Measuring Firm-Level Inflation Exposure: A Deep Learning Approach

Sudheer Chava[1] Wendi Du[1] Agam Shah[1] Linghang Zeng[2]

[1]Georgia Institute of Technology

[2]Babson College

AI & Machine Learning in Finance
August, 2022

Motivation

- Inflation affects asset prices (Fama and Schwert, 1977; Fama, 1981)
- Heterogeneity: Firms differ in their exposure to inflation
  - Firms differ in their ability to pass through cost pressure to consumers

Motivation

- Inflation affects asset prices (Fama and Schwert, 1977; Fama, 1981)
- Heterogeneity: Firms differ in their exposure to inflation
  - Firms differ in their ability to pass through cost pressure to consumers
- This paper:
  - Develop a novel text-based measure of firm-level inflation exposure
  - Study its implication for firm's stock price

This Study

Challenge: Measuring firm-level inflation exposure (cost pressure)

- Individual firm's input prices are not directly observable

Empirical method: Deep learning + firms' earnings conference calls
$\longrightarrow$ identify discussions on price changes

- Managers have first-hand information about prices (input & output prices)
- Analyze earnings call transcripts at the sentence level (increase vs. decrease, input vs. output)

Inflation exposure: #InputUp - #InputDown

Main Findings

- Aggregate inflation exposure strongly correlates with PPI (0.775)
- Inflation exposure leads to negative stock price reaction to earnings calls
    - Pricing power attenuates the negative reaction
    - Inflation exposure predicts higher cost of goods sold
- High-exposure firms perform worse on CPI release days, particularly on high-inflation & positive-shock days

How to Identify Price-Change Discussion?

- CEO of Sanderson Farms (SAFM) in 2021 Q2 earnings call

> Sanderson Farms operated very well during the second quarter of fiscal 2021 in all areas of our business. Improved poultry markets more than offset feed grain costs that were significantly higher compared to last year's record fiscal quarter, resulting in increased operating margins... In addition to improved domestic demand for chicken, export demand also improved during the quarter as a result of higher crude oil prices... Prices paid for corn and soybean meal increased significantly during the quarter compared to last year... We have priced all of our soy meal basis through October and most of our corn basis through September.

How to Identify Price-Change Discussion?

- Challenges:
  - Diverse vocabularies, not certain terminologies
    - $\longrightarrow X$ Dictionary method
  - Flexible syntactic patterns and various lengths
    - $\longrightarrow X$ Rule-based model, like two words within a fixed number of words
  - Harder when asking input- or output-related

How to Identify Price-Change Discussion?

- Challenges:
  - Diverse vocabularies, not certain terminologies
    - $\longrightarrow$ X Dictionary method
  - Flexible syntactic patterns and various lengths
    - $\longrightarrow$ X Rule-based model, like two words within a fixed number of words
  - Harder when asking input- or output-related
- Strategy: Identify price change with a state-of-the-art deep learning model
  - Sentence-level classification of price change
  - Direction $\Longrightarrow$ Up or Down?
  - Source $\Longrightarrow$ Input or Output?

High-Quality Price-Change Training Data

- Step 1: Sample Selection
  - **Intuition:** pick the ones with the most potentially price-change contents
  - **Strategy:** Count frequency of target words
  - Top 5 transcripts $\times$ Fama-French 12 Industries (no Fin. and Util.) in 2021H1

High-Quality Price-Change Training Data

- Step 2: Human Labeling
  - Separate each transcript into sentences
  - Labeling each sentence with 3 questions without using the context

Whether containing price-change related information?

Which direction of price change (up or down)?

Input- or output-related?

Table: Number of Sentences in Labeled Training Sample

	Target Words	No Target Words	Sum
Price Change	1,280 (95.88%)	55 (4.12%)	1,335 (100%)
No Price Change	3,430 (12.43%)	24,167 (87.57%)	27,597 (100%)
Total			28,932

- Target words are useful, but are not sufficient

Model Training & Labeling Sentences

Model Training

- Horse-race: BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), FinBERT (Araci, 2019)
- RoBERTa achieves the best performance with 90.44% test accuracy
- $\Longrightarrow$ Use RoBERTa to train and generate measures

Labeling Sentences

- RoBERTa makes predictions on earnings call data during 2007-2021
- Construct inflation exposure measure at firm level

Define Inflation Exposure

- For earnings call transcript of firm i at time t:

