Beyond the Bean

Adan R. Martinez-Ponce

About Me:

- **Major**: Data Analytics
- **Minor**: Economics
- **Hometown**: Racine, Wisconsin
- **Interests**: Men’s Soccer, Sports, Chess Club, Latin Student Union
- **Why Coffee?** Drink about one a day, and supply chain

Presentation Guide:

1. **Project Description**
    a. Solutions
    b. Data
    c. Exception
    d. Methods
2. Live Demonstration
3. Learning & Development
    a. Where I got my answers
4. Q&A / End

Project Outline

- **Goal**: Determine/ predict a price of coffee cup from the price shock of other factors such as cocoa beans, milk, sugar
- **What is it?** Machine Learning Model
- EDA on dataset
- Build interactive website & dashboard to showcase model
- Real World Application

Solutions I

Per Cup Model:

- Forecast Restaurant Coffee Cup Price in USA (data from Toast)
- Paired with Federal Reserve Economic Data (FRED)
- Local USA Milk, Sugar, Coco

Per Pound Global Model:

- Build separate model to predict price per pound, with Coco & Sugar.
  - Several factors can influence coffee prices, including sourcing, demand, labor, equipment, and overhead costs, especially weather

Solutions II

Website:

- Live website on CompSci04
- 13 week to week blog posts
- About me, Resume, Philosophy

Dashboard:

- Fully functional user input/output paired with interactives graphs

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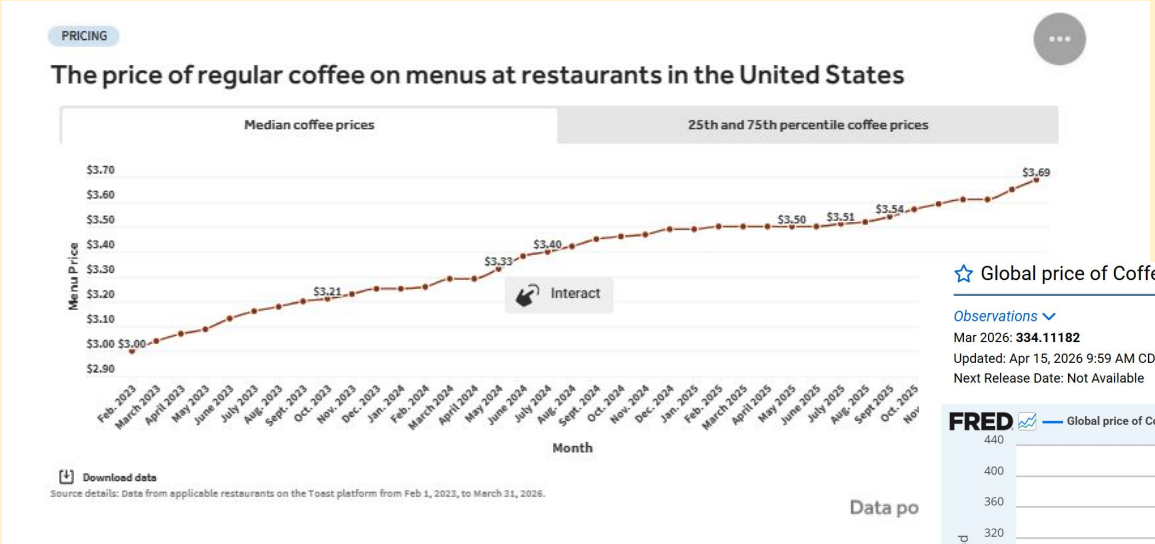
Data I

