The Treatment of Import and Export Prices

In International Comparisons

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Introduction

ICP uses the *nominal exchange rate* for the PPP on the trade balance.

Until version 7.1, PWT used the PPP for *domestic absorption (C+I+G)* as the PPP for the trade balance.

Since the "next generation" in PWT v8, that approach is called "real GDP on the expenditure side" *CGDP^e*. It is also called "command basis" GDP in the United States and "real national income" in the SNA and is intended to measure consumption possibilities.

There has also been another approach in PWT v8: construct PPPs for imports and exports using the *quality-adjusted unit-values* for these traded goods. This is called "real GDP on the output side" *CGDP^o*.

Robert Feenstra, Robert Inklaar and Marcel Timmer, "The Next Generation of the Penn World Table," ***American Economic Review***, 2015, 105(10), 3150-3182.

Robert Feenstra and John Romalis, "International Prices and Endogenous Quality," ***Quarterly Journal of Economics***, May 2014, 129(2), 477-528.

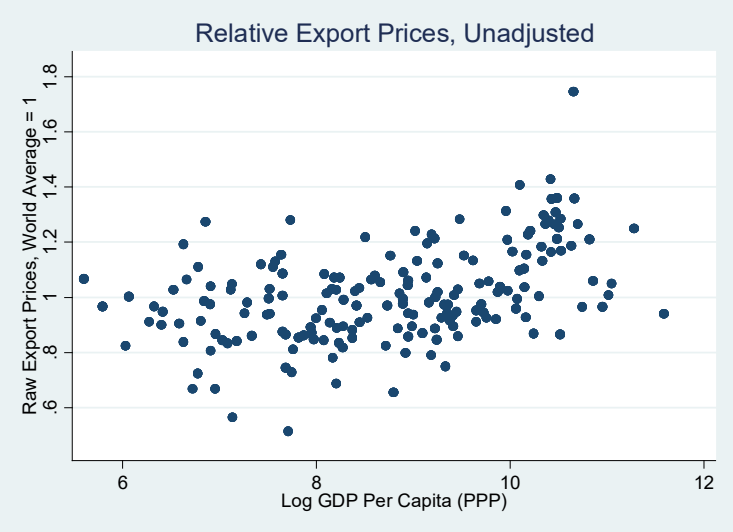
Introduction (cont'd)

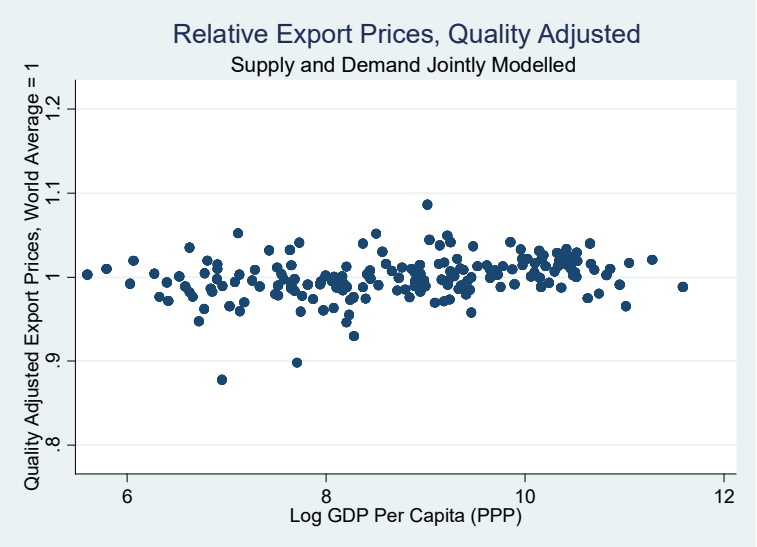
We would like to consider a *simpler procedure* for computing the PPPs for X and M, to give another "real GDP on the output side", or $CGDP^{o2}$.

Our goals:

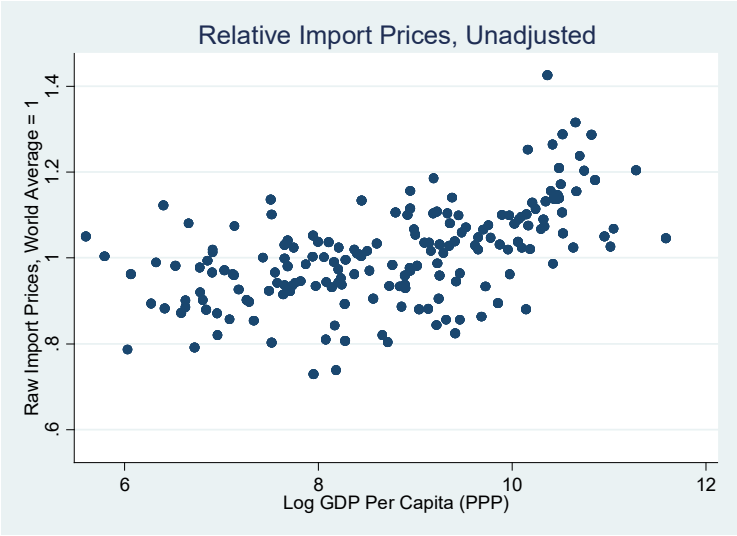
- Check how the quality-adjusted export and imports prices depend on the exchange rate. Method 1 is to update the PPPs for imports and exports using "pass-through" of the exchange rate.
- Method 2 is to use the exchange rate directly as the PPP for imports and exports (like the ICP). We will compare these two methods to existing PWT calculations of $CGDP^{e}$ and $CGDP^{o}$
- Examine whether it is possible to identify the country of origin for barcode prices collected worldwide, so as to distinguish *imports* from *domestically-produced* prices

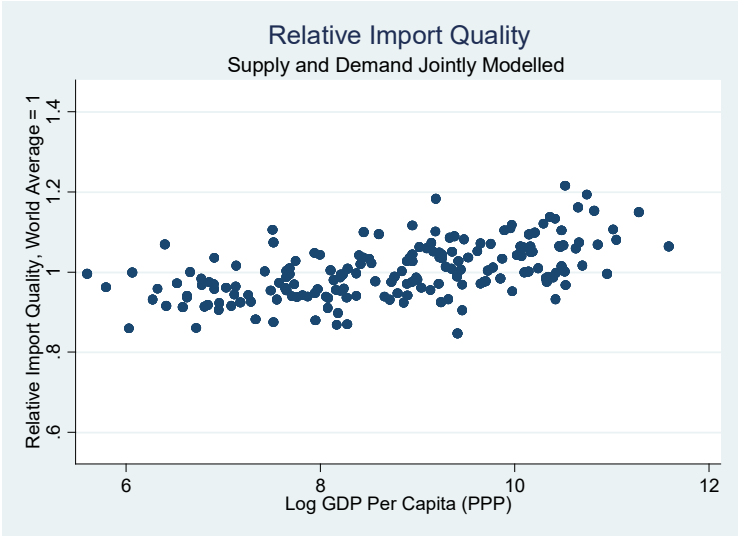
Feenstra and Romalis (2014): country export prices in 2007