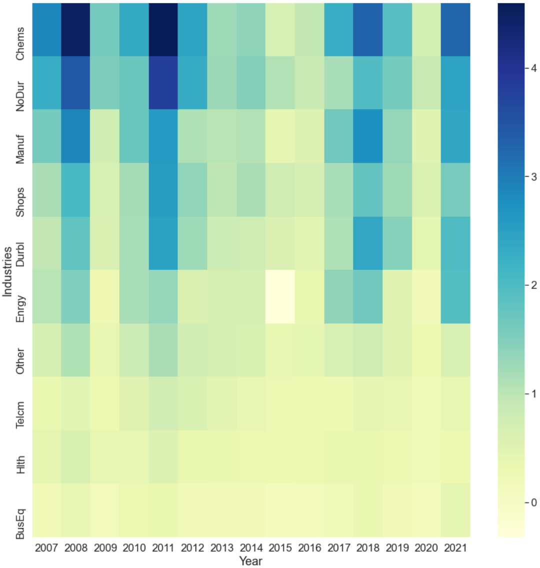
$$InflationExp_{i,t} = \frac{\#InputUp_{i,t} - \#InputDown_{i,t}}{\#SentencesinTranscript_{i,t}}$$

Data

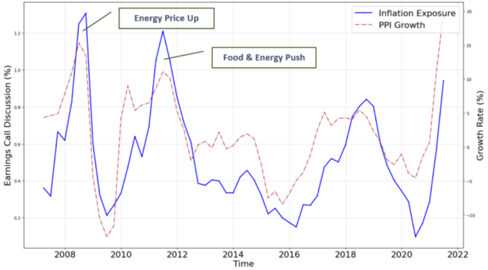
- Seeking Alpha (2007-2021):
  - Earnings conference calls of U.S. public firms
  - Textual transcripts of 102,112 earnings call
- Compustat, IBES, and CRSP: firm-level financial data

Textual Inflation Exposure by Industry × Year

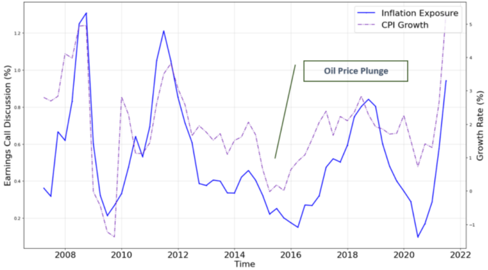
- Chemical, Nondurables, Manufacturing > Healthcare, Business Equipment



Textual Inflation Exposure & Official Inflation Measures



Panel A: PPI Growth Rate and Textual Inflation Exposure



Panel B: CPI Growth Rate and Textual Inflation Exposure

Summary Statistics

- Average number of sentences with price-change information is 5.561 for one earnings call
- Price-up discussion is nearly three times more than price-down discussion

	Mean	Median	Std. Dev.
#InputUp	2.779	1.000	4.985
#InputDown	0.605	0.000	1.531
InflationExp (Not Std %)	0.519	0.000	1.019
InflationExp (Std)	-0.000	-0.509	1.000

How Would Investors React the Inflation Exposure Measure?

- If the measure does not capture additional useful information on top of fundamentals $\longrightarrow$ No abnormal stock reaction
- If it does capture firm's true inflation exposure $\longrightarrow$ Price goes down if firms cannot pass through cost pressure to consumers

Empirical Specification

- Our baseline empirical specification is given below:

$$Y_{i,f,t} = \alpha + \beta InflationExp_{i,f,t} + Controls_{i,f,t} + \delta_{f,t} + \phi_i + \epsilon_{i,f,t}$$

  - $Y_{i,f,t}$: the stock market's response to the earnings conference call of firm i (operating in industry f) at time t
  - $Controls_{i,t}$: Vector of firm-level time-varying observable characteristics, particularly firm's performance
  - ϕ_i: Firm FE $\rightarrow$ Firm-specific, time-invariant characteristics
  - $\delta_{f,t}$: Industry $\times$ Time FE $\rightarrow$ Time-varying trends within industries
  - Double cluster standard errors at the firm and year-quarter levels

Immediate Market Reaction to High Inflation Exposure

Dep: CAR[−1,+1] (%)	(1)	(2)	(3)	(4)
InflationExp	-0.212***	-0.342***	-0.322***	-0.311***
	(-3.43)	(-4.88)	(-5.41)	(-5.87)
Size	-0.102***	-2.061***	-1.867***	-2.019***
	(-3.49)	(-15.36)	(-13.99)	(-16.59)
MTB	-0.194***	-0.177***	-0.194***	-0.167***
	(-3.86)	(-2.78)	(-3.32)	(-2.92)
Earnings surprise (%)	1.281***	1.303***	1.291***	1.291***
	(18.55)	(19.07)	(18.36)	(18.62)
PreEvent Return	-28.287	-49.545**	-53.035***	-62.918***
	(-1.30)	(-2.46)	(-3.58)	(-4.17)
Uncertainty	1.259***	0.910***	0.621***	0.647***
	(6.91)	(4.14)	(3.23)	(3.43)
SentimentOverall	2.374***	3.613***	3.992***	4.059***
	(22.61)	(18.16)	(27.09)	(27.14)
Observations	83,327	83,327	83,327	83,327
Adjusted R-squared	0.062	0.099	0.105	0.109
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

- One standard deviation ↑ of inflation exposure ⟶ 31.1 bps ↓ immediate price response

How Long is This Information Relevant?

