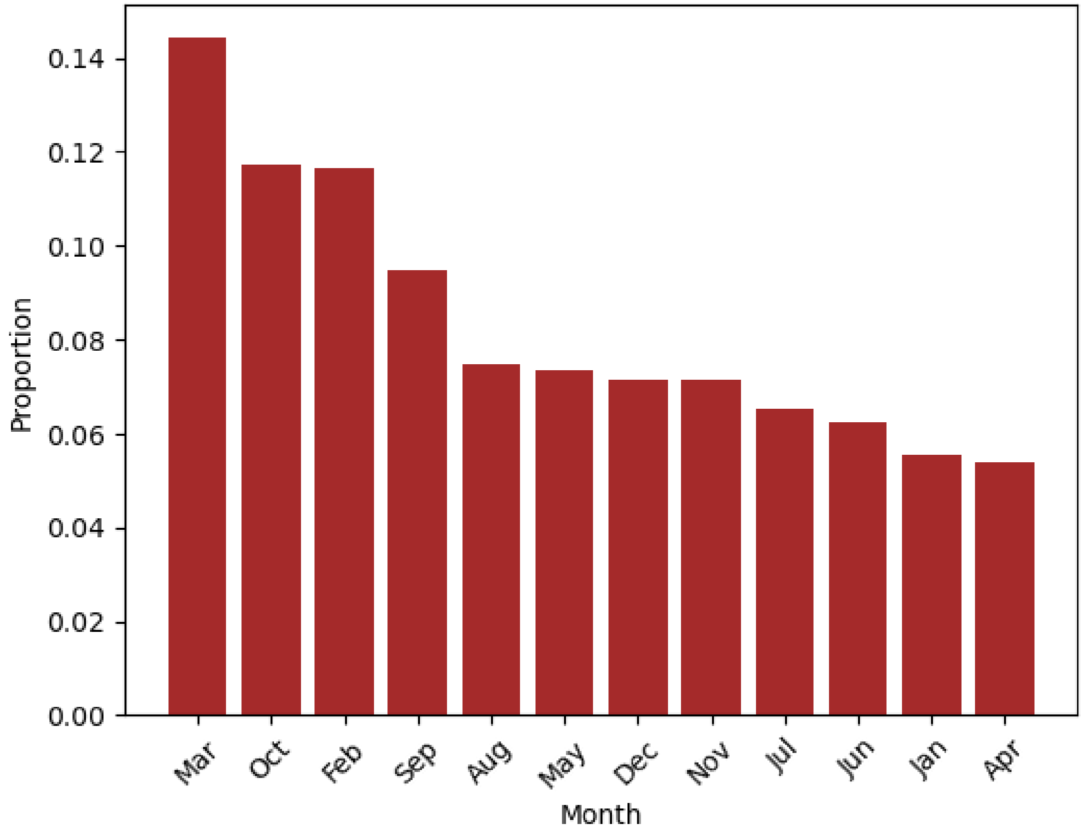



0.10
0.08
0.06
0.04
0.02
0.00
Proportion
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
Hour of Day


1.0
0.8
0.6
0.4
0.2
0.0
Proportion
card
cash
Cash Type


0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Proportion
Afternoon
Morning
Night
Time of Day


0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Proportion
Tue
Mon
Fri
Thu
Wed
Sat
Sun
Weekday