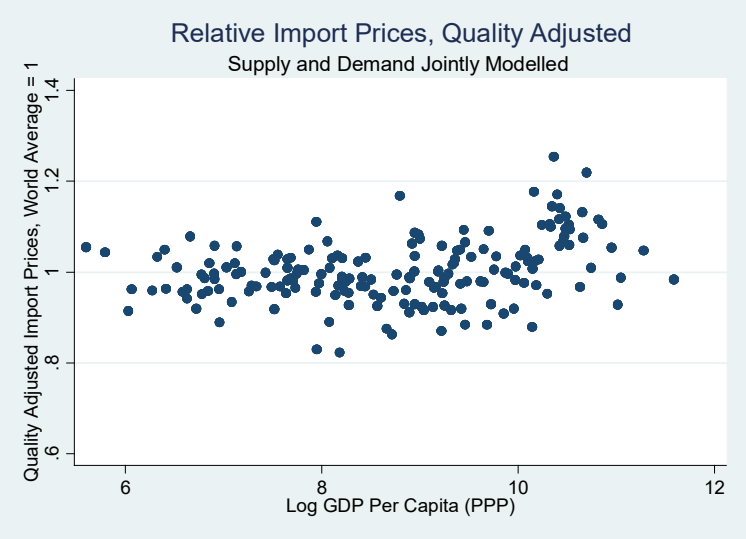




Feenstra and Romalis (2014): country import prices in 2007

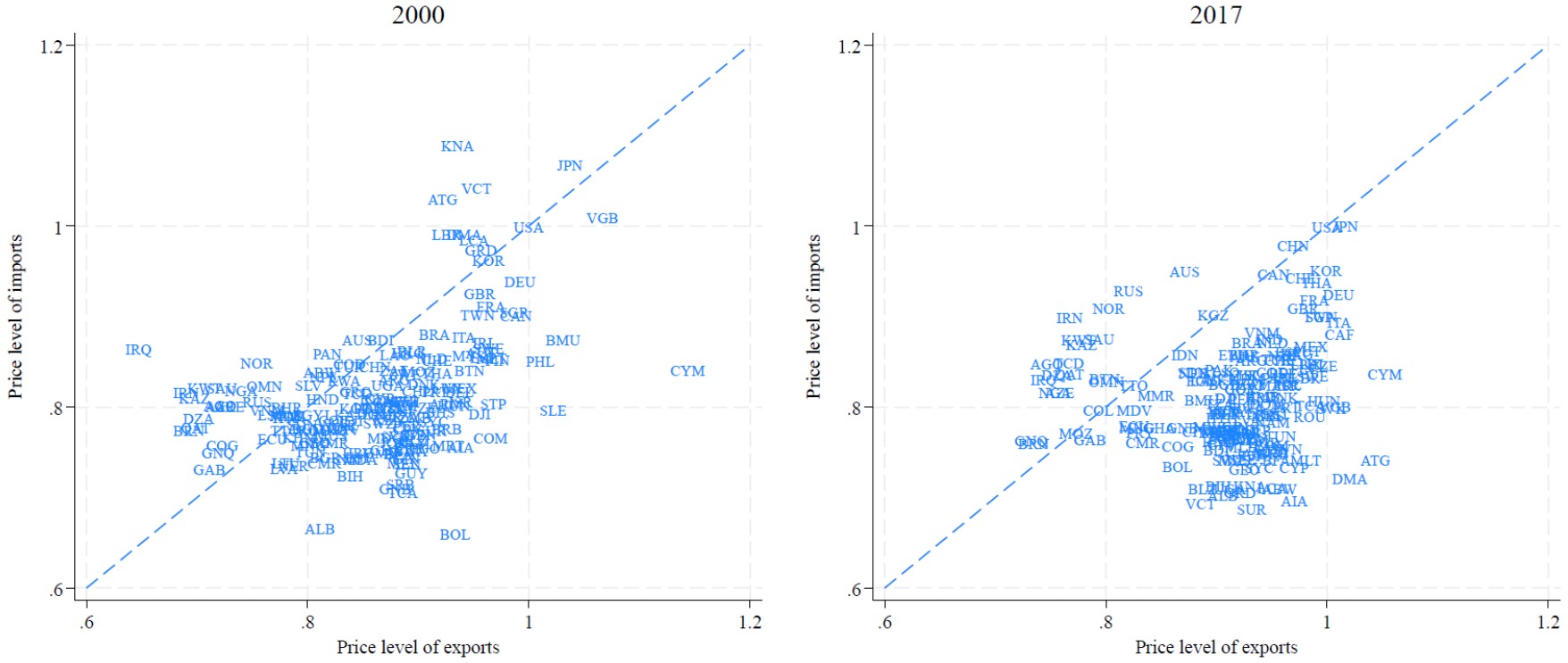






Summary results for 170 countries in 2000 and 2017, USA=1

Year	$PL^x > PL^m$	$PL^x < PL^m$
2000	129	41
2017	148	22



Compare *CGDP^e* and *CGDP^o* in "Next Generation" of PWT

Construct PPP indexes for exports and imports and apply those to measure real **"GDP in the output side"**:

$$CGDP_j^o = \frac{C_j + I_j + G_j}{PPP_j^{da}} + \frac{X_j}{PPP_j^x} - \frac{M_j}{PPP_j^m} \equiv \frac{GDP_j}{PPP_j^o},$$

An alternative solution is to use the PPP for domestic absorption (i.e. C+I+G) applied to net exports (X – M), **"GDP on the expenditure side"**:

$$CGDP_j^e = \frac{C_j + I_j + G_j}{PPP_j^{da}} + \frac{(X_j - M_j)}{PPP_j^{da}} = \frac{GDP_j}{PPP_j^{da}},$$

Our goal is to have a simpler method for computing *PPP^x* and *PPP^m* using the country exchange rates (relative to the US$)

Table 1: Exchange Rate Pass-through on Import Prices from NA data

	1950-2019		1984-2019		
	(1)	(2)	(3)	(4)	(5)
$\ln(e_{i,t})$	0.951***	0.208***	0.236***	0.201***	0.205***
	(0.00178)	(0.00573)	(0.00715)	(0.00856)	(0.00866)
$\ln(P_{i,t}^{DA,NA})$		0.774***	0.747***	0.749***	0.716***
		(0.00586)	(0.00721)	(0.00720)	(0.00948)
$\ln(e_{i,t}) \times Share_{i,t}^{M,H}$				0.0374***	0.0370***
				(0.0106)	(0.0120)
$\ln(e_{i,t}) \times Share_{i,t}^{M,R}$				0.129***	0.104***
				(0.0181)	(0.0185)
$\ln(P_{i,t}^{DA,NA}) \times Share_{i,t}^{M,H}$					0.0132
					(0.0144)
$\ln(P_{i,t}^{DA,NA}) \times Share_{i,t}^{M,R}$					0.156***
					(0.0241)
Country FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	11849	11849	7018	7014	7014

Table 2: Exchange Rate Pass-through on Export Prices from NA data

	1950-2019		1984-2019		
	(1)	(2)	(3)	(4)	(5)
$\ln(e_{i,t})$	0.943***	0.242***	0.308***	0.332***	0.335***
	(0.00187)	(0.00688)	(0.00967)	(0.0117)	(0.0118)
$\ln(P_{i,t}^{DA,NA})$		0.730***	0.654***	0.654***	0.605***
		(0.00703)	(0.00977)	(0.00976)	(0.0152)
$\ln(e_{i,t}) \times Share_{i,t}^{X,H}$				-0.0389***	-0.0381***
				(0.00825)	(0.00928)
$\ln(e_{i,t}) \times Share_{i,t}^{X,R}$				0.00409	-0.00616
				(0.0109)	(0.0110)
$\ln(P_{i,t}^{DA,NA}) \times Share_{i,t}^{X,H}$					0.0391***
					(0.0140)
$\ln(P_{i,t}^{DA,NA}) \times Share_{i,t}^{X,R}$					0.105***
					(0.0188)
Country FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	11849	11849	7018	6997	6997

Table 3: Pass-through on *Qual-Adjusted* Import Prices from PWT data

	1950-1984	1950-2019	1984-2019		
	(1)	(2)	(3)	(4)	(5)
$ln(e_{i,t})$	0.357***	0.740***	0.951***	0.958***	0.972***
	(0.0148)	(0.00751)	(0.00253)	(0.00280)	(0.0039)
$ln(P_{i,t}^{DA,PWT})$	0.653***	0.249***	0.0451***	0.0425***	0.027***
	(0.0153)	(0.00757)	(0.00249)	(0.00252)	(0.0039)
$ln(e_{i,t}) \times Share_{i,t}^{M,H}$				-0.00401**	-0.033***
				(0.00182)	(0.0076)
$ln(e_{i,t}) \times Share_{i,t}^{M,R}$				-0.0181***	-0.060***
				(0.00315)	(0.0105)
$ln(P_{i,t}^{DA,PWT}) \times Share_{i,t}^{M,H}$					0.031***
					(0.0079)
$ln(P_{i,t}^{DA,PWT}) \times Share_{i,t}^{M,R}$					0.047***
					(0.0114)
Country FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	4153	10399	6201	6201	6201

