SENTIMENT AND UNCERTAINTY INDICATORS USING ARTIFICIAL INTELLIGENCE

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OUTLINE

- 1. Introduction
- 2. Constructed Indicators
- 3. Effect on Forecast Errors
- 4. Conclusion

INTRODUCTION

- The usual methodology for calculating sentiment and uncertainty indicators is based on counting words, in two stages
 - 1. Selection of relevant news articles: using a dictionary of words that define a topic
 - 2. Quantification: using dictionaries of positive/negative terms, or terms that capture uncertainty
- · An LLM model could improve both the selection and the quantification steps
 - Problem: if the database is very big, asking an LLM about every news piece is not feasible
- But we can use **AI techniques** to improve in both steps:
 - 1. Selection: Retrieval Augmented Generation (RAG) technique and embedding models
 - 2. Quantification: Using GPT-4o-mini to quantify sentiment and uncertainty in each article
- Finally, we estimate how uncertainty indicators affect GDP forecast errors

STEP 1: SELECTION

- **Retrieval Augmented Generation**: a technique in NLP that combines two powerful components:
 - 1. Retrieval: Finding relevant documents or information from a large knowledge base
 - 2. **Generation**: Using a language model (like GPT) to generate an answer based on the retrieved information
- The source retrieval part is done through semantic search, using an **embedding model**
 - · A text embedding model is a function that transforms text into numbers
 - It projects news articles and economic topic definitions into a multidimensional space (e.g. 4096 dimensions)
 - · Each article is then classified into a topic based on cosine similarity

STEP 1: SELECTION

- Which embedding model performs best for our task? (Identifying news articles about specific economic topics in a Spanish-language database)
- We compare several embedding models using a random sample of 443 manually classified news articles and build an index to measure their relative performance



STEP 1: SELECTION

- Embeddings model selected: **multilingual-e5-large**: Strong performance; Free to use; Small (560M parameters); Fast (9 days to process the full >4M articles of the 2000-2025 database)
- Topics to be used in our sentiment and uncertainty indicators:
 - 1. Geopolitical tensions
 - 2. International trade and tariffs
 - 3. Exports markets and external demand
 - 4. Financial markets
 - 5. Prices of energy and other raw materials
 - 6. Inflation, prices and markups
 - 7. Wages and collective bargaining
 - 8. Fiscal policy and sustainability of public finances
 - 9. Housing market
 - 10. Confidence of agents and internal demand

STEP 2: QUANTIFICATION

- Once the relevant news articles have been selected...
 - 130.000 for each of the 10 topics (on average, 100 articles per week)
- We ask GPT-4o-mini to quantify the level of sentiment and uncertainty in each article
- · The prompt is long and detailed
 - It includes a step to verify that the article is relevant to the assigned topic
 - It contains ten examples (different for each topic) of headlines and the value of sentiment and uncertainty that we would assign to them
- For each topic and month, we calculate the average sentiment and uncertainty scores across all relevant articles



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UNCERTAINTY AND SENTIMENT INDICATORS











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UNCERTAINTY AND FORECAST ERROR

How does uncertainty affect GDP forecast error? $FE_t = \alpha + \beta U_t + \Gamma X + \varepsilon_t$



	1 quarter ahead GDP forecast error			
	(1)	(2)	(3)	
Uncertainty	0.050***	0.040*	0.039*	
	(0.018)	(0.022)	(0.021)	
dummy 2020g1	3.138***	3.113***	3.229***	
	(0.021)	(0.053)	(0.066)	
forecast error(t-1)		0.078	0.205	
		(0.116)	(0.140)	
gdp growth			0.028	
			(0.019)	
Constant	0.143***	0.130***	0.094***	
	(0.020)	(0.024)	(0.027)	
R-squared	0.778	0.783	0.805	
Observations	84	83	83	

EFFECT ON FORECAST ERROR

Which measures contribute the most? We analyze the first two principal components (74% of total variance)

- → PC 1: reflects mainly internal factors (Spanish economy)
- \rightarrow PC 2: captures mainly external influences

