



presents

SEMICONDUCTORS SHORTAGE

AND THEIR IMPACT ON US INFLATION

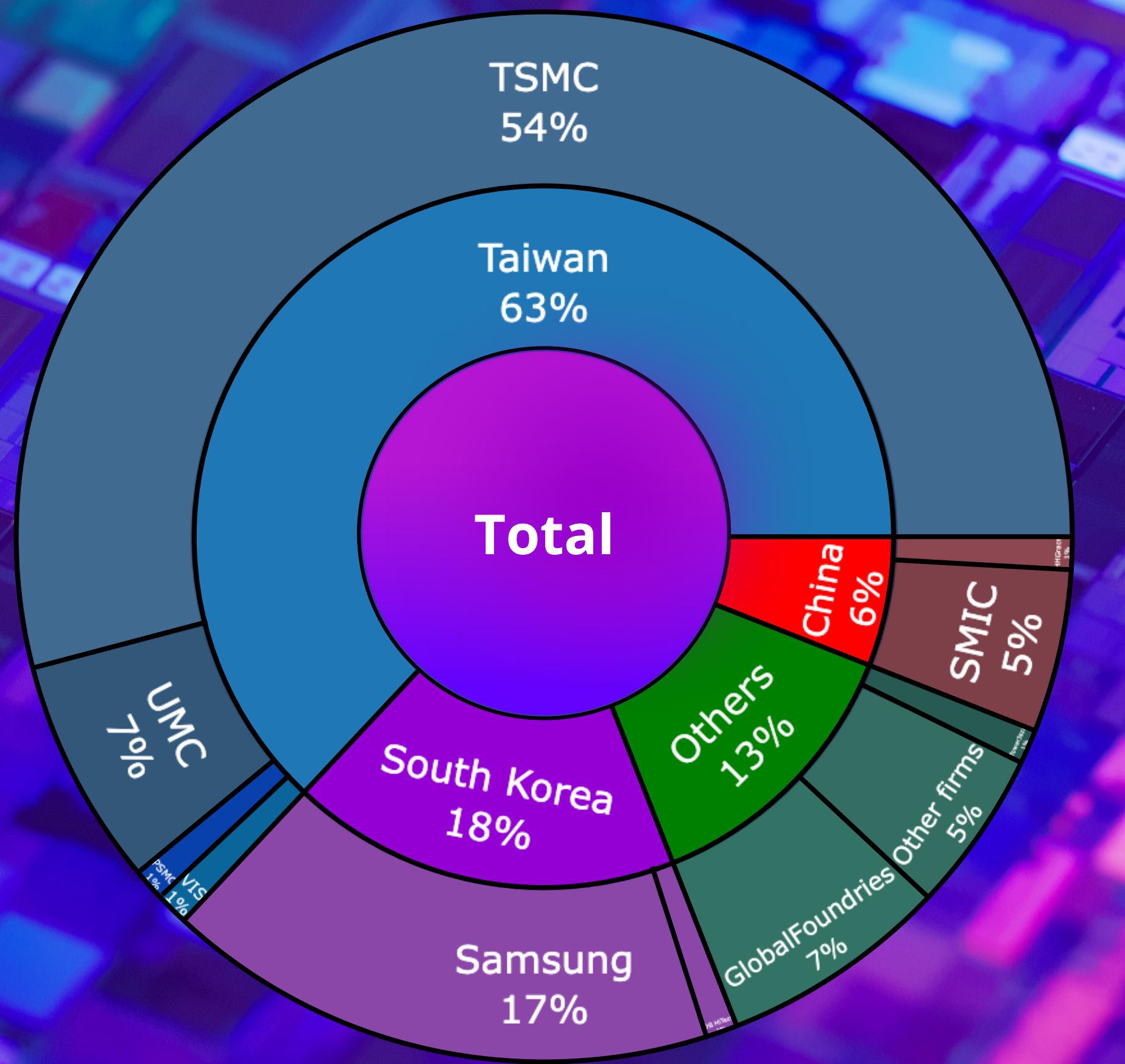


1

TSMC'S HEGEMONY

in semiconductor manufacturing

Microchips have become a key strategic material, and the semiconductor industry has become a field every nation is trying to dominate



Semiconductors manufacturers by **MARKET SHARE**

The Taiwanese firm "TSMC" has a central role in this market: in 2020 it accounted for 54% of total foundry revenue globally and despite the current crisis, TSMC continues to hold on to its role as world leader.

1

```
fig = px.sunburst(  
    data_frame=sms,  
    path=['Total', 'Geography', 'Company'],  
    values='Market_share'
```



Plotting them together

```
fig, ax = plt.subplots(2,1,figsize=(20,10),sharex=True)
plt.tight_layout(pad=4.0)

sns.lineplot(x="Date",y="Price",data=tsmc_medium_price,ax=ax[0])
ax[0].set_title("Tsmc\n",fontsize=25)
ax[0].set_xlabel("Date",fontsize=20)
ax[0].set_ylabel("Price",fontsize=20)

sns.lineplot(inflation_value,ax=ax[1], color = '#CC33FF')
ax[1].set_title("Inflation\n",fontsize=25)
ax[1].set_xlabel("\nDate",fontsize=20)
ax[1].set_ylabel("Value",fontsize=20)

plt.suptitle("Plotting them together",fontsize=30, y=1.05)

mplcyberpunk.add_gradient_fill(ax[0], gradient_start='bottom')
mplcyberpunk.add_gradient_fill(ax[1], gradient_start='bottom')

sns.despine(left=True, bottom=True)
plt.show()
```

Considerations

The increase of demand and the shortage of supply during pandemic increased the price of microchips and TSMC stock prices.

This situation is one of the main cause of growing inflation in US, because chips have become a really important part for many devices (not only in IT sector) and for many industries.

Plotting them together





There's a clear correlation between those 2 graphics: that's because chips are used in many sectors of the economy, not only in IT.

One of them is the cars sector: this one in particular has greatly suffered from the combination of the Covid 19 pandemic and the chip crisis