[12]:
```
#Full Model
full_formula = "money ~ hour_of_day + cash_type + coffee_name + time_of_day +␣
↪weekday + month_name"
full_mod = smf.ols(full_formula, data=coffee).fit()
print(full_mod.summary())
print("AIC full model:", full_mod.aic)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  money   R-squared:                       0.978
Model:                            OLS   Adj. R-squared:                  0.978
Method:                 Least Squares   F-statistic:                     5668.
Date:                Thu, 11 Sep 2025   Prob (F-statistic):               0.00
Time:                        12:14:50   Log-Likelihood:                -4029.5
No. Observations:                3635   AIC:                             8117.
Df Residuals:                    3606   BIC:                             8297.
Df Model:                          28
Covariance Type:            nonrobust
================================================================================
======================
```

```
                                         coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------------
Intercept                             28.3809      0.135    210.487      0.000
28.117      28.645
cash_type[T.cash]                      1.9813      0.082     24.071      0.000
1.820       2.143
coffee_name[T.Americano with Milk]     5.0052      0.041    122.739      0.000
4.925       5.085
coffee_name[T.Cappuccino]              9.8824      0.046    215.750      0.000
9.793       9.972
coffee_name[T.Cocoa]                   9.7770      0.057    170.596      0.000
9.665       9.889
coffee_name[T.Cortado]                 0.2853      0.054      5.287      0.000
0.179       0.391
coffee_name[T.Espresso]               -4.7084      0.071    -66.313      0.000
-4.848      -4.569
coffee_name[T.Hot Chocolate]           9.9176      0.055    179.955      0.000
9.810      10.026
coffee_name[T.Latte]                   9.8856      0.041    238.857      0.000
9.804       9.967
time_of_day[T.Morning]                -0.1236      0.050     -2.476      0.013
-0.221      -0.026
time_of_day[T.Night]                  -0.0503      0.053     -0.957      0.339
-0.153       0.053
weekday[T.Mon]                        -0.0098      0.045     -0.220      0.826
-0.097       0.078
weekday[T.Sat]                         0.0442      0.047      0.950      0.342
-0.047       0.135
weekday[T.Sun]                        -0.0030      0.048     -0.062      0.951
-0.097       0.091
weekday[T.Thu]                        -0.0476      0.045     -1.047      0.295
-0.137       0.041
weekday[T.Tue]                        -0.0347      0.044     -0.787      0.432
-0.121       0.052
weekday[T.Wed]                        -0.0343      0.046     -0.752      0.452
-0.124       0.055
month_name[T.Aug]                     -5.4470      0.071    -77.253      0.000
-5.585      -5.309
month_name[T.Dec]                     -2.5134      0.071    -35.376      0.000
-2.653      -2.374
month_name[T.Feb]                     -2.4756      0.065    -37.941      0.000
-2.604      -2.348
month_name[T.Jan]                     -2.5138      0.075    -33.456      0.000
-2.661      -2.367
month_name[T.Jul]                     -4.7882      0.073    -65.859      0.000
-4.931      -4.646
```

```
month_name[T.Jun]                         -0.5743      0.073     -7.859      0.000
-0.718      -0.431
month_name[T.Mar]                         -1.3813      0.062    -22.133      0.000
-1.504      -1.259
month_name[T.May]                         -0.6166      0.070     -8.861      0.000
-0.753      -0.480
month_name[T.Nov]                         -2.5000      0.071    -34.995      0.000
-2.640      -2.360
month_name[T.Oct]                         -2.4977      0.065    -38.289      0.000
-2.626      -2.370
month_name[T.Sep]                         -5.1645      0.067    -76.514      0.000
-5.297      -5.032
hour_of_day                                0.0042      0.008      0.494      0.621
-0.012       0.021
==============================================================================
Omnibus:                     1996.907   Durbin-Watson:                   0.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            19650.873
Skew:                           2.447   Prob(JB):                         0.00
Kurtosis:                      13.286   Cond. No.                         237.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
AIC full model: 8117.099077791354
```

[14]:

```python
#Examine VIF for multicollinearity
X=full_mod.model.exog
features=full_mod.model.exog_names
vif_data = pd.DataFrame()
vif_data["feature"] = features
vif_data["VIF"] = [variance_inflation_factor(X, i) for i in range(X.shape[1])]
vif_data = vif_data[vif_data["feature"] != "Intercept"]
print(vif_data)
```

```
                              feature       VIF
1                     cash_type[T.cash]  1.085652
2   coffee_name[T.Americano with Milk]  1.955621
3            coffee_name[T.Cappuccino]  1.672578
4                 coffee_name[T.Cocoa]  1.374555
5               coffee_name[T.Cortado]  1.442946
6              coffee_name[T.Espresso]  1.200778
7        coffee_name[T.Hot Chocolate]  1.458122
8                 coffee_name[T.Latte]  1.938477
9              time_of_day[T.Morning]  3.725417
10               time_of_day[T.Night]  4.066860
11                     weekday[T.Mon]  1.736439
12                     weekday[T.Sat]  1.669770
```

```
13                    weekday[T.Sun]  1.620571
14                    weekday[T.Thu]  1.696247
15                    weekday[T.Tue]  1.758006
16                    weekday[T.Wed]  1.682200
17                 month_name[T.Aug]  2.308853
18                 month_name[T.Dec]  2.240928
19                 month_name[T.Feb]  2.936855
20                 month_name[T.Jan]  1.978495
21                 month_name[T.Jul]  2.161284
22                 month_name[T.Jun]  2.097183
23                 month_name[T.Mar]  3.223839
24                 month_name[T.May]  2.210337
25                 month_name[T.Nov]  2.265712
26                 month_name[T.Oct]  2.953383
27                 month_name[T.Sep]  2.618734
28                       hour_of_day  8.615598
```