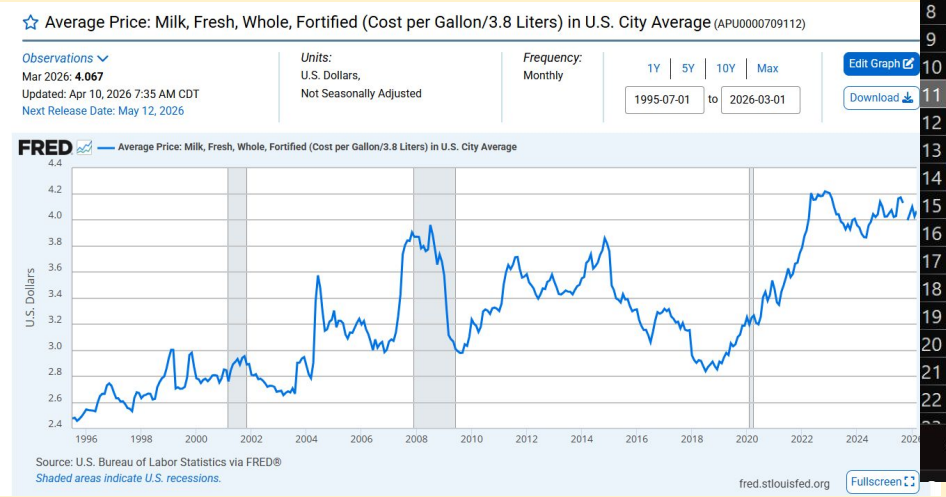


Data from Toast

Global Price Per Pound

Data II

Milk Sample



Raw Dataset (merged)

I11

	A	B	C	D	E	F	G	H
1	observation_date	Coffee_Lb_Price	Cocoa_Price	Sugar_Price	Milk_Price			
2	1/1/2003	2.999	2190.138111	0.43	2.686			
3	2/1/2003	2.924	2230.35225	0.427	2.689			
4	3/1/2003	2.933	1993.113009	0.427	2.656			
5	4/1/2003	3.008	1932.194531	0.427	2.674			
6	5/1/2003	2.937	1732.51745	0.431	2.685			
7	6/1/2003	2.931	1579.108465	0.429	2.676			
8	7/1/2003	2.944	1562.709909	0.431	2.708			
9	8/1/2003	2.921	1565.54768	0.435	2.666			
10	9/1/2003	2.919	1625.388516	0.426	2.904			
11	10/1/2003	2.825	1481.681288	0.425	2.905			
12	11/1/2003	2.779	1510.00935	0.411	2.937			
13	12/1/2003	2.875	1627.281285	0.422	2.947			
14	1/1/2004	2.892	1626.397853	0.429	2.879			
15	2/1/2004	2.856	1566.086028	0.426	2.814			
16	3/1/2004	2.932	1504.428407	0.426	2.786			
17	4/1/2004	2.908	1435.668066	0.427	2.906			
18	5/1/2004	2.831	1412.961189	0.425	3.374			
19	6/1/2004	2.75	1407.885456	0.425	3.574			
20	7/1/2004	2.878	1567.864379	0.429	3.479			
21	8/1/2004	2.878	1727.333603	0.426	3.297			
22	9/1/2004	2.874	1541.136667	0.426	3.149			

master~pound

Data III

Primary Data Sources

Variable	Source / Domain
Median Coffee Price	Toast POS Restaurant Data
CPI_USA	FRED: Consumer Price Index (All Urban Consumers)
CPI_Coffee	FRED: CPI for Roasted Coffee
Milk	FRED: Milk (Fresh, Whole, Fortified)
Sugar	FRED: Sugar (White, All Sizes)
Cocoa	Trading Economics: Cocoa Commodities

Extended Data Preview (Q1 2026)

Showing the most recent rows reflecting the latest economic updates.

Date	Median Price	CPI_USA	Milk ($)	Sugar ($)	Cocoa ($)
Jan 2026	3.61	326.58	4.100	1.022	4201
Feb 2026	3.65	327.46	4.026	1.016	3673
Mar 2026	3.69	330.30	4.067	0.996	3255