2

USED CARS MARKET

after the COVID-19 pandemic

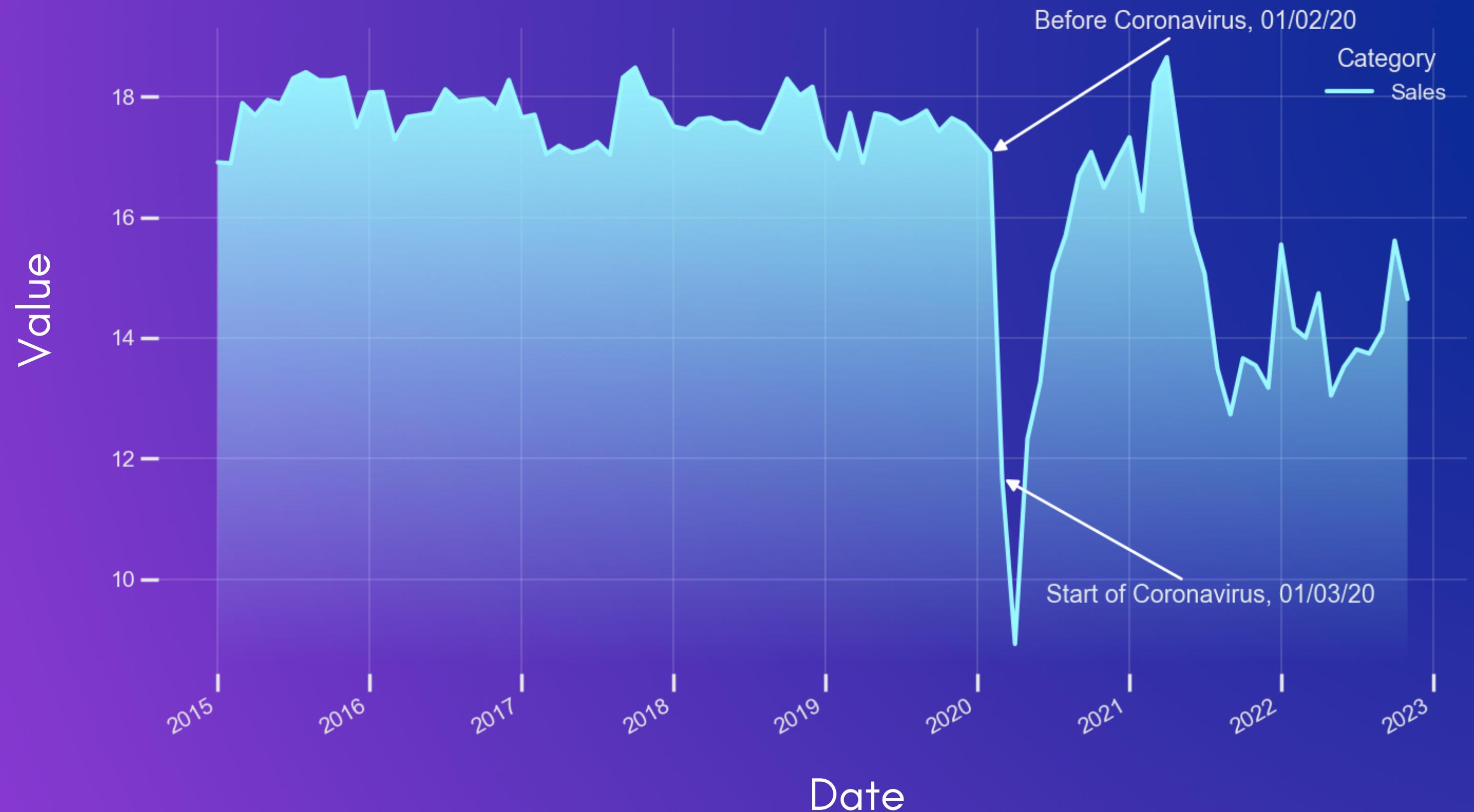
Many U.S. and European auto manufacturers shut down production to help stop the disease's spread.

Semiconductor producers, concentrated in Asia, responded by shifting production toward chips for electronic devices such as computers and games.

COVID-19

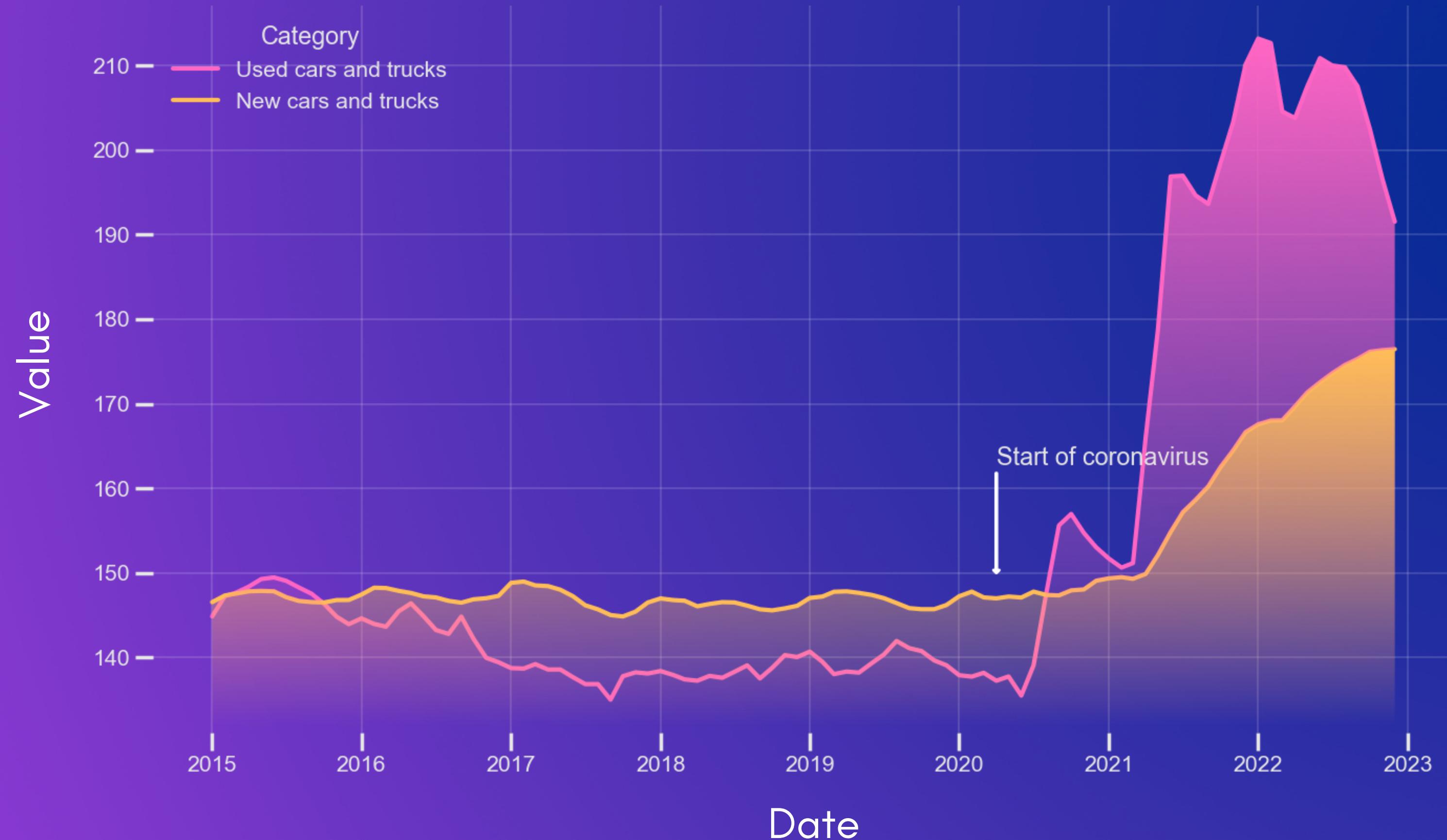
The diminished supply of new cars in the U.S. market provided support for higher used car prices.

Total vehicle sales



According to an analysis by Richmond Fed economist Alex Wolman, the increase in motor vehicle prices ranked as one of the “main culprits” of the U.S. inflationary increase through November 2021.