Table 4: Pass-through on *Qual-Adjusted* Export Prices from PWT data

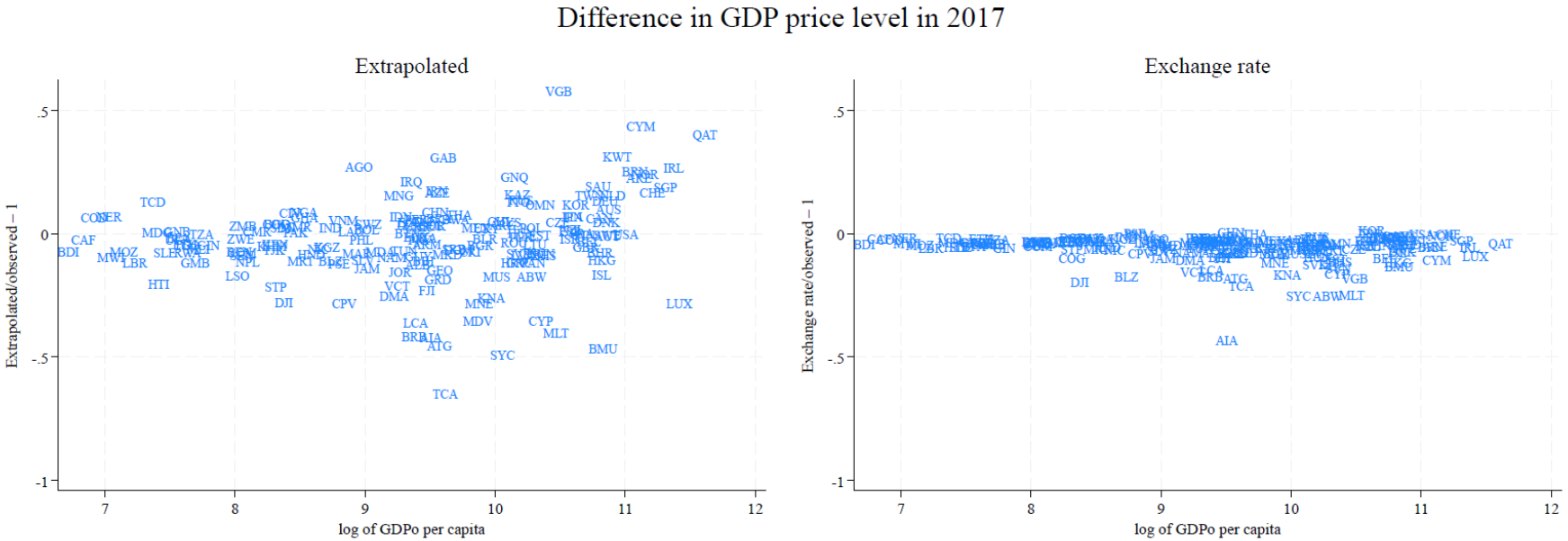
	1950-1984	1950-2019	1984-2019		
	(1)	(2)	(3)	(4)	(5)
$ln(e_{i,t})$	0.399***	0.807***	0.984***	0.992***	0.985***
	(0.0168)	(0.00793)	(0.00330)	(0.00351)	(0.0051)
$ln(P_{i,t}^{DA,PWT})$	0.604***	0.186***	0.0150***	0.0156***	0.025***
	(0.0173)	(0.00799)	(0.00325)	(0.00323)	(0.0056)
$ln(e_{i,t}) \times Share_{i,t}^{X,H}$				-0.0132***	-0.00942
				(0.00135)	(0.0058)
$ln(e_{i,t}) \times Share_{i,t}^{X,R}$				-0.00175	0.023***
				(0.00177)	(0.0075)
$ln(P_{i,t}^{DA,PWT}) \times Share_{i,t}^{X,H}$					-0.00545
					(0.0063)
$ln(P_{i,t}^{DA,PWT}) \times Share_{i,t}^{X,R}$					-0.029***
					(0.0086)
Country FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	4153	10399	6201	6193	6193

Computing real GDP Price levels using exchange rate

How do the price levels of real output GDP compare in 2017 using:

Method 1: Extrapolation of PPP^x and PPP^m (from 2000) using full pass-through of the exchange rate, versus,

Method 2: using the exchange rate as the PPP for X and M (like the ICP)



Extrapolated uses the BEC-level export and import PPPs for the year 2000 and extrapolates to 2017 using the change in the exchange rate. Exchange rate uses the 2017 exchange rate instead of export and import PPPs

Left panel is between ±50 log points, whereas right is much less but with downward bias

GDP Price levels – Omitting countries with population < 1 mill

How do the price levels of real output GDP compare in 2017 using:

Method 1: Extrapolation of PPP^x and PPP^m (from 2000) using full pass-through of the exchange rate, versus,

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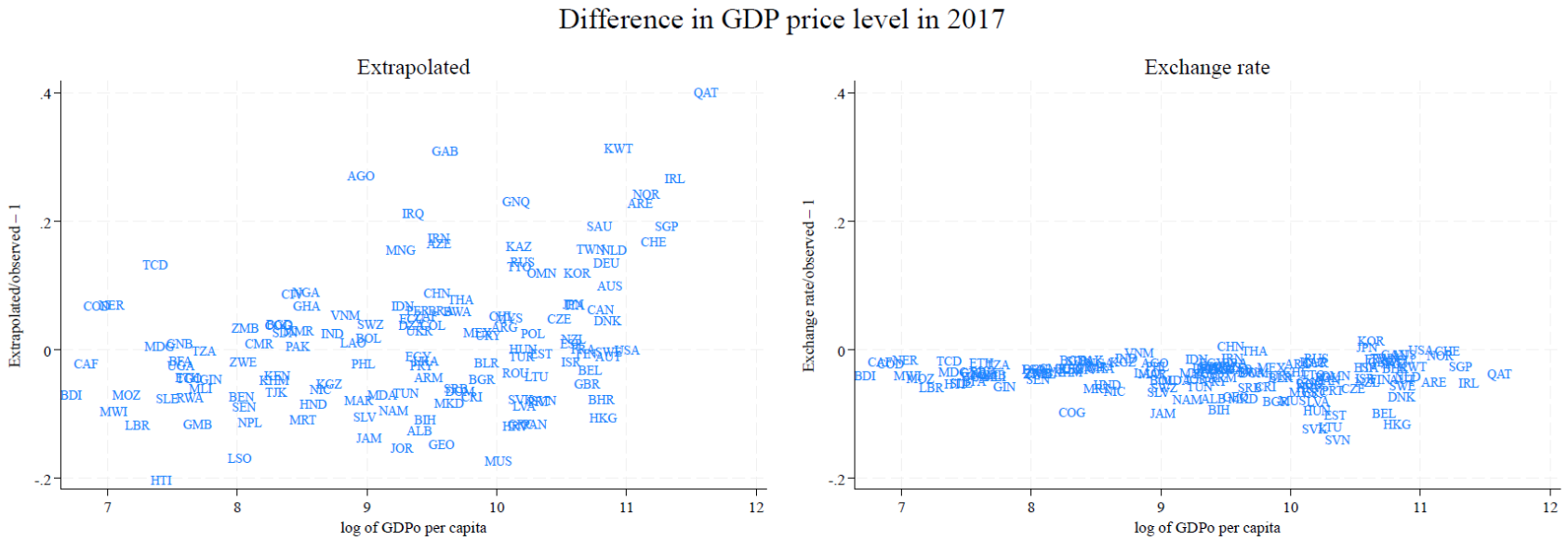


Extrapolated uses the BEC-level export and import PPPs for the year 2000 and extrapolates to 2017 using the change in the exchange rate. Exchange rate uses the 2017 exchange rate instead of export and import PPPs

Left panel is between 40 and -20 log points, and right is less but with downward bias

Conclude: Only use Method 2 resulting in $CGDP^{o2}$

Method 2 calculation of PPP^{x2} and PPP^{m2} using GK system

Compute **reference prices** for domestic goods, exports, imports, and overall real-output GDP:

$$\pi_{j,t}^{2} = \frac{\sum_{i=1}^{N}\left(\frac{p_{ij,t}}{PPP_{i,t}^{o2}}\right)q_{ij,t}}{\sum_{i=1}^{N} q_{ij,t}}, \quad \pi_{j,t}^{x2} = \frac{\sum_{i=1}^{N}\left(\frac{e_{i,t}}{PPP_{i,t}^{o2}}\right)x_{ij,t}}{\sum_{i=1}^{N} x_{ij,t}}, \quad \pi_{j,t}^{m2} = \frac{\sum_{i=1}^{N}\left(\frac{e_{i,t}}{PPP_{i,t}^{o2}}\right)m_{ij,t}}{\sum_{i=1}^{N} m_{ij,t}},$$

$$PPP_{i,t}^{o2} = \frac{GDP_{i,t}}{\pi_t'^{2} q_{i,t} + \pi_t'^{x2} x_{i,t} - \pi_t'^{m2} m_{i,t}}$$

Substituting from $PPP_{i,t}^{o2}$, the **price levels for exports & imports** are:

$$PL_{i,t}^{z2} = \frac{PPP_{i,t}^{z2}}{e_{i,t}} = \left[\sum_{j=1}^{6}\left(\frac{\sum_{h=1}^{N}(1/PL_{h,t}^{o2})z_{hj,t}}{\sum_{h=1}^{N} z_{hj,t}}\right)\frac{z_{ij,t}}{\sum_{k=1}^{6} z_{ik,t}}\right]^{-1}, \quad z=x,m$$