[15]:

```python
#Remove hour_of_day
full_formula2 = "money ~ cash_type + coffee_name + time_of_day + weekday +␣
 ↪month_name"
full_mod2 = smf.ols(full_formula2, data=coffee).fit()
print(full_mod2.summary())
print("AIC full model:", full_mod2.aic)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  money   R-squared:                       0.978
Model:                            OLS   Adj. R-squared:                  0.978
Method:                 Least Squares   F-statistic:                     5879.
Date:                Thu, 11 Sep 2025   Prob (F-statistic):               0.00
Time:                        12:15:08   Log-Likelihood:                -4029.7
No. Observations:                3635   AIC:                             8115.
Df Residuals:                    3607   BIC:                             8289.
Df Model:                          27
Covariance Type:            nonrobust
================================================================================
======================
                                         coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------------
Intercept                             28.4384      0.068    416.523      0.000
28.305      28.572
cash_type[T.cash]                      1.9822      0.082     24.089      0.000
1.821       2.144
coffee_name[T.Americano with Milk]     5.0050      0.041    122.752      0.000
4.925       5.085
coffee_name[T.Cappuccino]              9.8823      0.046    215.775      0.000
```

```
9.792        9.972
coffee_name[T.Cocoa]                  9.7777       0.057    170.680       0.000
9.665        9.890
coffee_name[T.Cortado]                0.2849       0.054      5.280       0.000
0.179        0.391
coffee_name[T.Espresso]              -4.7085       0.071    -66.323       0.000
-4.848       -4.569
coffee_name[T.Hot Chocolate]          9.9195       0.055    180.433       0.000
9.812       10.027
coffee_name[T.Latte]                  9.8859       0.041    238.916       0.000
9.805        9.967
time_of_day[T.Morning]               -0.1432       0.030     -4.721       0.000
-0.203       -0.084
time_of_day[T.Night]                 -0.0292       0.031     -0.948       0.343
-0.090        0.031
weekday[T.Mon]                       -0.0092       0.045     -0.207       0.836
-0.097        0.078
weekday[T.Sat]                        0.0452       0.046      0.973       0.330
-0.046        0.136
weekday[T.Sun]                       -0.0026       0.048     -0.055       0.956
-0.097        0.091
weekday[T.Thu]                       -0.0467       0.045     -1.029       0.303
-0.136        0.042
weekday[T.Tue]                       -0.0340       0.044     -0.771       0.441
-0.120        0.052
weekday[T.Wed]                       -0.0339       0.046     -0.743       0.458
-0.123        0.056
month_name[T.Aug]                    -5.4459       0.070    -77.283       0.000
-5.584       -5.308
month_name[T.Dec]                    -2.5121       0.071    -35.384       0.000
-2.651       -2.373
month_name[T.Feb]                    -2.4758       0.065    -37.949       0.000
-2.604       -2.348
month_name[T.Jan]                    -2.5127       0.075    -33.459       0.000
-2.660       -2.366
month_name[T.Jul]                    -4.7861       0.073    -65.955       0.000
-4.928       -4.644
month_name[T.Jun]                    -0.5722       0.073     -7.845       0.000
-0.715       -0.429
month_name[T.Mar]                    -1.3812       0.062    -22.133       0.000
-1.504       -1.259
month_name[T.May]                    -0.6151       0.070     -8.849       0.000
-0.751       -0.479
month_name[T.Nov]                    -2.4990       0.071    -34.998       0.000
-2.639       -2.359
month_name[T.Oct]                    -2.4968       0.065    -38.294       0.000
-2.625       -2.369
month_name[T.Sep]                    -5.1633       0.067    -76.558       0.000
```

```
-5.296      -5.031
==============================================================================
Omnibus:                     1998.605   Durbin-Watson:                   0.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            19703.208
Skew:                           2.449   Prob(JB):                         0.00
Kurtosis:                      13.301   Cond. No.                         19.9
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
AIC full model: 8115.3454454385865
```