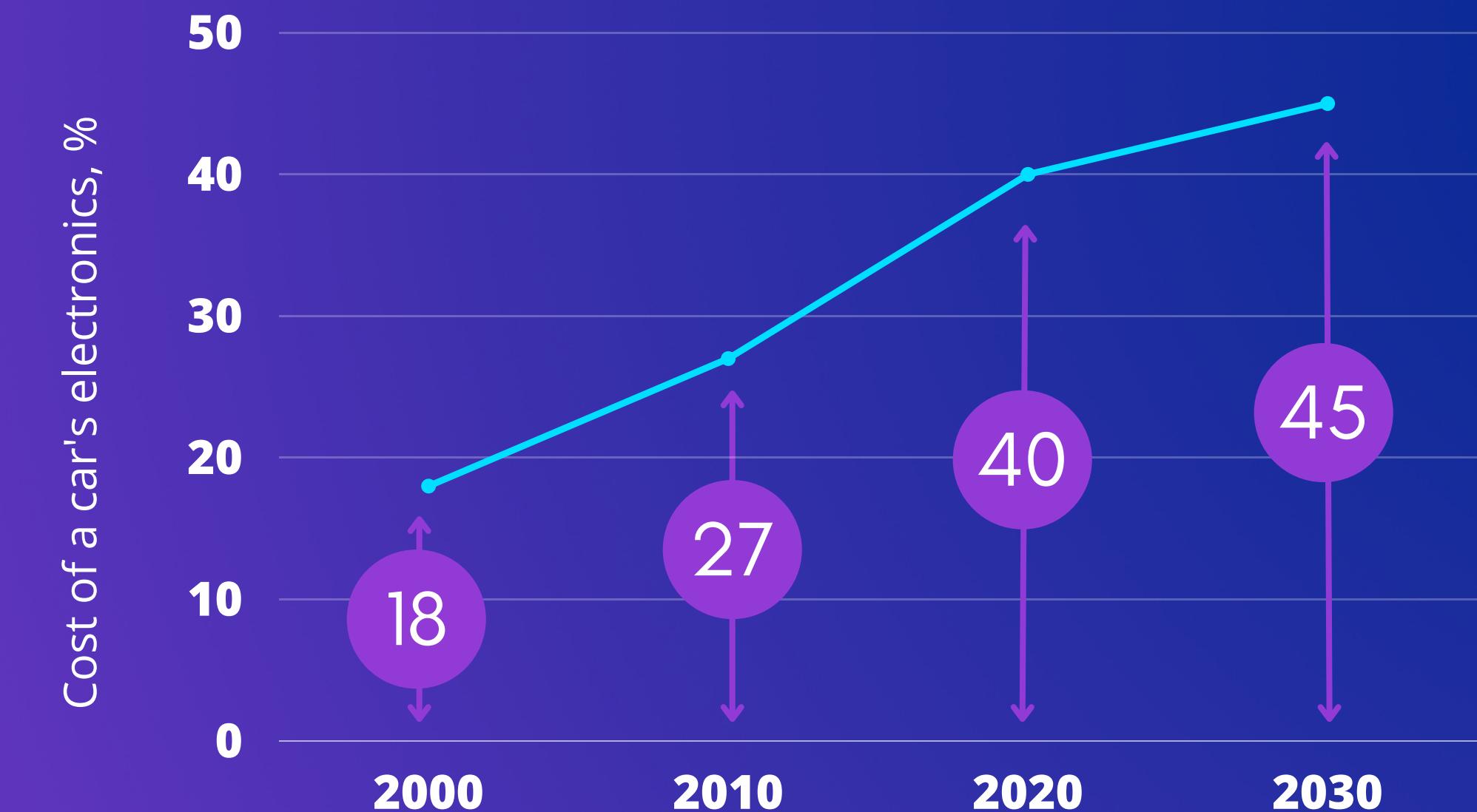
Value of new and used motor vehicles



Influence of electronics in the cost of the vehicle

Electronics have gone from being just 18% of a car's cost in 2000, to being 40% of its cost in 2020, and projected to be 45% by 2030.

Electronics are responsible for a steadily rising percentage of a new car's total cost, according to Deloitte.