	(1)	(2)	(3)
Depvar (%):	CAR[+2,+30]	CAR[+2,+60]	CAR[+2,+90]
InflationExp	-0.139	-0.199	-0.484***
	(-1.45)	(-1.49)	(-3.36)
Observations	83,326	83,326	83,326
Adjusted R-squared	0.130	0.169	0.208
Controls	✓	✓	✓
Firm FE	✓	✓	✓
FF12 × YearQtr FE	✓	✓	✓

- Negative long-run drift after the earnings conference call
- Investors do not fully price in the inflation exposure immediately

The Source $\times$ Direction of Price Change

Depvar:	*CAR[−1,+1] (%)*			
	(1)	(2)	(3)	(4)
InputUp	-0.518***	-0.558***	-0.553***	-0.536***
	(-7.66)	(-7.19)	(-8.22)	(-8.97)
InputDown	0.303***	0.186***	0.153**	0.146**
	(4.66)	(2.78)	(2.16)	(2.26)
OutputUp	0.382***	0.221***	0.244***	0.242***
	(6.02)	(3.34)	(3.79)	(3.78)
OutputDown	-0.215***	-0.258***	-0.249***	-0.267***
	(-3.72)	(-3.67)	(-3.69)	(-4.15)
Observations	83,327	83,327	83,327	83,327
Adjusted R-squared	0.063	0.099	0.105	0.110
Controls	✓	✓	✓	✓
Firm FE		✓	✓	✓
YearQtr FE			✓	
FF12 × YearQtr FE				✓

- Negative stock price reaction to discussion of input price increase and output price down
- Investors react positively to the discussion of decreasing input and increasing output price

How about Firms with Pricing Power?

- Textual pricing power measure (PP):

$$\frac{\#OutputUp}{\#InputUp + 1}$$

- Dummy variable $HighPP$ equals to one if a firm is above the median, otherwise 0

Depvar: CAR$[-1,+1]$ (%)	(1)	(2)	(3)
InflationExp	-0.553***	-0.635***	-0.631***
	(-6.69)	(-8.86)	(-9.33)
HighPP	0.432**	0.221**	0.182*
	(2.35)	(2.10)	(1.83)
InflationExp × HighPP	0.265***	0.396***	0.412***
	(3.03)	(5.71)	(6.26)
Observations	83,327	83,327	83,327
Adjusted R-squared	0.099	0.105	0.109
Controls	✓	✓	✓
Firm FE	✓	✓	✓
YearQtr FE		✓	
FF12 × YearQtr FE			✓

Why do Investors React Negatively?

	(1)	(2)	(3)
Depvar:	COGS	Materials	Wages
InflationExp	0.022***	0.018***	0.003**
	(7.37)	(6.66)	(2.51)
Observations	28,445	28,432	28,446
Adjusted R-squared	0.908	0.880	0.843
Firm FE	✓	✓	✓
FF12 $\times$ Year FE	✓	✓	✓

- The analysis is conducted at firm-year level
- Firms with $\uparrow$ inflation exposure have $\uparrow$ cost of goods sold, particularly material costs

Event Studies on CPI Releases

- High-exposure firms may have different price actions to CPI releases from low-exposure firms, particularly when inflation is more salient
- Event panel regressions

$$Y_{i,t} = \alpha + \beta InflationExp_{i,t} + Controls_{i,t} + \theta_t + \epsilon_{i,t}$$

  - $Y_{i,t}$: CAR around CPI releases for firm i at time t
  - θ_t: Event FE

Event Studies on CPI Releases

	(1)	(2)	(3)	(4)
Depvar:	CAR[0,0]	CAR[0,5]	CAR[0,5] Salient	CAR[0,5] Non-salient
InflationExp	-0.039***	-0.061	-0.292*	-0.022
	(-2.91)	(-1.42)	(-2.06)	(-0.54)
Observations	182,387	182,387	17,884	164,503
Adjusted R-squared	0.036	0.035	0.055	0.032
Controls	✓	✓	✓	✓
Event FE	✓	✓	✓	✓

- Salient days: Positive inflation shock on high inflation (CPI $>$ 2%) days
- Alternative specification using triple interactions shows similar results

Conclusion

- Develop a novel text-based firm-level inflation exposure using deep learning models
    - The measure and methodology can be useful for other finance settings
- Shed light on the linkage between inflation exposure and asset prices at the firm level
    - Earning announcement days & CPI release days
- Strong correlation between textual inflation measure and inflation index