This is a weighted harmonic mean of $PL_{h,t}^{o2} = PPP_{h,t}^{o2}/e_{h,t}$

Diff. between 2017 $CGDP^{o2}$ (with nominal exch. rate) and $CGDP^{o}$

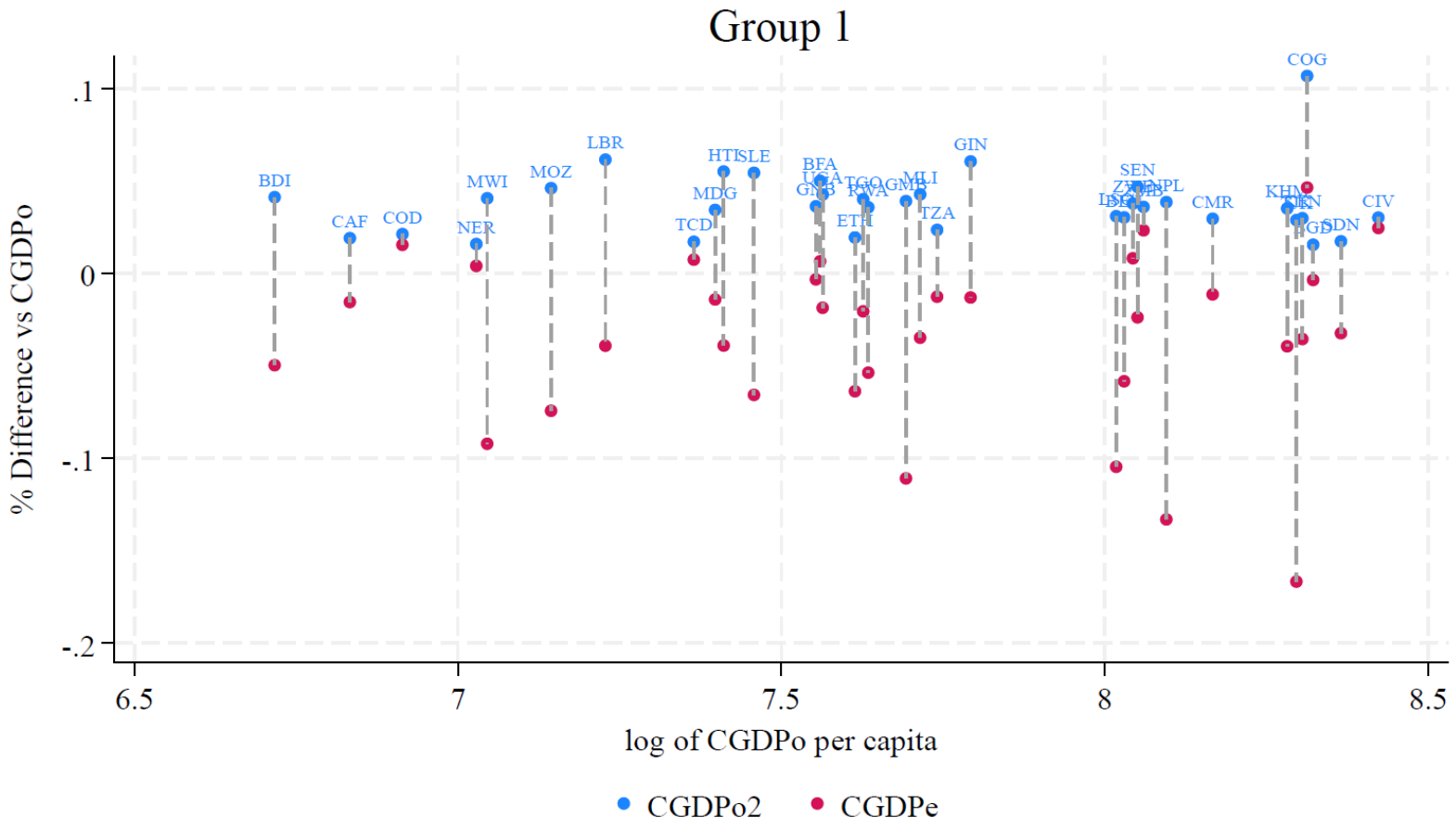
$$\underbrace{\frac{CGDP_j^{o2}-CGDP_j^{o}}{CGDP_j^{o}}}_{\text{Gap2}}=\underbrace{\left(\frac{PL_j^{x}}{PL_j^{x2}}-\frac{PL_j^{m}}{PL_j^{m2}}\right)}_{\text{Terms of trade2}}\underbrace{\frac{1}{2}\left(\frac{X_j/PPP_j^{x}}{CGDP_j^{o}}+\frac{M_j/PPP_j^{m}}{CGDP_j^{o}}\right)}_{\text{Real Openess}}$$

$$+\underbrace{\left[\frac{1}{2}\left(\frac{PL_j^{x}}{PL_j^{x2}}+\frac{PL_j^{m}}{PL_j^{m2}}\right)-1\right]}_{\text{Relative traded Price}}\underbrace{\left(\frac{X_j/PPP_j^{x}}{CGDP_j^{o}}-\frac{M_j/PPP_j^{m}}{CGDP_j^{o}}\right)}_{\text{Real Balance of Trade share}}$$

Conclude:

- When $PL^x > PL^m$ the first term will create a *positive difference* in *CGDP* (which is a *negative difference* in the price level).
- $PL^x < PL^{x2}$ and $PL^m < PL^{m2}$ for low-income countries, second term is positive for *trade deficit* countries, creating a *positive diff* in CGDP (which is a *negative difference* in the price level).

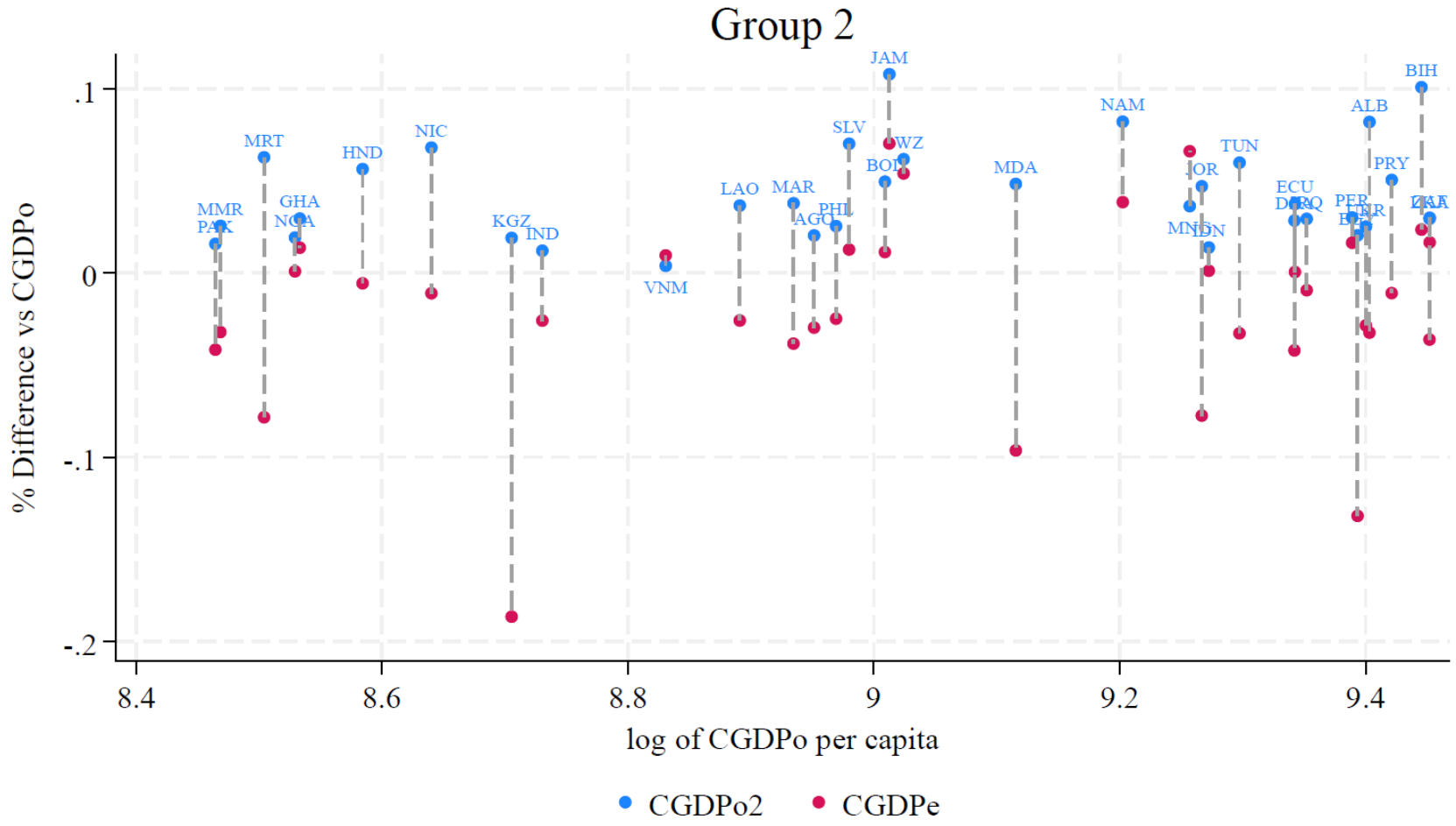
Difference with Real GDP^o: 140 countries with pop. > 1 mill