Heatmap

```
# Computing the correlation matrix
corr = items_2017_2018.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))
np.fill_diagonal(mask, False)

# Set up the matplotlib figure
plt.subplots(figsize=(14, 12))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, annot=True, fmt='.2f', center=0, square=True,
            cbar_kws=dict(shrink=.95), vmin=-1, vmax=1, annot_kws=dict(fontsize=12))

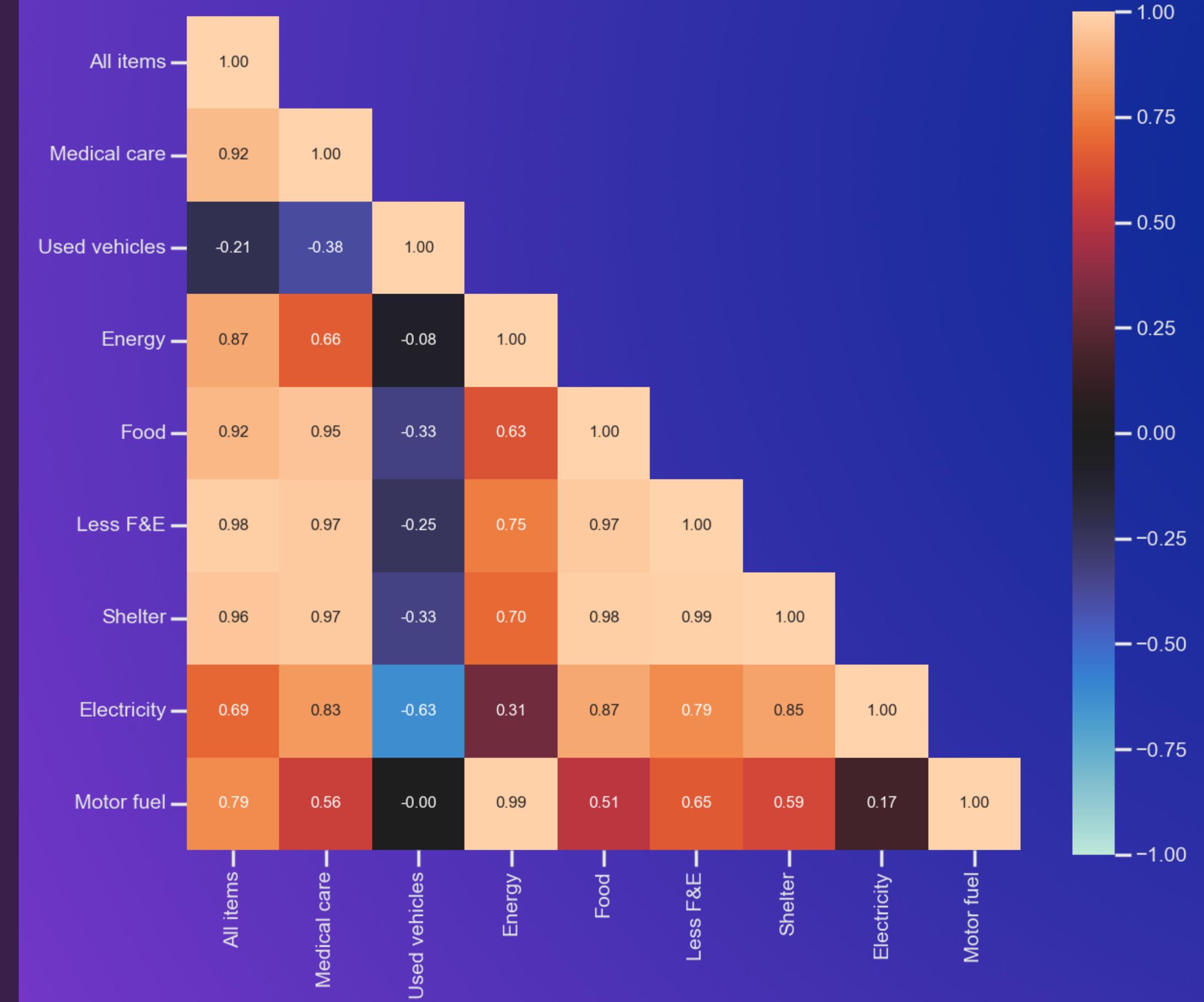
# Set title
plt.title("Items Correlation on CPI\n", fontsize=25)
plt.xticks(rotation=90)

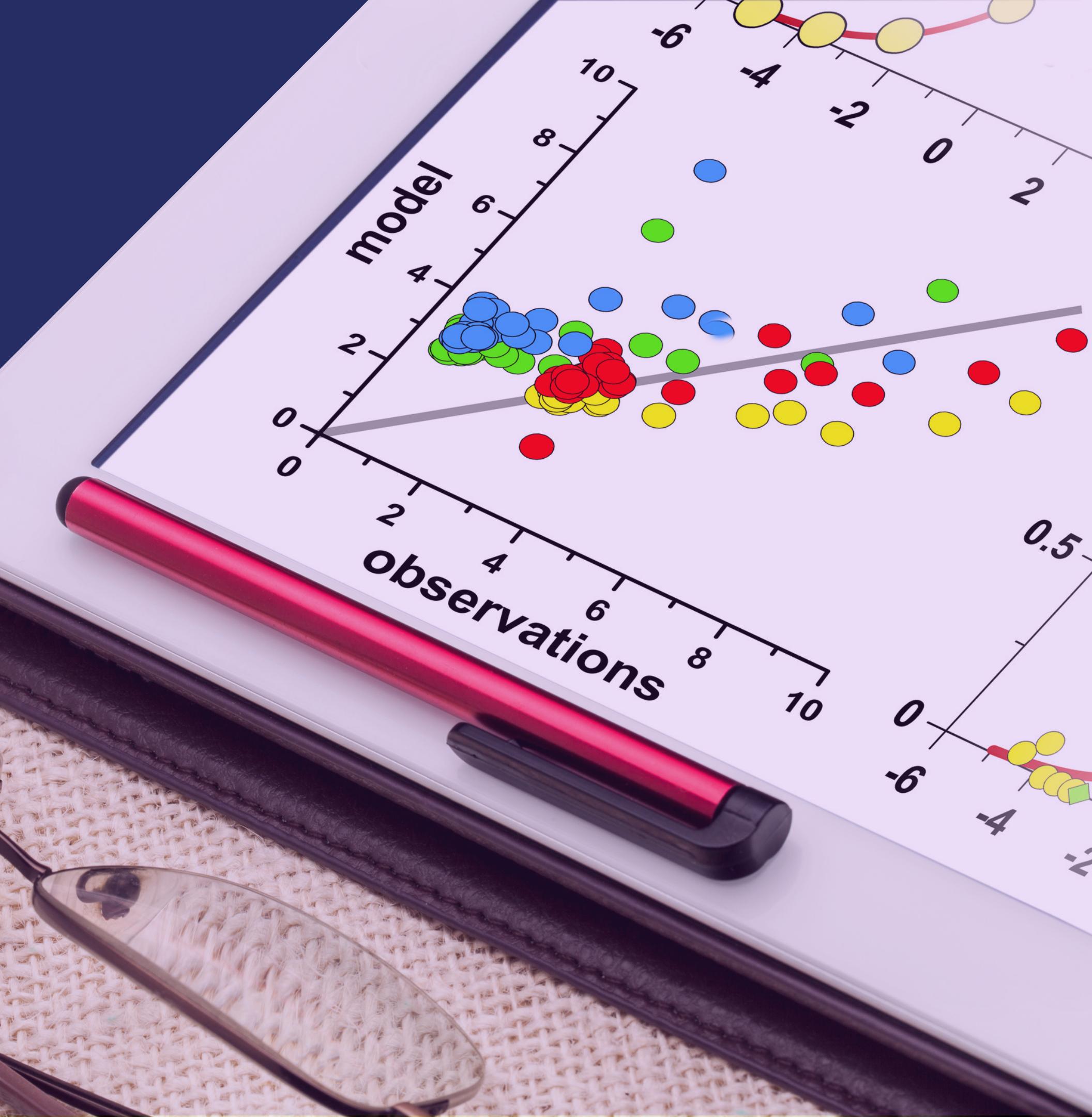
plt.show()
```

Heatmap

These plot give us the opportunity to evaluate pairwise correlations between all parameters.

As can be seen from the graph, the value of used cars is rather small for all baskets: from this it can be deduced that the trend of the used car index is independent of all the others.



A scatter plot showing the relationship between 'model' values on the y-axis and 'observations' on the x-axis. The x-axis ranges from 0 to 10, and the y-axis ranges from -10 to 10. Data points are colored by category: red, green, blue, and yellow. A solid grey regression line shows a positive slope, while a dashed red regression line shows a steeper positive slope. A red pen lies across the plot.

3

COMPARING

regression lines with varying slopes

In this example we are going to compare two regression lines; we are interested in how do the two variables used cars index and timing (before Covid and after Covid) affect the CPI on response.