Variable	PC 1	PC 2
Geopolitics	0.23	0.57
International trade	0.52	0.80
Global demand	0.83	0.32
Financial markets	0.85	-0.21
Energy prices	0.66	-0.34
Inflation, markups	0.94	0.13
Wages	0.73	-0.48
Fiscal policy	0.75	0.15
Housing market	0.83	-0.41
Confidence, demand	0.94	0.04



	1 quarter ahead GDP forecast error			
	(1)	(2)	(3)	
PC 1	0.014 (0.009)		0.016 * (0.009)	
PC 2		0.028 ** (0.013)	0.031 ** (0.013)	
Constant	0.131*** (0.025)	0.132*** (0.025)	0.137*** (0.024)	
Controls	YES	YES	YES	
R-squared	0.780	0.782	0.790	
Observations	83	83	83	

FORECAST ERROR AT HIGHER HORIZONS

	FE(1)	FE(2)	FE(3)	FE(4)
PC1	0.019**	0.075**	0.108**	0.074
PC2	(0.008) 0.033 *	(0.038) 0.232 ***	(0.045) 0.315 ***	(0.069) 0.299 **
	(0.018)	(0.079)	(0.094)	(0.144)
Constant	0.144***	0.541***	0.890***	1.218***
	(0.021)	(0.095)	(0.113)	(0.175)
Dummy 2020Q2	YES	YES	YES	YES
R ²	0.795	0.524	0.858	0.742
N	77	77	77	77
	FE(5)	FE(6)	FE(7)	FE(8)
PC1	FE(5) 0.091	FE(6) 0.015	FE(7) -0.058	FE(8) -0.147
PC1	FE(5) 0.091 (0.085)	FE(6) 0.015 (0.105)	FE(7) -0.058 (0.117)	FE(8) -0.147 (0.130)
PC1 PC2	FE(5) 0.091 (0.085) 0.371**	FE(6) 0.015 (0.105) 0.316	FE(7) -0.058 (0.117) 0.271	FE(8) -0.147 (0.130) 0.143
PC1 PC2	FE(5) 0.091 (0.085) 0.371** (0.177) 1.670***	FE(6) 0.015 (0.105) 0.316 (0.217) 2.022***	FE(7) -0.058 (0.117) 0.271 (0.242) 2.416***	FE(8) -0.147 (0.130) 0.143 (0.268) 2.789***
PC1 PC2 Constant	FE(5) 0.091 (0.085) 0.371** (0.177) 1.670*** (0.215)	FE(6) 0.015 (0.105) 0.316 (0.217) 2.032*** (0.264)	FE(7) -0.058 (0.117) 0.271 (0.242) 2.416*** (0.294)	FE(8) -0.147 (0.130) 0.143 (0.268) 2.788*** (0.326)
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PC1 PC2 Constant Dummy 2020Q2 R ²	FE(5) 0.091 (0.085) 0.371** (0.177) 1.670*** (0.215) YES 0.644	FE(6) 0.015 (0.105) 0.316 (0.217) 2.032*** (0.264) YES 0.544	FE(7) -0.058 (0.117) 0.271 (0.242) 2.416*** (0.294) YES 0.486	FE(8) -0.147 (0.130) 0.143 (0.268) 2.788*** (0.326) YES 0.438



• 2006Q4: Low PC1, Low PC2 2012Q4: High PC1, Low PC2

• 2022Q4: High PC1, High PC2 2024Q4: Low PC1, High PC2



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CONCLUSION

- We apply recent AI techniques to construct uncertainty and sentiment indicators for the Spanish economy
- Using text embedding models, we classify >4 million news pieces into 10 different topics, using ChatGPT models we quantify their uncertainty and sentiment measures
- The constructed uncertainty indicators correlate strongly with GDP forecast errors, with international uncertainty showing a particularly large impact
- Next steps:
 - We can use the indicators for different topics to generate risk scenarios, e.g., to accompany our forecasts, or for stress testing
 - · Analyze the effect of different uncertainty measures on economic activities

Thank you for your attention!

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Sentiment