Lowest-income 35 countries, **Ranking:** $CGDP^{o2}_{i,t} > CGDP^{o}_{i,t} > CGDP^{e}_{i,t}$,

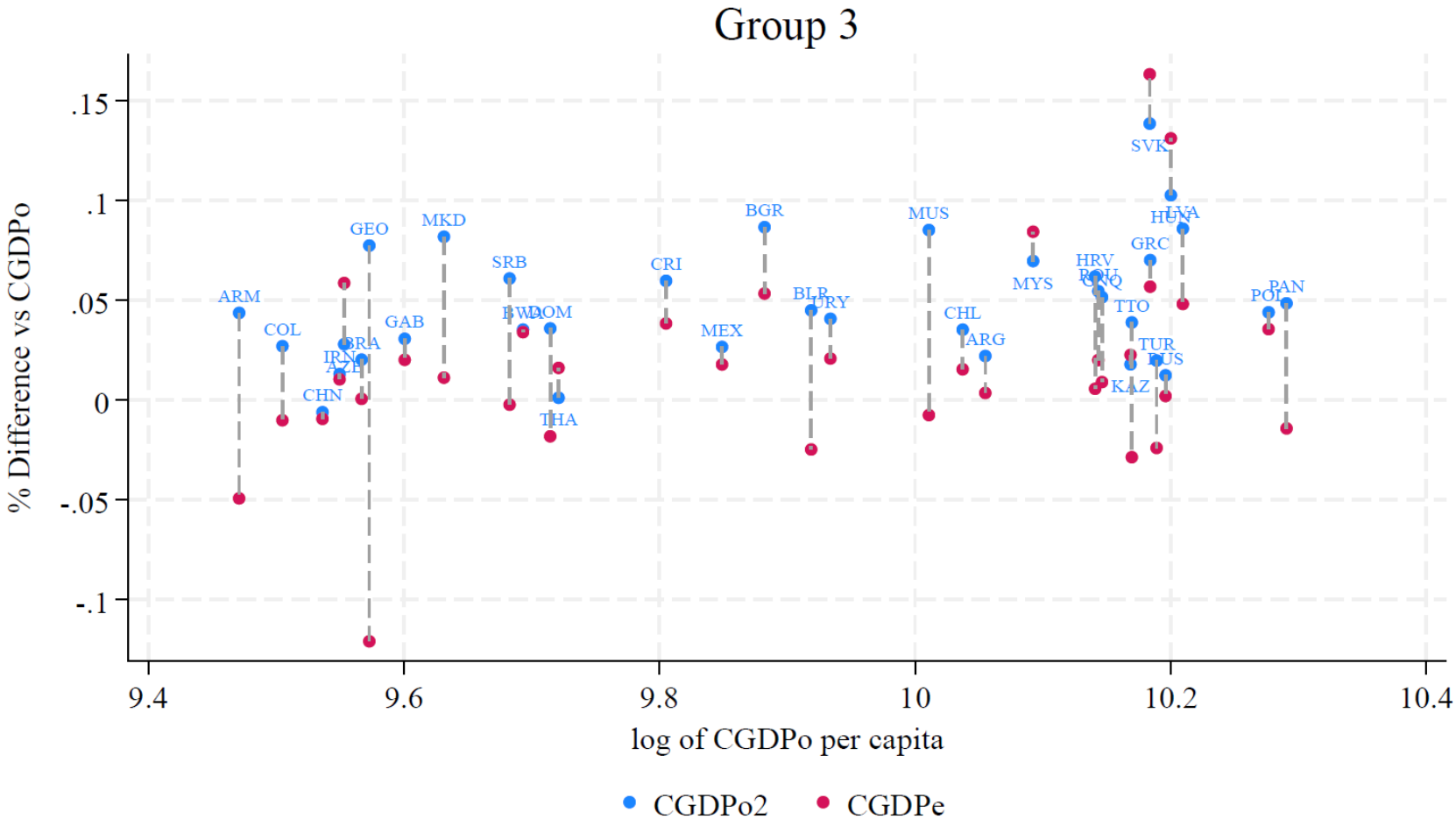
except for Dem. Rep. of the Congo (COD), Chad (TCD), Cote d'Ivoire (CIV).

Difference with Real GDP^o: 140 countries with pop. > 1 mill



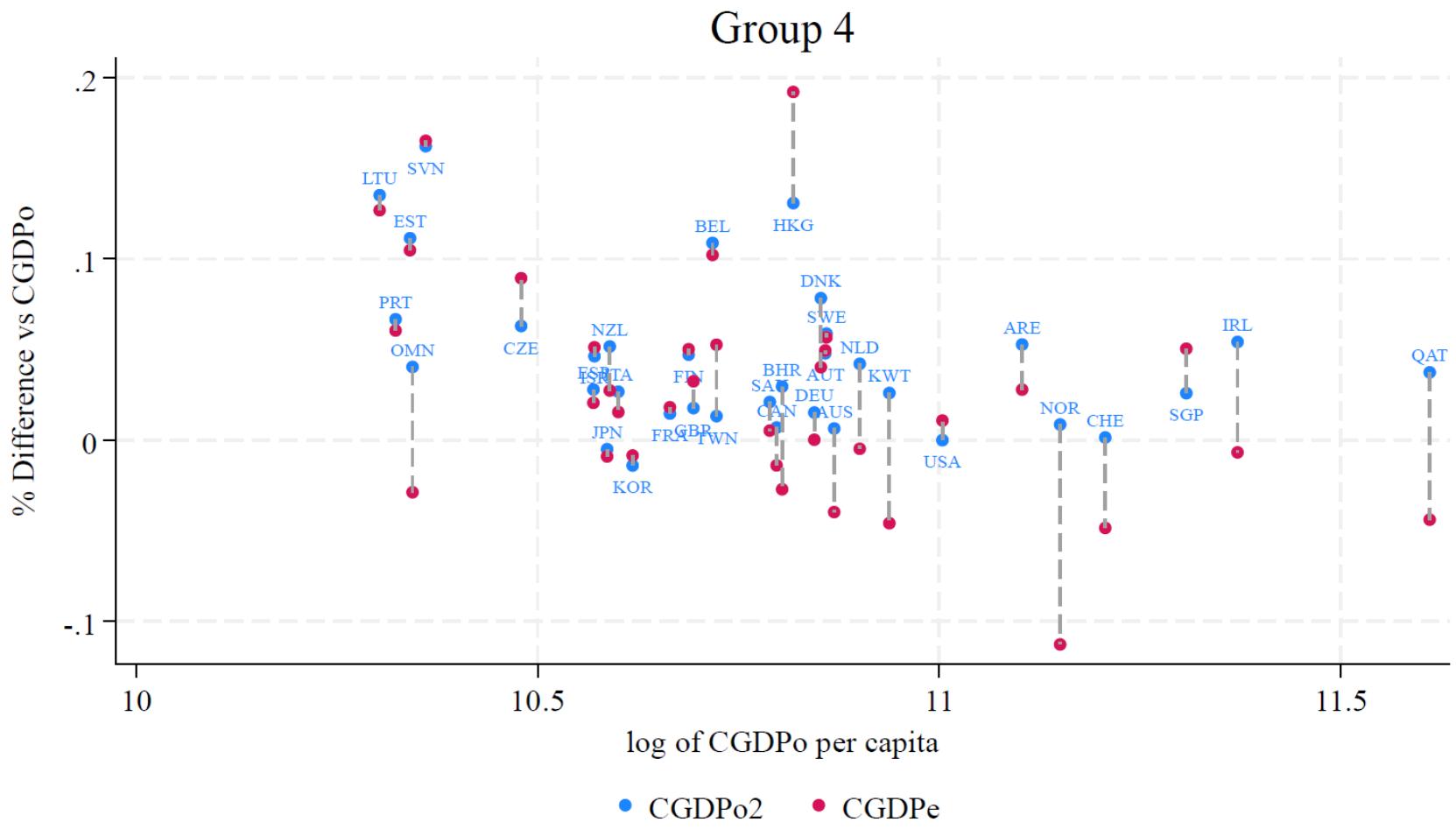
Some exceptions to ranking, & for Vietnam: $CGDP_{i,t}^{o2} \approx CGDP_{i,t}^{o} \approx CGDP_{i,t}^{e}$

Difference with Real GDP^o: 140 countries with pop. > 1 mill



More exceptions to ranking, & for China: $CGDP_{i,t}^{o2} \approx CGDP_{i,t}^{o} \approx CGDP_{i,t}^{e}$

Difference with Real GDP^o: 140 countries with pop. > 1 mill



The most exceptions, for Japan & South Korea: $CGDP_{i,t}^{o2} \approx CGDP_{i,t}^{o} \approx CGDP_{i,t}^{e}$

Preliminary conclusions

1) Our goal is to simplify the calculation of PPP^x and PPP^m, and potentially change the calculation of $CGDP^o$ in PWT.