Scatterplot

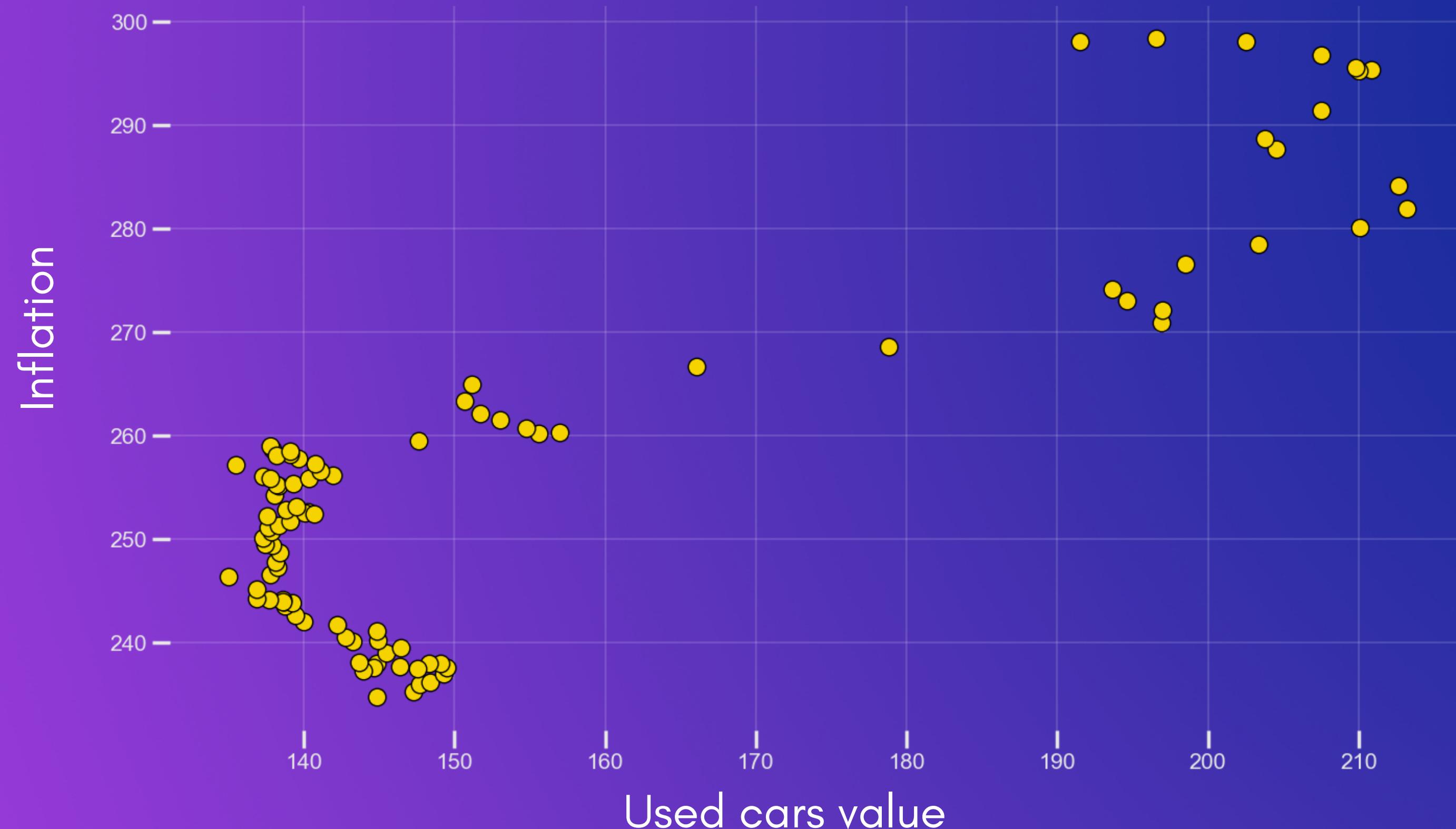
```
fig, ax = plt.subplots(figsize=(20, 8))
sns.scatterplot(x=indexes["Used Vehicles"],
                 y=indexes["CPI"],
                 sizes=60, alpha=1,
                 edgecolor="black",
                 linewidth=1,
                 color="#F5D300")

ax.set_title("\nScatterplot Used cars - Inflation\n", fontsize=25)
ax.set_ylabel("Inflation", fontsize=20)
ax.set_xlabel("\nUsed cars value", fontsize=20)

sns.despine(left=True, bottom=True)

plt.show()
```

The relationship between used cars and inflation





Our model

LINEAR REGRESSION

We are interested in finding out how the relation between used vehicles index and CPI changed during the pandemic.

BEFORE COVID

$$y = \beta_0 + \beta_{1B} X + \varepsilon$$

AFTER COVID

$$y = \beta_0 + \beta_{1A} X + \varepsilon$$



X = index of used vehicles



y = average value of CPI



Timing



Defining new variables

```
fig, ax = plt.subplots(figsize=(20, 8))
sns.scatterplot(x=indexes["Used Vehicles"],
                 y=indexes["CPI"],
                 hue=indexes["Post Covid yes"],
                 style=indexes["Post Covid yes"],
                 sizes=60, alpha=1,
                 edgecolor="black",
                 linewidth=1,
                 markers=['s', 'o'])

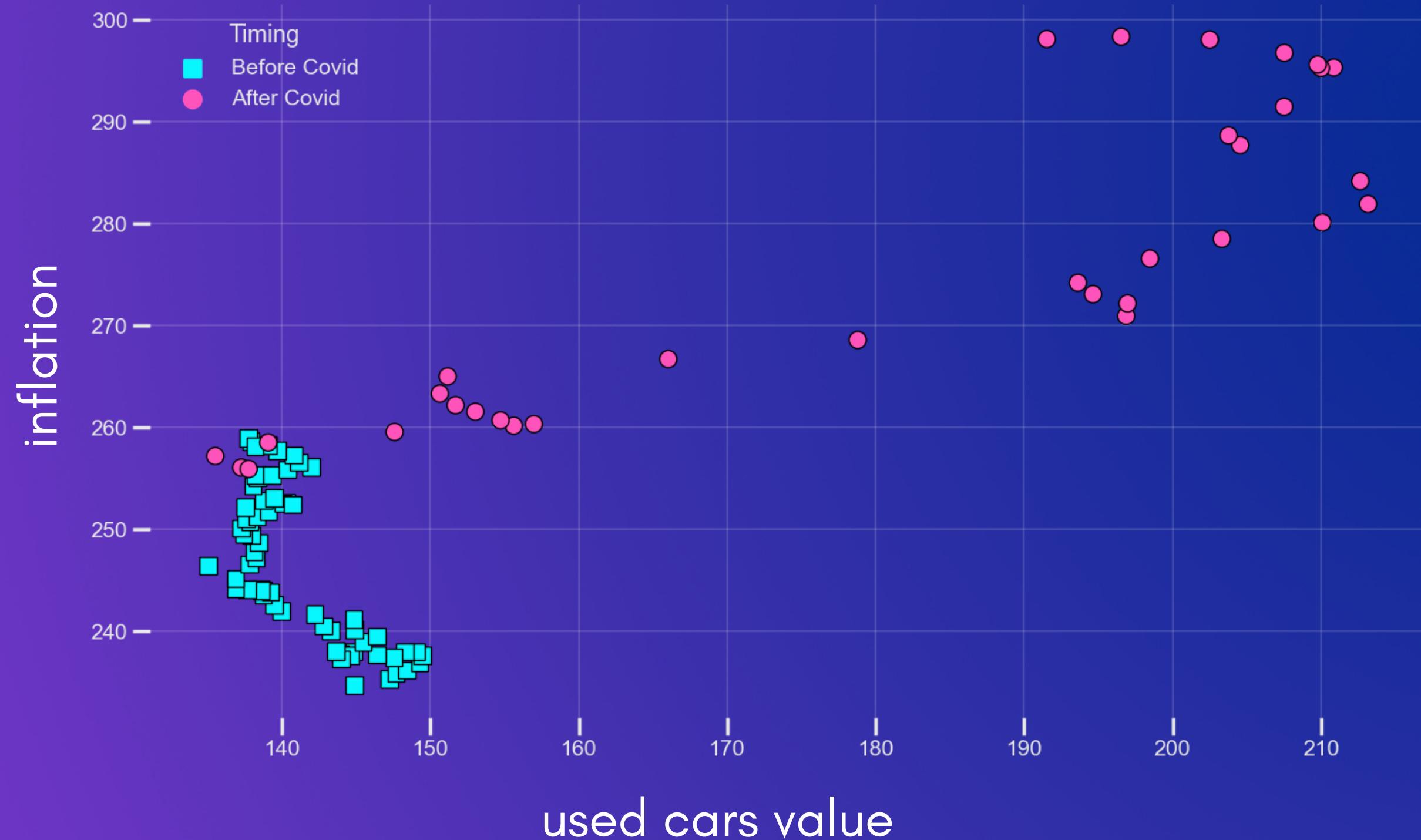
ax.set_title("\nScatterplot Used cars - Inflation\n", fontsize=25)
ax.set_ylabel("Inflation", fontsize=20)
ax.set_xlabel("\nUsed cars value", fontsize=20)

handles, labels = ax.get_legend_handles_labels()
ax.legend(handles, ['Before Covid', 'After Covid'],
          title="Timing")
sns.despine(left=True, bottom=True)
plt.show()
```