[16]:

```python
#Stepwise regression (both; based on AIC)
def stepwise_aic(data, response, predictors):
    best_aic = float('inf')
    best_combo = None

    for k in range(1, len(predictors)+1):
        for combo in itertools.combinations(predictors, k):
            formula = "{} ~ {}".format(response, ' + '.join(combo))
            model = smf.ols(formula, data=data).fit()
            if model.aic < best_aic:
                best_aic = model.aic
                best_combo = combo
    return best_combo, best_aic

predictors = ["cash_type", "coffee_name", "time_of_day", "weekday",␣
 ↪"month_name"]
best_features, best_aic = stepwise_aic(coffee, "money", predictors)

print("\nBest predictors (AIC):", best_features)
print("Best AIC:", best_aic)

#Reduced model with the selected predictors
reduced_formula = "money ~ " + " + ".join(best_features)
red_mod = smf.ols(reduced_formula, data=coffee).fit()
print(red_mod.summary())
print("AIC reduced model:", red_mod.aic)
```

```
Best predictors (AIC): ('cash_type', 'coffee_name', 'time_of_day', 'month_name')
Best AIC: 8108.529583122794
                            OLS Regression Results
==============================================================================
Dep. Variable:                  money   R-squared:                       0.978
Model:                            OLS   Adj. R-squared:                  0.978
Method:                 Least Squares   F-statistic:                     7560.
```

```
Date:                Thu, 11 Sep 2025   Prob (F-statistic):               0.00
Time:                        12:15:46   Log-Likelihood:                -4032.3
No. Observations:                3635   AIC:                             8109.
Df Residuals:                    3613   BIC:                             8245.
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
======================
                                           coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------------
Intercept                               28.4293      0.062    457.930      0.000
28.308      28.551
cash_type[T.cash]                        1.9856      0.082     24.149      0.000
1.824       2.147
coffee_name[T.Americano with Milk]       5.0061      0.041    122.991      0.000
4.926       5.086
coffee_name[T.Cappuccino]                9.8833      0.046    216.129      0.000
9.794       9.973
coffee_name[T.Cocoa]                     9.7783      0.057    171.139      0.000
9.666       9.890
coffee_name[T.Cortado]                   0.2884      0.054      5.358      0.000
0.183       0.394
coffee_name[T.Espresso]                 -4.7128      0.071    -66.491      0.000
-4.852      -4.574
coffee_name[T.Hot Chocolate]             9.9176      0.055    180.657      0.000
9.810      10.025
coffee_name[T.Latte]                     9.8855      0.041    239.062      0.000
9.804       9.967
time_of_day[T.Morning]                  -0.1460      0.030     -4.834      0.000
-0.205      -0.087
time_of_day[T.Night]                    -0.0350      0.031     -1.141      0.254
-0.095       0.025
month_name[T.Aug]                       -5.4445      0.070    -77.323      0.000
-5.583      -5.306
month_name[T.Dec]                       -2.5106      0.071    -35.384      0.000
-2.650      -2.371
month_name[T.Feb]                       -2.4807      0.065    -38.095      0.000
-2.608      -2.353
month_name[T.Jan]                       -2.5132      0.075    -33.520      0.000
-2.660      -2.366
month_name[T.Jul]                       -4.7892      0.072    -66.097      0.000
-4.931      -4.647
month_name[T.Jun]                       -0.5707      0.073     -7.832      0.000
-0.714      -0.428
month_name[T.Mar]                       -1.3823      0.062    -22.171      0.000
-1.504      -1.260
```

```
month_name[T.May]                            -0.6202      0.069     -8.931      0.000
-0.756      -0.484
month_name[T.Nov]                            -2.4946      0.071    -34.982      0.000
-2.634      -2.355
month_name[T.Oct]                            -2.5011      0.065    -38.386      0.000
-2.629      -2.373
month_name[T.Sep]                            -5.1621      0.067    -76.593      0.000
-5.294      -5.030
==============================================================================
Omnibus:                     1999.178   Durbin-Watson:                   0.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            19644.994
Skew:                           2.451   Prob(JB):                         0.00
Kurtosis:                      13.280   Cond. No.                         19.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
AIC reduced model: 8108.529583122794
```

[17]:

```
#To answer Q3
full_formula3 = "money ~ hour_of_day + weekday"
modpredQ3 = smf.ols(full_formula3, data=coffee).fit()
print(modpredQ3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  money   R-squared:                       0.039
Model:                            OLS   Adj. R-squared:                  0.037
Method:                 Least Squares   F-statistic:                     21.22
Date:                Thu, 11 Sep 2025   Prob (F-statistic):           3.26e-28
Time:                        12:15:46   Log-Likelihood:                -10876.
No. Observations:                3635   AIC:                         2.177e+04
Df Residuals:                    3627   BIC:                         2.182e+04
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
==
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--
Intercept         28.5592      0.334     85.461      0.000      27.904
29.214
weekday[T.Mon]     0.1936      0.291      0.666      0.505      -0.376
0.763
weekday[T.Sat]    -0.2369      0.302     -0.784      0.433      -0.829
0.355
```

```
weekday[T.Sun]      0.1212       0.311       0.390       0.697       -0.488
0.731
weekday[T.Thu]     -0.2269       0.297      -0.765       0.444       -0.808
0.355
weekday[T.Tue]      0.0566       0.288       0.197       0.844       -0.507
0.621
weekday[T.Wed]     -0.2458       0.298      -0.826       0.409       -0.829
0.338
hour_of_day         0.2280       0.019      12.017       0.000        0.191
0.265
==============================================================================
Omnibus:                      226.579   Durbin-Watson:                   1.488
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              194.868
Skew:                          -0.494   Prob(JB):                     4.84e-43
Kurtosis:                       2.443   Cond. No.                         109.
==============================================================================

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

[2]:
```python
import os
os.environ["PATH"] += os.pathsep + "/Library/TeX/texbin"
```

[ ]:
```

```