Data Prep: Deltas & Scaling

date.x	Median Pr	clean_date	DateID	date.y	CPI_USA	CPI_Coffe	milk	sugar	coco	CLB	Delta_Milk	Delta_Sugar	Delta_Cocoa	Delta_Coffee
3/1/2023	3.04	3/23/2026	3/1/2023	3/1/2023	301.643	239.478	4.098	0.88	2884	6.184	-0.065	0.004	162	0.04
4/1/2023	3.07	4/23/2026	4/1/2023	4/1/2023	302.858	237.183	4.042	0.893	3171	6.04	-0.056	0.013	287	0.03
5/1/2023	3.09	5/23/2026	5/1/2023	5/1/2023	303.316	238.576	4.042	0.899	2991	6.094	0	0.006	-180	0.02
6/1/2023	3.13	6/23/2026	6/1/2023	6/1/2023	304.099	237.471	3.985	0.918	3188	6.091	-0.057	0.019	197	0.04
7/1/2023	3.16	7/23/2026	7/1/2023	7/1/2023	304.615	238.433	3.971	0.932	3415	6.141	-0.014	0.014	227	0.03
8/1/2023	3.18	8/23/2026	8/1/2023	8/1/2023	306.138	236.862	3.927	0.95	3297	6.091	-0.044	0.018	-118	0.02
9/1/2023	3.2	9/23/2026	9/1/2023	9/1/2023	307.374	237.098	3.965	0.971	3582	6.085	0.038	0.021	285	0.02
10/1/2023	3.21	10/23/2026	10/1/2023	10/1/2023	307.653	236.496	3.927	0.963	3852	6.178	-0.038	-0.008	270	0.01
11/1/2023	3.23	11/23/2026	11/1/2023	11/1/2023	308.087	234.11	3.997	0.958	4244	6.169	0.07	-0.005	392	0.02
12/1/2023	3.25	12/23/2026	12/1/2023	12/1/2023	308.735	230.788	4.008	0.956	4244	6.092	0.011	-0.002	0	0.02
1/1/2024	3.25	1/24/2026	1/1/2024	1/1/2024	309.794	236.506	3.958	0.975	5009	6.124	-0.05	0.019	765	0
2/1/2024	3.26	2/24/2026	2/1/2024	2/1/2024	311.022	233.865	3.94	0.984	6769	6.094	-0.018	0.009	1760	0.01
3/1/2024	3.29	3/24/2026	3/1/2024	3/1/2024	312.107	234.126	3.893	0.984	8939	5.964	-0.047	0	2170	0.03
4/1/2024	3.29	4/24/2026	4/1/2024	4/1/2024	313.016	232.507	3.868	1.006	12218	6.063	-0.025	0.022	3279	0
5/1/2024	3.33	5/24/2026	5/1/2024	5/1/2024	313.14	232.674	3.864	1.001	9300	5.991	-0.004	-0.005	-2918	0.04
6/1/2024	3.38	6/24/2026	6/1/2024	6/1/2024	313.131	233.741	3.956	1.004	9619.6	6.253	0.092	0.003	319.6	0.05
7/1/2024	3.4	7/24/2026	7/1/2024	7/1/2024	313.566	237.454	3.983	1.004	7736.5	6.307	0.027	0	-1883.1	0.02
8/1/2024	3.42	8/24/2026	8/1/2024	8/1/2024	314.131	231.804	4.044	1.004	8848	6.311	0.061	0	1111.5	0.02
9/1/2024	3.45	9/24/2026	9/1/2024	9/1/2024	314.851	234.789	4.021	1.007	7669	6.47	-0.023	0.003	-1179	0.03
10/1/2024	3.46	10/24/2026	10/1/2024	10/1/2024	315.564	236.364	4.041	1.003	7756	6.644	0.02	-0.004	87	0.01
11/1/2024	3.47	11/24/2026	11/1/2024	11/1/2024	316.449	238.626	4.138	1	8613	6.868	0.097	-0.003	857	0.01
12/1/2024	3.49	12/24/2026	12/1/2024	12/1/2024	317.603	239.449	4.101	0.992	11867	6.776	-0.037	-0.008	3254	0.02
1/1/2025	3.49	1/25/2026	1/1/2025	1/1/2025	319.086	243.911	4.025	1.011	11167	7.019	-0.076	0.019	-700	0

Models :

Metric	Local Micro	Global Macro
Unit	Price Per Cup ($)	Price Per Pound ($/lb)
Sensitivity	Low (Sticky)	High (Volatile)
Method	Linear Regression	Arima
Target MAE	$0.0078	$0.0540