DEFINING NEW VARIABLES

$$X_2 = \begin{cases} 0 & \text{if before Covid} \\ 1 & \text{if after Covid} \end{cases}$$

$$X_3 = X_1 * X_2$$



BEFORE COVID

$$y = \beta_0 + \beta_1 X_1 + \beta_2(0) + \beta_3 X_1(0) + \varepsilon$$

$$= \beta_0 + \beta_1 X_1 + \varepsilon$$

Rearranging the factors, we can see that:

- β_2 is the difference in the intercepts
- β_3 is the difference in the slopes

If the lines are the same, β_2 and β_3 should be 0

AFTER COVID

$$y = \beta_0 + \beta_1 X_1 + \beta_2(1) + \beta_3 X_1(1) + \varepsilon$$

$$= \beta_0 + \beta_2 + (\beta_1 + \beta_3)X_1 + \varepsilon$$

LINEAR MODEL

lm(formula = CPI ~ Used + Dummy + Interaction, data = inflation)

Residuals:

Min	1Q	Median	3Q	Max
-11.8470	-4.8421	-0.3167	3.6086	17.7858

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	440.7795	28.4606	15.487	< 2e-16 ***
Used	-1.3768	0.2015	-6.833	8.86e-10 ***
Dummy	-249.1557	29.3353	-8.493	3.36e-13 ***
Interaction	1.8399	0.2052	8.966	3.41e-14 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Residual standard error: 6.097 on 92 degrees of freedom

Multiple R-squared: 0.8816, Adjusted R-squared: 0.8777

F-statistic: 228.2 on 3 and 92 DF, p-value: < 2.2e-16

ANOVA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Used	1	20851.8	20851.8	560.860	< 2.2e-16 ***
Dummy	1	1616.7	1616.7	43.485	2.652e-09 ***
Interaction	1	2989.0	2989.0	80.397	3.414e-14 ***
Residuals	92	3420.4	37.2		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Hypothesis	Interpretation	p-Value
$H_0: \beta_3 = 0 \beta_0\beta_1\beta_2$	Same slopes with varying intercepts	3.41e-14
$H_0: \beta_2 = 0 \beta_0\beta_1\beta_3$	Same intercepts with varying slopes	3.36e-13
$H_0: \beta_2 = 0 \beta_0\beta_1$	Same intercepts with not varying slopes	2.652e-09

Lmplot

```
g = sns.lmplot(x="Used Vehicles", y="CPI",
                 hue="Post Covid yes",
                 data=indexes,
                 scatter_kws={'s': 160,
                               'edgecolor': 'black'},
                 line_kws={
                     'lw': 5,
                     # 'ls': '--'
                 },
                 height=(10), aspect=1.5,
                 markers=['s', 'o'])

g.fig.suptitle("\nScatterplot Used cars - Inflation\n", fontsize=25)
g.set_axis_labels(x_var="Used Vehicles", y_var="CPI", fontsize=20)

# title
g._legend.set_title("Timing")

# replace labels
new_labels = ['Before Covid', 'After Covid']
for t, l in zip(g._legend.texts, new_labels):
    t.set_text(l)

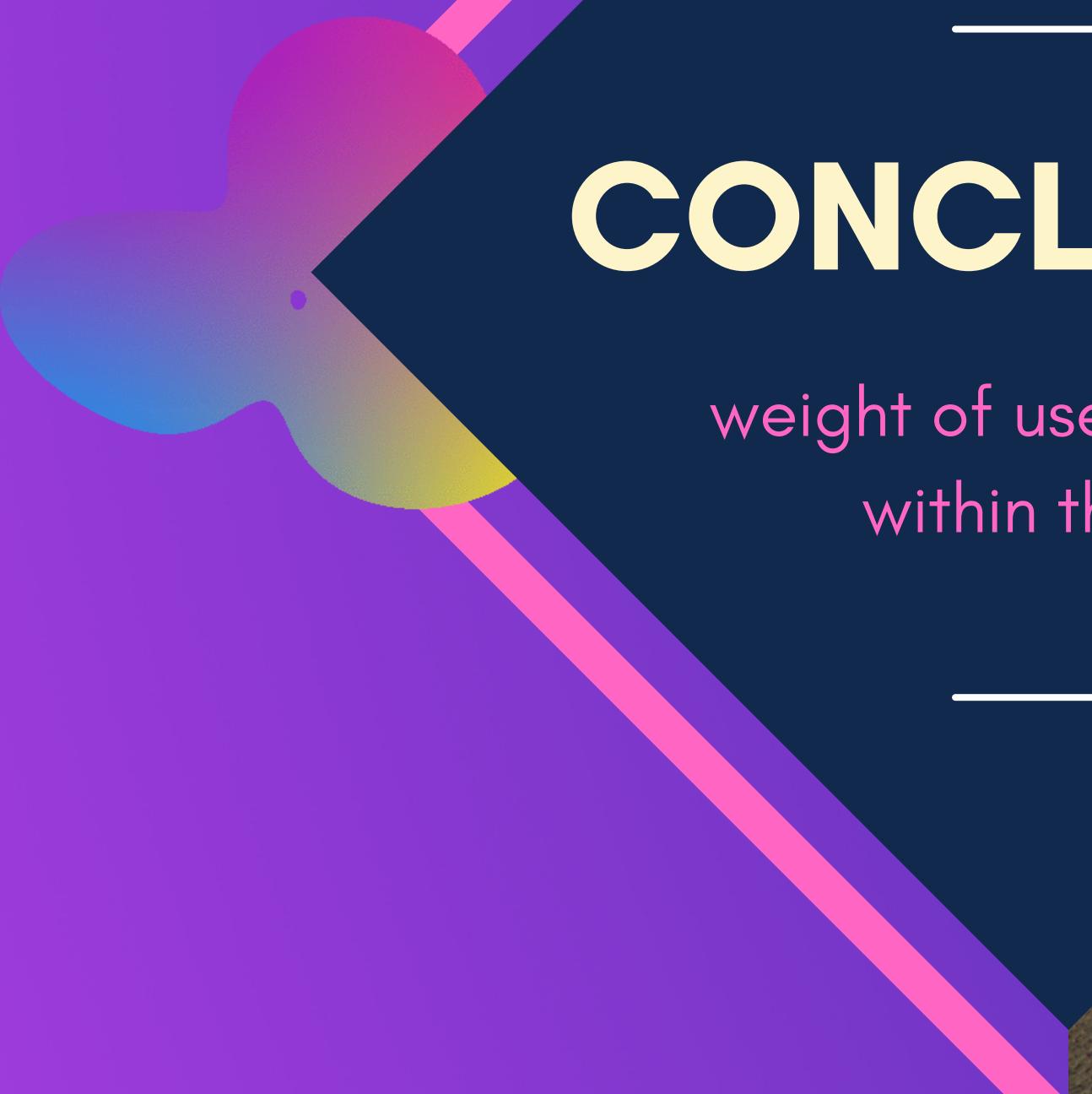
g.tight_layout(pad=.4)

mplcyberpunk.make_lines_glow( )

sns.despine(left=True, bottom=True)

plt.show()
```





CONCLUSION

weight of used vehicles
within the CPI



U.S. Bureau of labor statistics **does not** publish monthly relative importance data. We calculated it according to the methodology of the Bureau.