2) Method 1: Despite the fact that there is *complete pass-through* of exchange rates to PPP^x and PPP^m, updating those import and export prices using the exchange rate leads to erratic results as compared to the current calculation of $CGDP^o$.

3) Method 2: Using the *nominal exchange rate* as PPP for imports and exports, like the ICP, leads to results $CGDP^{o2} > CGDP^o$ for 120 out of 140 countries, though usually within 10% of $CGDP^o$.

4) *Gini coefficients of real GDP per-capita* over 140 countries:

0.513 using $CGDP^o_{i,t} \approx$ 0.512 using $CGDP^{o2}_{i,t}$, and 0.493 using $CGDP^e_{i,t}$. So $CGDP^o_{i,t}$ and $CGDP^{o2}_{i,t}$ give *broadly similar* results.

Can we use online data to get *import* prices?

- Cavallo, Diewert, Feenstra, Inklaar & Timmer (2018) showed that online prices can be used to construct quarterly PPPs that approximate ICP results

TABLE 1—MULTILATERAL PRICE LEVEL INDEX
(PLI=PPP/E), USA=1

	2011		2014	
	BPP	ICP	BPP	OECD
Argentina	0.79	—	1.05	—
Australia	1.52	1.53	1.24	1.36
Brazil	1.44	1.20	1.17	—
Canada	1.08	1.30	1.15	1.29
China	0.71	0.93	0.97	—
Germany	1.12	1.30	1.20	1.35
Japan	2.57	2.01	1.58	1.42
Netherlands	1.21	1.29	1.22	1.27
South Africa	1.11	0.96	0.91	-
United Kingdom	1.14	1.25	1.26	1.37
United States	1.00	1.00	1.00	1.00
Mean absolute difference				
All countries		15%		
OECD		17%		9%

Can we use online data to get *import* prices?

- Cavallo, Feenstra & Inklaar (2021) used online barcode counts to measure product variety across countries → we identified imported vs domestic using crowdsourced surveys.

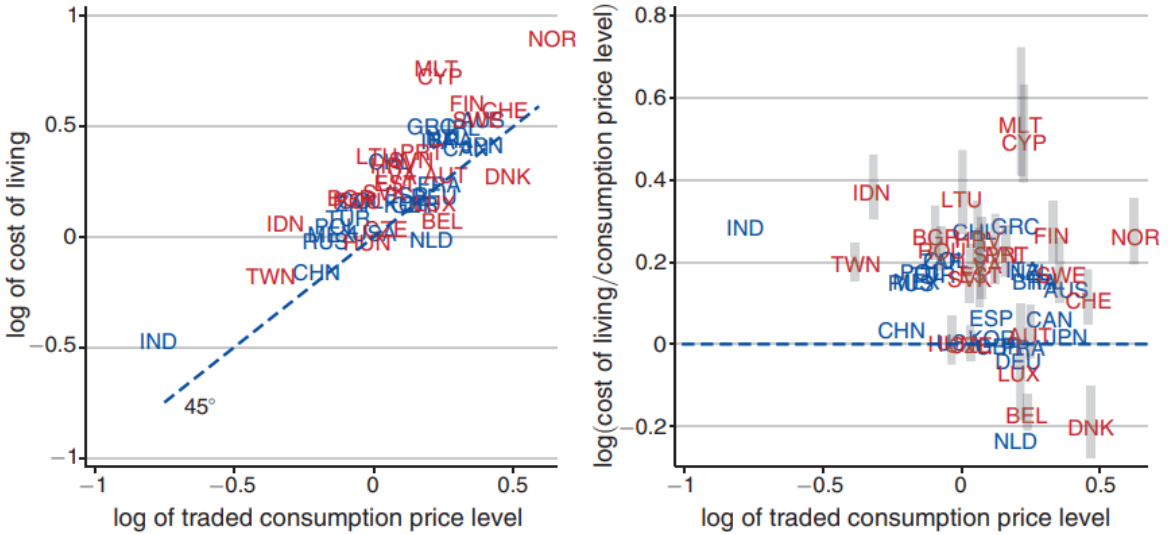
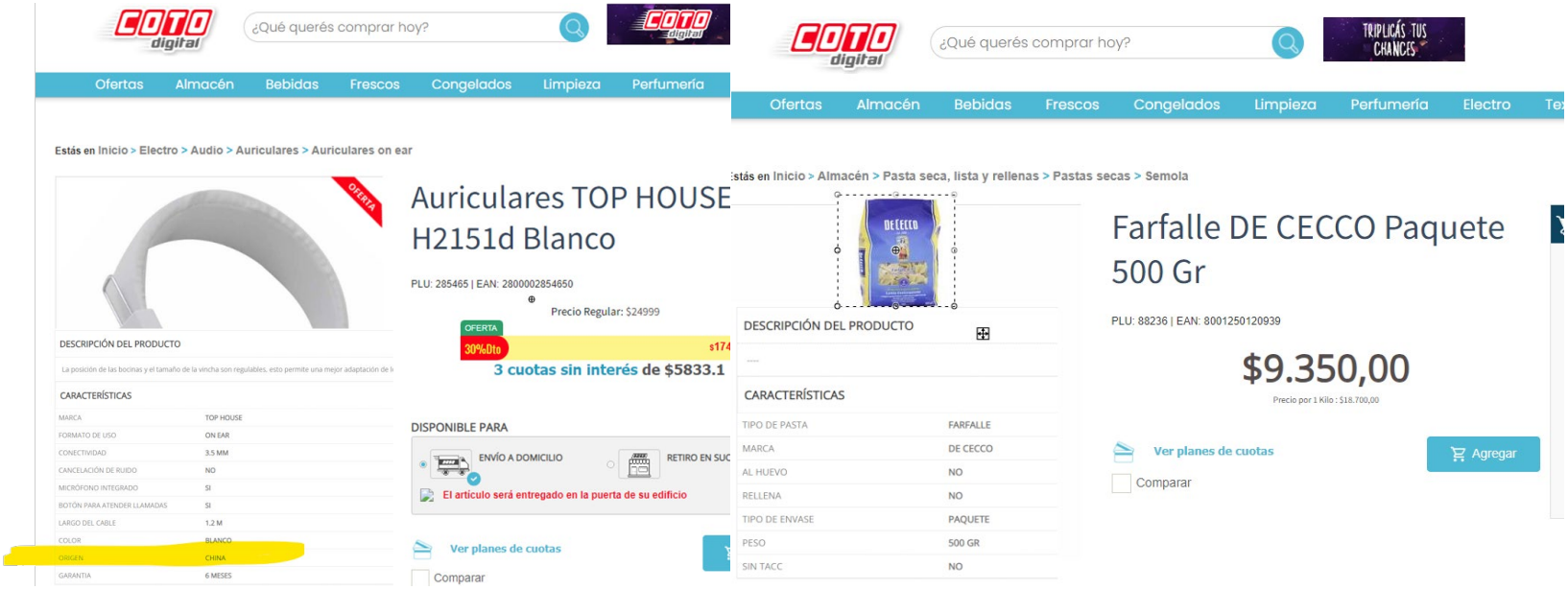


FIGURE 6. COST OF LIVING (WITH PRODUCT VARIETY) VERSUS THE TRADED CONSUMPTION PRICE LEVEL (LOG SCALE, USA = 0)