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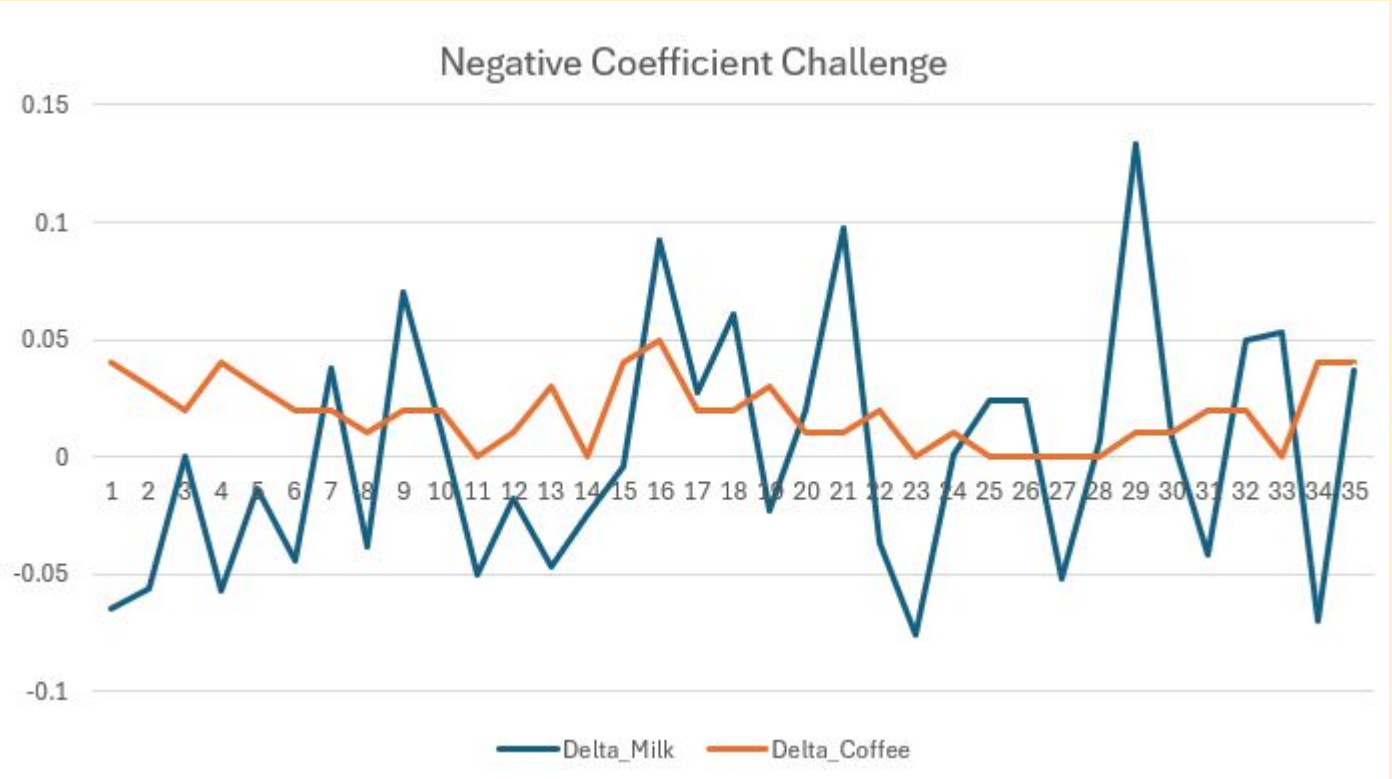
Exceptions

This is what I did not solve:

- Sticky pricing (takes a few months for restaurants to increase)
- **Negative Coefficients**
- Other factors such as labor & demand cause coffee price change
- Water Price, coffee is 80% water

Negative Coefficient



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Methods + Tools:

- **Notepad ++:** HTML & CSS Style, Python
- **R Studio:** Data Cleaning & Model Work + Results
- **Excel:** EDA & Pivot Tables
- **Python:** Dynamic Model
- **HTML & Javascript & Jinja:** Dashboard graph
  - Models: Linear Regression & Arima