How to estimate an updated relative importance

$$(1) \times (3) / (2) = (4)$$

repeat for each row and normalize to 100

Estimating an updated relative importance for new vehicles for January 2022

Item	Published relative importance Dec. 2021 (1)	Index Dec. 2021 (2)	Index Jan 2022 (3)	Updated weight Jan. 2022 (4)	Updated weight Jan. 2022 (normalized all items=100)
New Vehicles	4.11	166.65	167.58	<u>4.13*</u>	<u>4.10**</u>
All items	100	280.13	281.93	100.65	Normalized to 100.000



Cars' relative importance trend

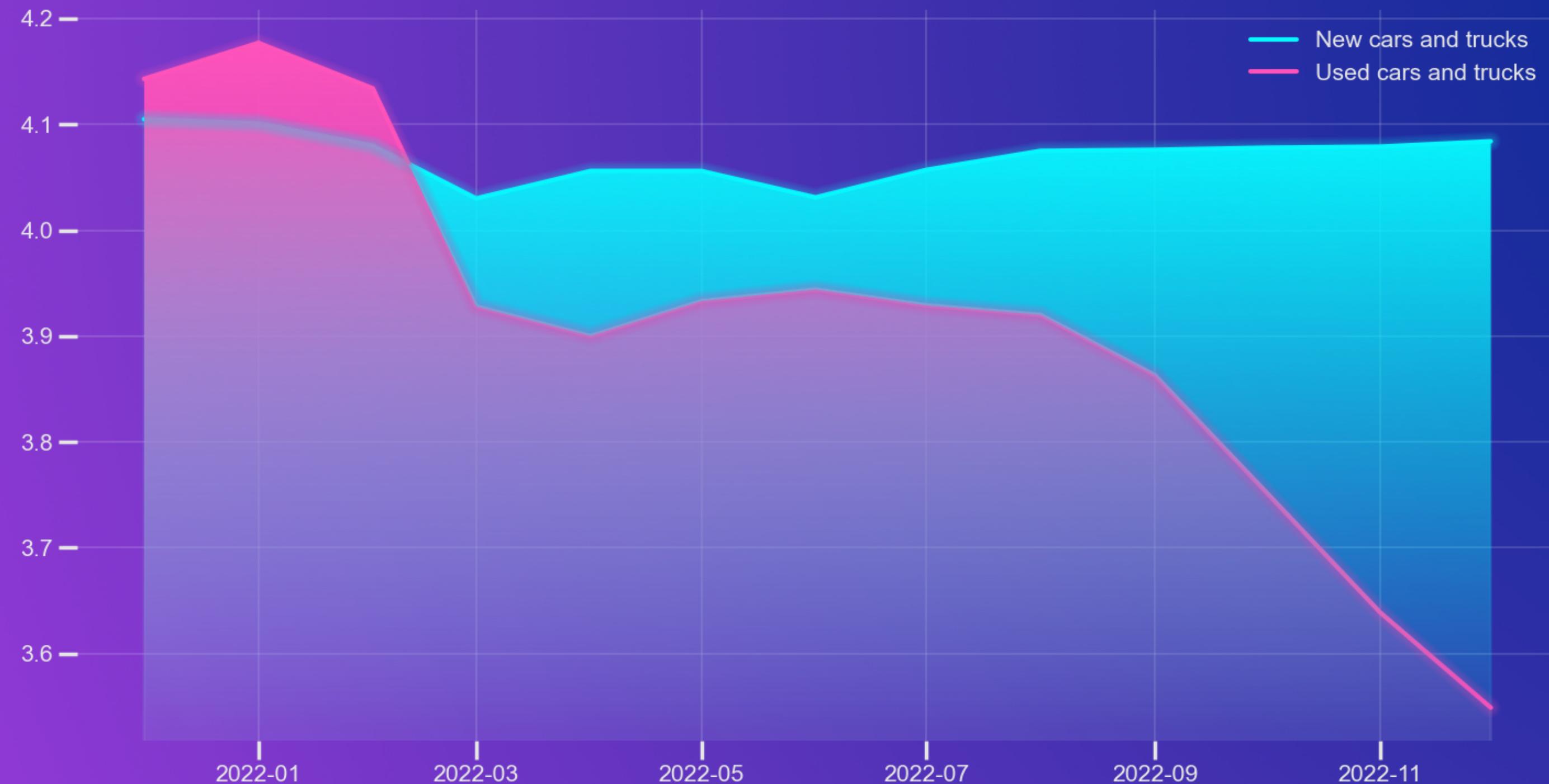
```
fig, ax = plt.subplots(figsize=(20, 10))
plt.tight_layout(pad=4.0)

sns.lineplot(x=indexes_from_2021.index,
              y=indexes_from_2021['Relative Importance New'], label="New cars and trucks")
sns.lineplot(x=indexes_from_2021.index,
              y=indexes_from_2021['Relative Importance Used'], label="Used cars and
trucks")
ax.set_title("Relative importance\n", fontsize=25)
ax.set_xlabel("\nDate", fontsize=20)
ax.set_ylabel("Percentage", fontsize=20)
ax.legend()

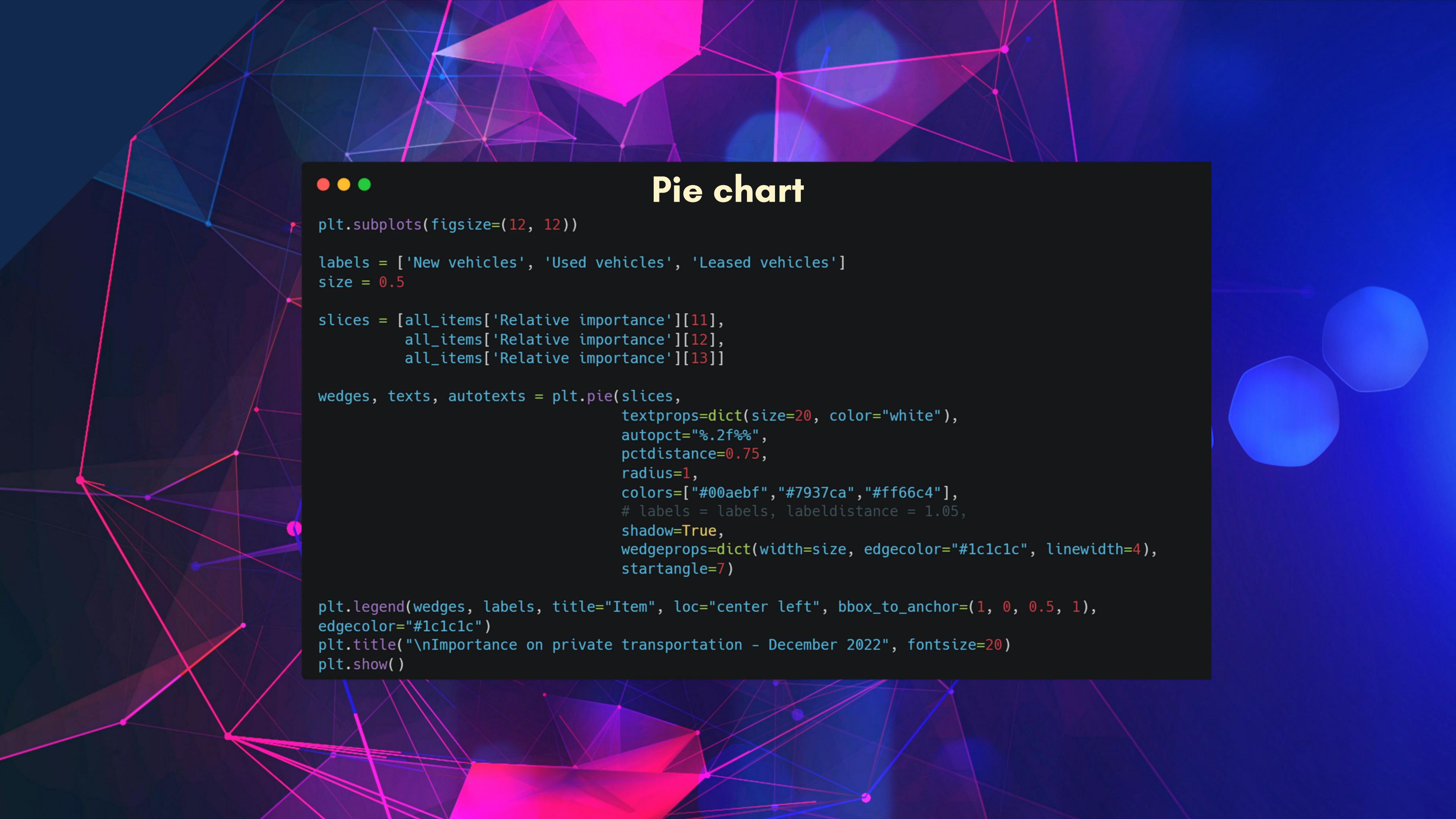
mplcyberpunk.add_gradient_fill(gradient_start='bottom',
                                # alpha_gradientglow=0.5
                                )

sns.despine(left=True, bottom=True)
plt.show()
```