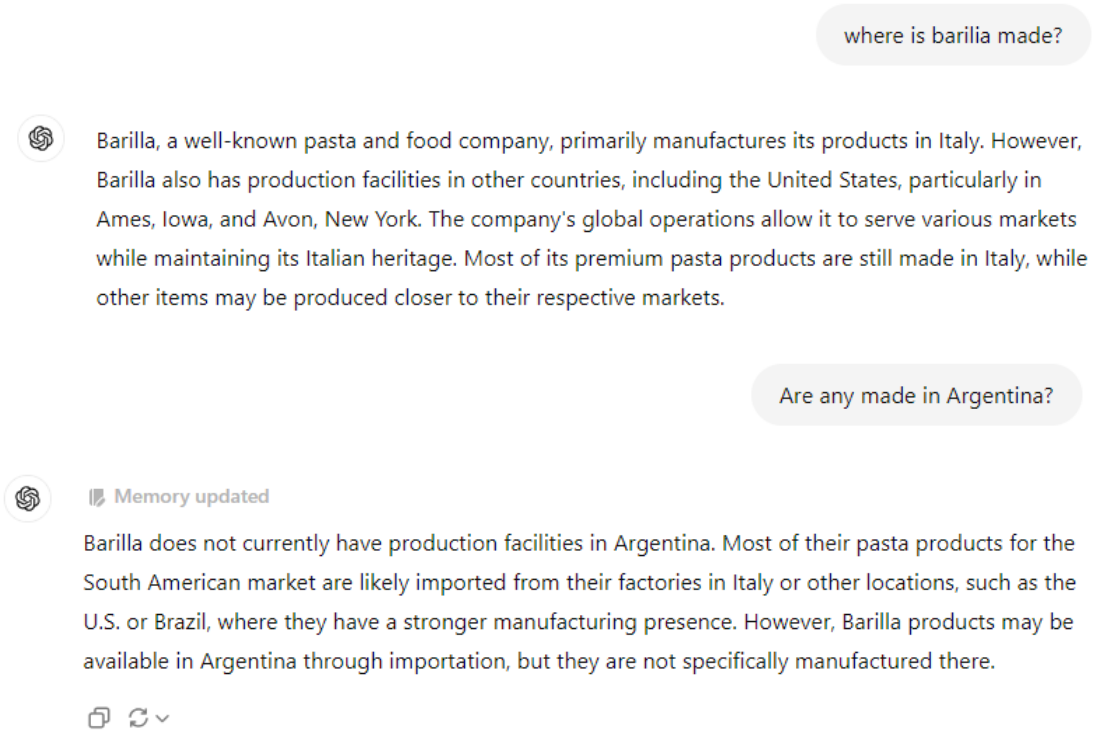
Can we use online data to get *import* prices?

- Challenge → country of origin information is <u>seldom</u> available online or in scanner/barcode databases

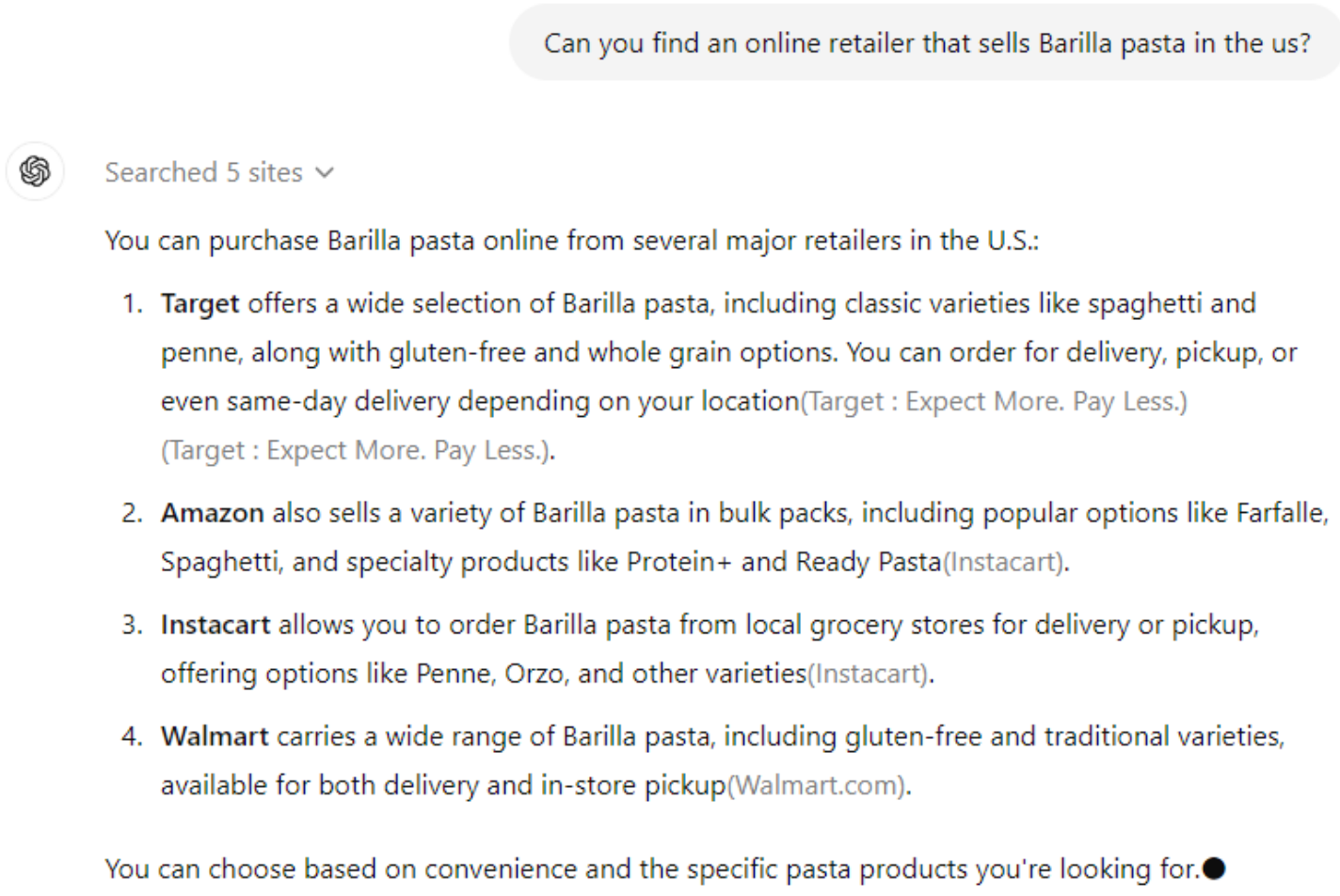


Could AI recognize whether a product is imported or domestic?

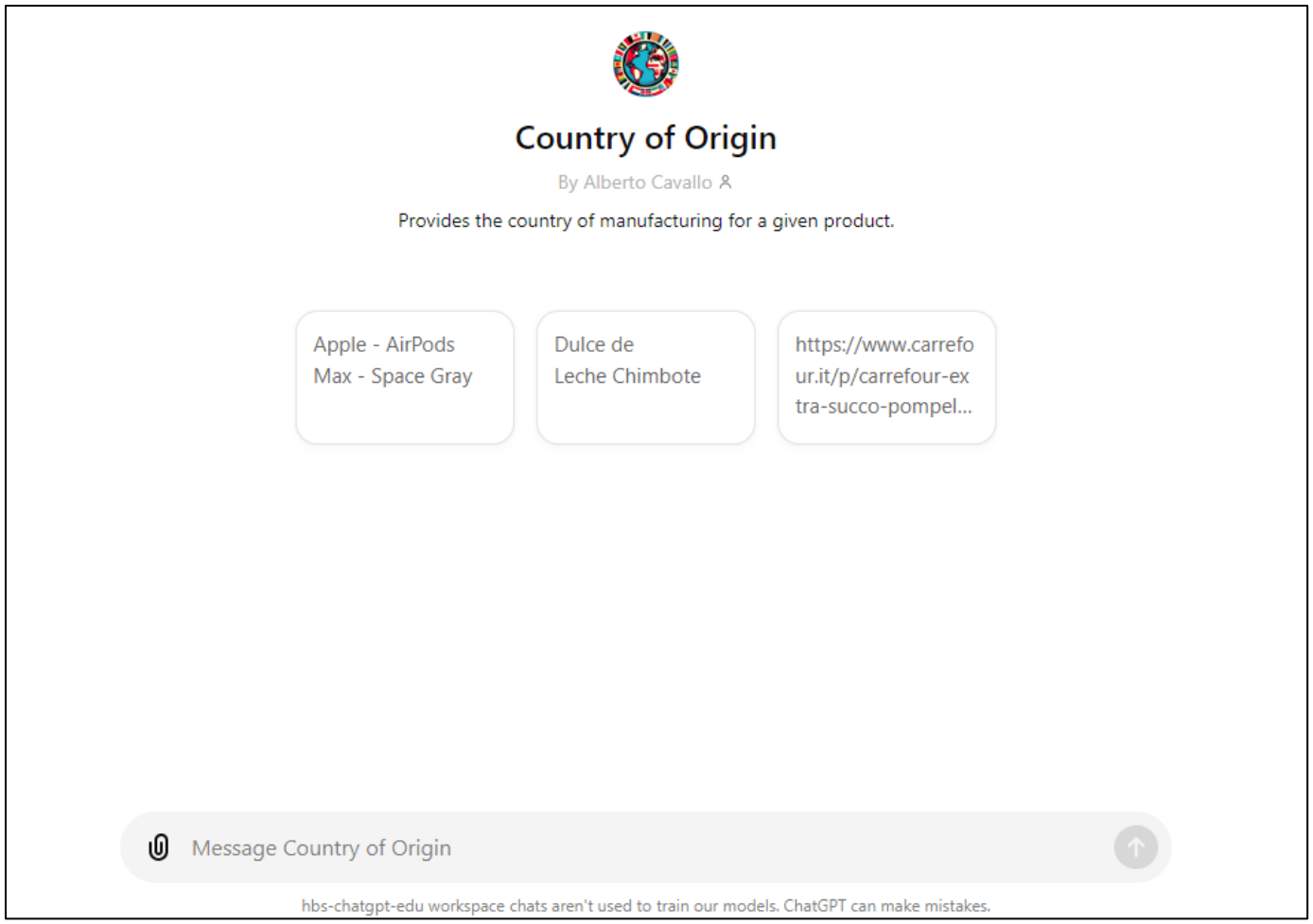
- Large language models (LLMs) like ChatGPT's are trained on information available online about products
  - Can link well-known brands to manufacturing countries.