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Original Ideas / Dashboard

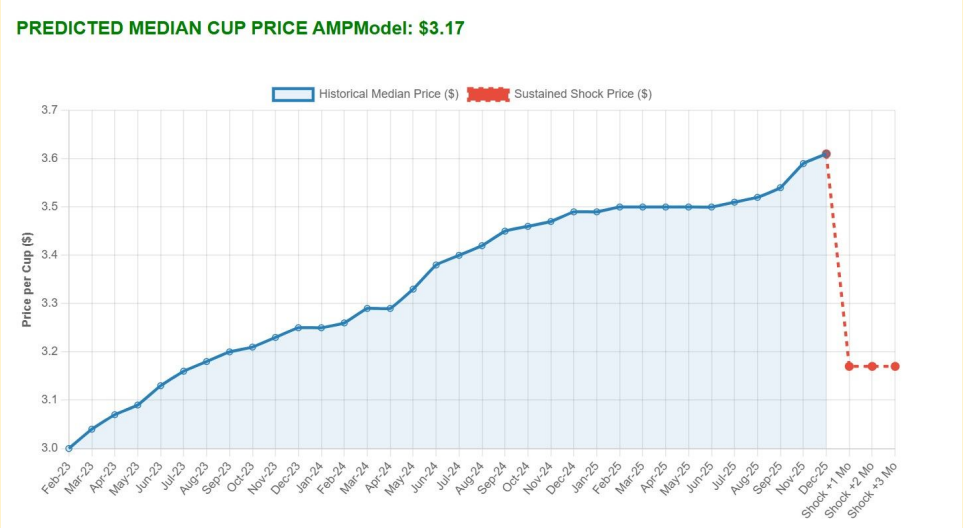
```
========================================
   THE COMMODITY SHOCK SIMULATOR
========================================
Type 'up', 'down', or 'same' for each.

Milk price (up/down/same): down
Sugar price (up/down/same): down
Cocoa price (up/down/same): down

----------------------------------------
SCENARIO: Milk down | Sugar down | Cocoa down
PREDICTED MEDIAN CUP PRICE: $2.46
----------------------------------------

Milk price (up/down/same): up
Sugar price (up/down/same): up
Cocoa price (up/down/same): up

----------------------------------------
SCENARIO: Milk up | Sugar up | Cocoa up
PREDICTED MEDIAN CUP PRICE: $4.24
----------------------------------------
```



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Beyond the Bean

Move the sliders to simulate a percentage shock, then click Submit.

Local Market Shock (US Per Cup)

Milk Shock (%): Current Price: $4.07

1%

US Sugar Shock (%): Current Price: $1.00

50%

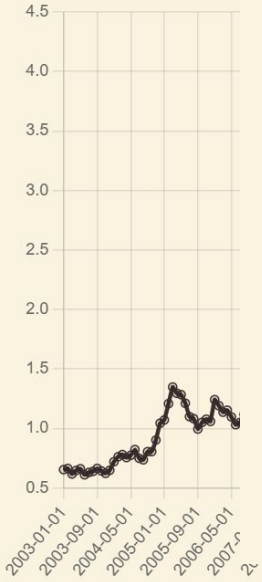
US Cocoa Shock (%): Current Price: $3165.00