Relative importance of new and used cars



Pie chart



```
plt.subplots(figsize=(12, 12))

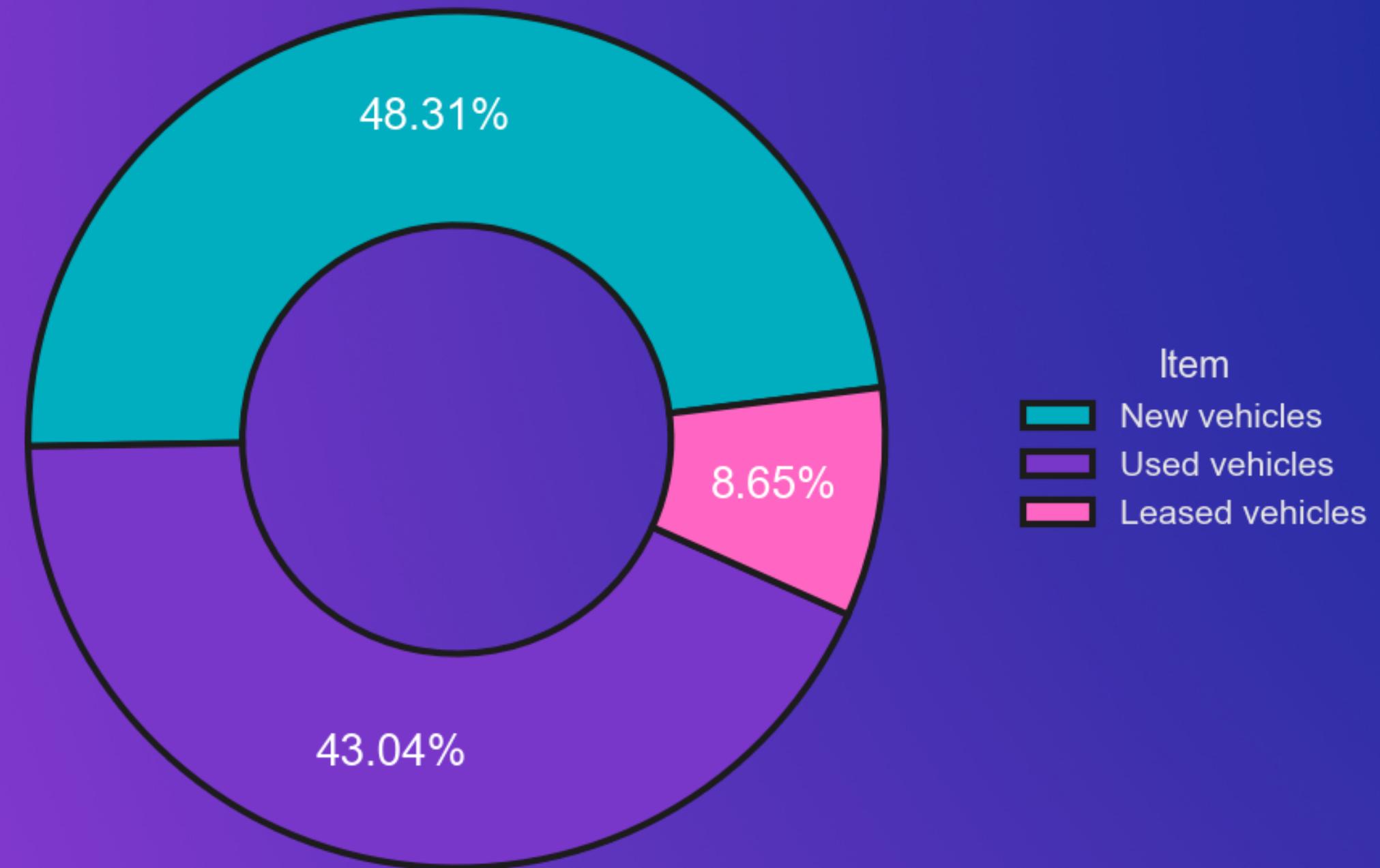
labels = ['New vehicles', 'Used vehicles', 'Leased vehicles']
size = 0.5

slices = [all_items['Relative importance'][11],
          all_items['Relative importance'][12],
          all_items['Relative importance'][13]]

wedges, texts, autotexts = plt.pie(slices,
                                    textprops=dict(size=20, color="white"),
                                    autopct="% .2f %%",
                                    pctdistance=0.75,
                                    radius=1,
                                    colors=["#00aebe", "#7937ca", "#ff66c4"],
                                    # labels = labels, labeldistance = 1.05,
                                    shadow=True,
                                    wedgeprops=dict(width=size, edgecolor="#1c1c1c", linewidth=4),
                                    startangle=7)

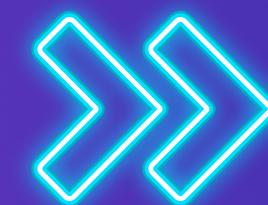
plt.legend(wedges, labels, title="Item", loc="center left", bbox_to_anchor=(1, 0, 0.5, 1),
           edgecolor="#1c1c1c")
plt.title("\nImportance on private transportation - December 2022", fontsize=20)
plt.show()
```

Importance on private transportation



CONCLUSION

Gas crisis and pandemic both affected the semiconductor market. This lead to important consequences for US inflation. In particular, we discovered that in the last years, used cars value index gathered a lot more weight in the CPI (from 1% to almost 5%).





THANK
YOU!