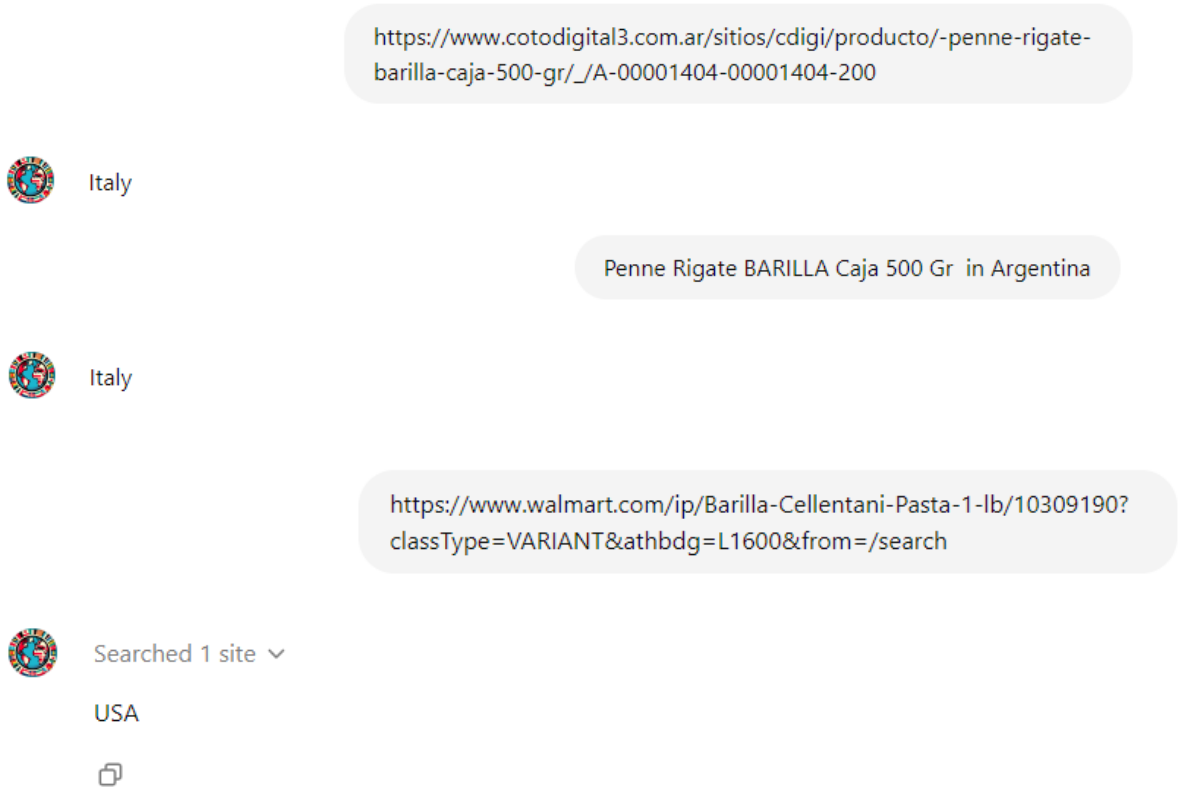
- ChatGPT can also search online for additional information in real time → eg. websites currently selling the product



- We built a custom ChatGPT, trained to find the country of origin of a good based on a product description or retailer URL



- Interactively, it works extremely well…



- But scaling this up requires the use of APIs and some prompt-engineering

Test 1: OpenAI's API

3 retailers in Argentina, Korea and Russia, 300 random products with origin information manually obtained

1 Prompt 1

I submit a product name or URL. It will answer with a list of probable countries and the most likely country. The GPT will answer with the format: *Probable countries of origin: list of countries, Most likely country of origin:* `country`.

1.1 Description + URL

Table 1: gpt-3.5.turbo

	Country of origin (%)	Imp/Dom (%)	True in possible countries (%)
Argentina	29.3	46.5	52.5
Korea	39.0	39.0	64.0
Russia	66.0	69.0	75.0
All countries	44.8	51.5	63.9

Note: the cost for 300 products was 0.02 dollars (39223 tokens: 228 and 5382 tokens).

Table 2: gpt-4o-mini

	Country of origin (%)	Imp/Dom (%)	True in possible countries (%)
Argentina	35.4	49.5	73.7
Korea	41.0	45.0	90.0
Russia	71.0	75.0	90.0
All countries	49.2	56.5	84.6

Note: the cost for 300 products was 0.01 dollars (38016 tokens: 312 and 6814 tokens).

5 Prompt 5

This specification aims to improve Prompt 2 by providing three different examples to the GPT model. The three examples are as follows:

The text of the prompt:

> I will submit a product name and URL. Your task is to return a list of probable countries of origin and identify the most likely country of origin. You should analyze the content of the provided URL and use the product name to aid in your assessment. Scrape the webpage to look for keywords, metadata, or other indicators that can reliably suggest the country of origin.
>
> Output Format:
>
> - Probable countries of origin: <list of countries>
> - Most likely country of origin: <country name>
>
> Instructions:
>
> - Be very conservative in your judgment. If you encounter any uncertainty or ambiguity, leave the output as ' ; '.
> - Do not make guesses. Only provide an answer if you are 100% certain about the country of origin.
> - Scrape the webpage content thoroughly, focusing on details like manufacturer information, product descriptions, and any metadata that might indicate the country of origin.
> - If the information found is conflicting or inconclusive, include a disclaimer stating that the country of origin couldn't be determined with confidence.
>
> Product Info: {product_info}
> Product URL: {product_url_}

Table 26: gpt-4o-mini

	Country of origin (%)	Imp/Dom (%)	True in possible countries (%)	Imp/Dom using possible country (%)
Argentina	85.9	85.9	84.1	85.9
Korea	77.8	77.8	84.2	77.8
Russia	75.0	81.2	75.0	81.2
All countries	81.6	83.3	81.7	83.3

Note: The sample includes 65 products from Argentina, 18 from Korea, and 32 from Russia.

OpenAI's API is not yet able to search online → this significantly reduces its performance

Test 2: Perplexity API (with real-time online search)

US Walmart and Target, 1000 products with origin scraped from the web

USA Preliminary Results (2/25)	Perplexity (online search model)				ChatGPT Interactive	
	Walmart		Target		Target	
Measure	Observations	Accuracy	Observations	Accuracy	Observations	Accuracy
Total accuracy category prediction (Domestic/Imported)	500	75%	500	80%	123	91.87%
Total accuracy category prediction (excluding low confidence)	403	73.20%	381	81.10%		
Total accuracy category prediction for prediction=="domestic"	193	60.62%	148	72.30%	30	73.33%
Total accuracy category prediction for prediction=="imported"	307	80.04%	352	83.24%	93	97.85%
"not specified" prediction as a predictor of "imported"	97	82.47%	119	86.47%		
Total accuracy country prediction	500	48.60%	500	48.80%	112	72.32%
Total accuracy country prediction (excluding low confidence)	403	60.30%	381	64.04%		
Total accuracy country prediction for prediction=="usa"	193	60.62%	149	71.81%		
Total accuracy country prediction for prediction=="canada"	39	82.05%	43	97.67%	18	88.90%
Total accuracy country prediction for prediction=="mexico"	20	100%	16	100%	11	100%
Total accuracy country prediction for prediction=="china"	77	55.84%	87	52.87%	35	60%

-This model is able to accurately detect imported/domestic in a large sample, about 80% of the time.

-For country predictions, it performs well for Mexico and Canada, but not so well for China (overlap with US products)

Some conclusions on AI use for import prices:

- A product name and URL are sufficient for generating a good prediction.
- Online search capabilities significantly enhance AI accuracy.
- Modern search models (e.g., Perplexity) can determine whether a product is domestic or imported with ~80% accuracy.
- Predicting the specific country of origin is more challenging, but these models are continously improving—the interactive ChatGPT can already reach ~70% accuracy.
- AI can also help with:
  - Data cleaning, such as standardizing package sizes into common units.
  - ICP classification at the item level.