0%

Simulate Custom Shocks

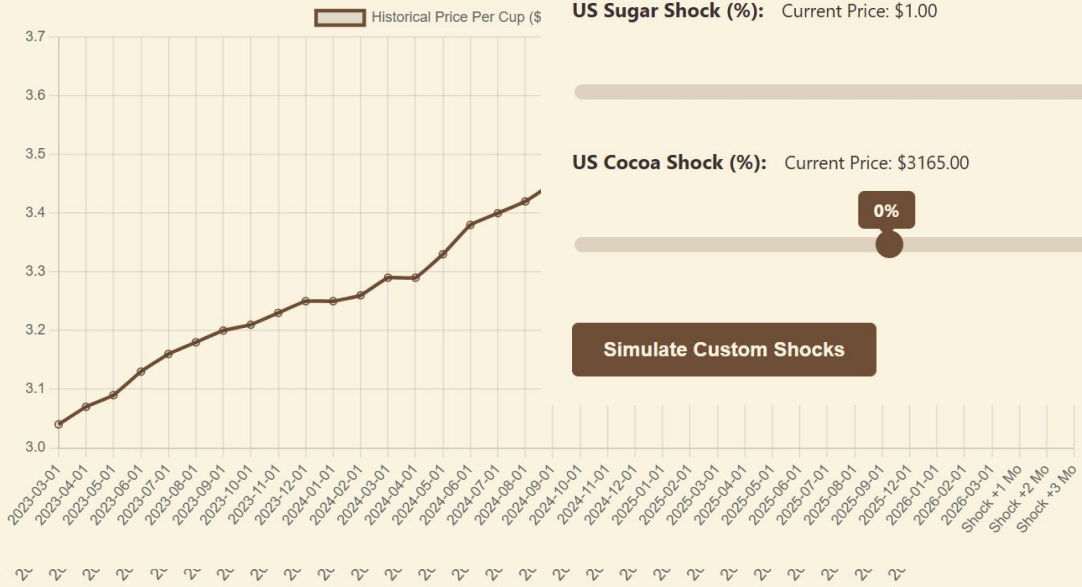
Global Macro Ma

After shocks, new price



Local Micro Market (Price Per Cup)

After shocks, new price is: $3.39 (Base: $3.69)



Real World Application:

- **Business Owners**:
  - Forecast Future Prices
  - If Overcharging or undercharging price of coffee
  - New Business Owners
- **Coffee Drinkers**:
  - Waying to invest in coffee machine

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Strategies: Where and how I found my answers

Classes:

- **CS 330** (html & web design)
  - CS courses for writing & understanding code
- **Data 301** & **Econ 326** (model & data manipulation)
- **Data 201 & CS 205:** Higher Level of Programming

Other:

- Previous Capstones
- Working with students
- **Flask Lab** (venv dashboard)
- **Professionalism** (Internships)

Extensions:

Senior who will take over my project next year should consider these enhancements and extensions as further research:

- Update Data
- Expand to size, flavor, and type of bean
- Merge price per pound with price per cup
- Get more data

Thank You!

Especially Dr. Dunbar &
All Professors!

Part 4: Q&A

About Data

About the Toast Menu Price Monitor:

- The Menu Price Monitor, powered by Toast, uncovers key menu pricing trends across the restaurant industry through aggregated sales data from restaurants on the Toast platform, which has approximately 164,000 locations as of Dec. 31, 2025

What affects coffee prices the most?

- Weather is among the most influential factors affecting coffee prices in recent years. Coffee requires very specific conditions to grow and is primarily sourced from an area known as the “bean belt,” which lies between the Tropic of Cancer and the Tropic of Capricorn.
- Extreme weather, including both droughts and flooding, has put a strain on coffee production over the past few years, but demand has continued to grow.

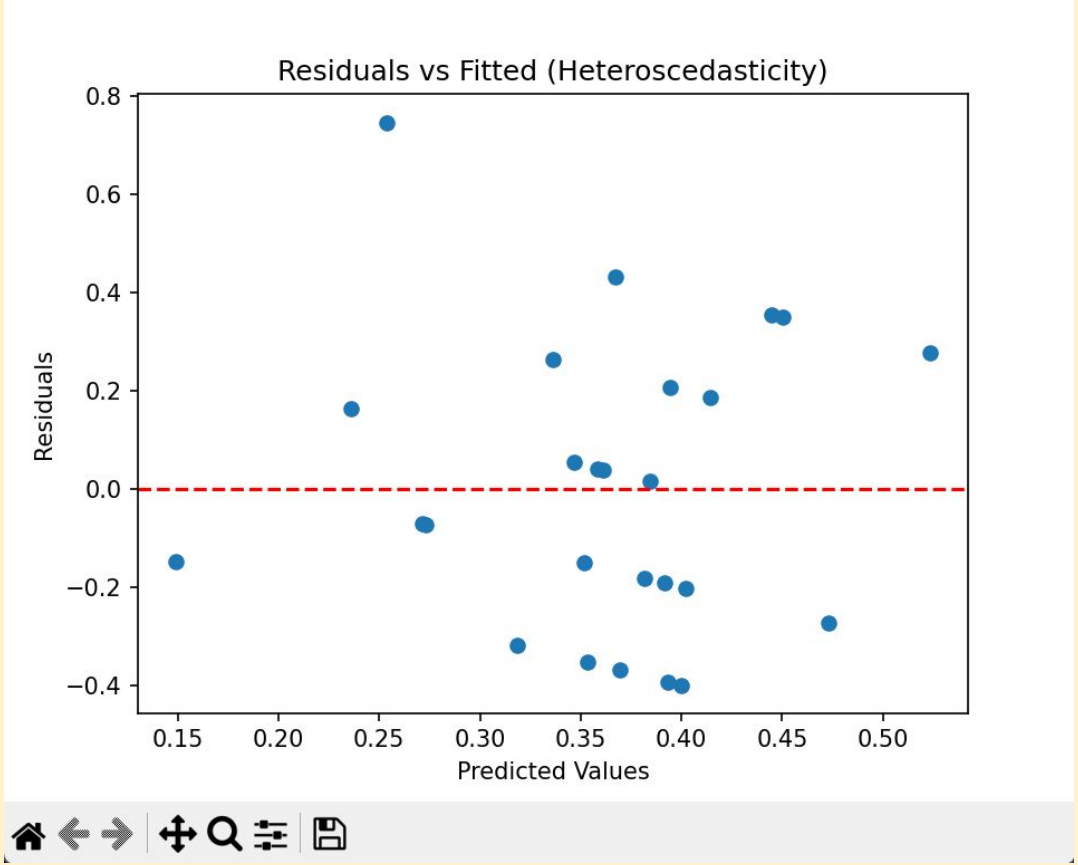
Sticky Pricing

- **Sticky Pricing:** When those global waves hit the US, they don't immediately change the price of a latte. The restaurant manager (and the supermarket) acts as a shock absorber. They eat the costs, use "Sticky Pricing" strategies, and only raise prices when they absolutely have to.

Model Tests

- **Heteroskedasticity** LM Per Cup model: Does not suffer

```
> print("Anything under 5 is valid")
[1] "Anything under 5 is valid"
> print(vif(lm_model))
 Scaled_Milk Scaled_Sugar Scaled_Cocoa
    1.014815     1.094065     1.107846
>
> print(" Heteroscedasticity (BP) ")
[1] " Heteroscedasticity (BP) "
> print("P-value > 0.05 is target")
[1] "P-value > 0.05 is target"
> print(bptest(lm_model))
```



Lm Local Model Results :

```
> summary(lm_model)

Call:
lm(formula = Scaled_Coffee ~ Scaled_Milk + Scaled_Sugar + Scaled_Cocoa,
    data = df_local)

Residuals:
     Min       1Q   Median       3Q      Max
-0.31454 -0.15239 -0.01828  0.12994  0.52658

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.87436    0.15039   5.814 2.35e-06 ***
Scaled_Milk  -0.19510    0.14287  -1.366  0.18222
Scaled_Sugar -0.75658    0.20768  -3.643  0.00101 **
Scaled_Cocoa -0.08772    0.15482  -0.567  0.57519
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1998 on 30 degrees of freedom
Multiple R-squared:  0.3674,    Adjusted R-squared:  0.3042
F-statistic: 5.808 on 3 and 30 DF,  p-value: 0.002966

>
```

Arima Model Results :

```
> summary(arimax_model)
Series: y_global
Regression with ARIMA(1,0,0) errors

Coefficients:
         ar1  intercept  Delta_Sugar  Delta_Cocoa
      0.2458     0.0096       0.0136        1e-04
s.e.  0.0613     0.0089       0.0055        1e-04

sigma^2 = 0.01254:  log likelihood = 213.87
AIC=-417.74   AICc=-417.52   BIC=-399.66

Training set error measures:
                       ME      RMSE        MAE      MPE     MAPE      MASE
Training set -6.922117e-06 0.1111625 0.07847083 73.02148 191.6348 0.7480012
                     ACF1
Training set 0.004452412
```

Deltas:

- Using Deltas achieves **Stationarity** in time-series data. prices constantly drift upward due to macroeconomic inflation, which creates false correlations in Linear Regression and ruins ARIMA forecasts. By differencing the data (calculating the Delta), we removed the underlying trend. This allowed the models to isolate the actual, immediate relationship between a commodity supply shock and the retail price response."