

Measuring Conflict Inflation[†]

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PRELIMINARY

Abstract

This paper tests the [Rowthorn \(1977\)](#) conjecture that inflation is driven by conflict or disagreement over relative prices with a novel news-based measure of price conflict over 1860-2023. The price conflict index (PCI) varies significantly over time with persistent spikes around the McKinley tariffs, during the Great Depression, and before the Volcker disinflation. Variation in the PCI stems from industrial actions, tax rate changes, and political pressure on the Fed. The PCI robustly predicts changes in the actual prices of goods and services, real GDP growth, real wages, unemployment, and stock returns. Topical analysis reveals that disagreements on wages and between employees and employers are particularly important. The effects on state-level inflation are driven by tradable rather than non-tradable goods, implying national price setting. Overall, this paper provides empirical support for the conflict-based theory of price fluctuations.

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1 Introduction

The mechanism behind inflation fluctuations is central to macroeconomics. In recent years, [Lorenzoni and Werning \(2023a\)](#) have initiated a resurgence of academic interest in the [Rowthorn \(1977\)](#) conjecture that general inflation is driven by aspirational conflict—or disagreement—on relative prices by various economic stakeholders. Inflation persistence has also been linked to the canonical wage-price spiral ([Blanchard, 1986](#); [Lorenzoni and Werning, 2023b](#)). Classic and recent contributions to the distributive conflict view of inflation have been predominantly theoretical. In the present paper, we provide the first empirical test of the theory using state-of-the-art methods and data that spans 160 years. We provide empirical support for the conflict theory of price fluctuations and make all the newly constructed data publically available.

We obtain the digitized archive of The New York Times over 1860-2023. Our data includes the universe of article headlines and (for the vast majority) leading paragraphs. With around 60,000 articles per year on average, the data features close to 10 million entries, each around 100 words in length. To analyze this voluminous textual dataset, we leverage tools from Generative Artificial Intelligence (GenAI), namely OpenAI’s flagship Large Language Model (LLM) GPT-4o. We feed every article into a chat instance of the LLM via its Application Programming Interface (API) and ask it to identify instances of price conflict based on a carefully constructed prompt. Our multi-step prompt engineering approach, which trades off over- and under-fitting the models, has yielded a baseline prompt which proves to be remarkably robust to various alterations. Equipped with the baseline prompt, our algorithm produces a binary outcome for every article in every quarter that takes the value of unity if a price or wage conflict was detected and zero otherwise. We then aggregate this measure and build our baseline Price Conflict Index (PCI) that spans 660 quarters.

We perform an array of validation tests to ensure that our procedure delivers a measure that is economically meaningful. First, we validated our quarterly index of price conflict with actual, realized inflation data. Our index exhibits a very high contemporaneous correlation with the realized U.S. GDP implicit price deflator changes as well as real wage changes. Second, we have experimented with various configurations of model temperature (“creativity” of the LLM). Third, we have worked across numerous vintages of OpenAI’s LLMs and arrived at an optimal setup that efficiently combines accuracy and financial cost. Fourth, our approach allows for filtering out words such as “inflation” or “deflation”. We remove all articles that include either of these two words to ensure that the model captures the right context without simply counting keywords. Fourth, to ensure

that we are not erroneously capturing instances of military, as opposed to price, conflict, we also post-filter out any article that includes the words “military” or “war”. Fifth, it is well known that GenAI models are probabilistic in nature. As a result, running the same prompt on the same model vintage can at times produce materially different outcomes. This further implies that the issue of Type-I or Type-II errors can be of first order. To deal with the threat of counting false positives or rejecting false negatives, we run the same baseline prompt five times and only retain cases that register a “yes” response every single time. Sixth, prompts can be pre-initiated with persona shaping statements such as “You are a professor of economic history”. These so-called system prompts ask the model to focus on a subset of its knowledge before proceeding with a more specific query. This can potentially increase accuracy of text reading. We experiment with task prompts that do or do not include system prompts. Reassuringly, none of the above robustness checks alter any of our measures or results.

In addition to producing aggregate indices of price conflict, we also create several novel topical measures. First, we decompose price conflict by stakeholder type. Analyzing article contents in further detail using the LLM, we construct indices of disagreement between employees vs employers, consumers vs companies, domestic firms vs foreign firms, domestic firms among themselves, and any stakeholder vs the government. Second, we decompose the baseline price conflict index by price type and construct indices of disagreement on wages, prices of goods and services, real estate prices, interest rates, energy prices, tariffs, and taxes.

What are the drivers of disagreement about prices and wages? To understand the origins of price conflict, we try to explain our baseline indicators with an array of potential explanatory factors including the monetary base from [Jordà et al. \(2016\)](#), the average labor income tax rate, house prices, geopolitical risk from [Caldara and Iacoviello \(2022\)](#), the short-term interest rate, fiscal revenues, fiscal expenditures, the history of worker strikes over 1881-1981, inter-country wars across the world, oil prices, the index of tariff intensity from [Irwin \(2010\)](#), and a new index of political pressure on the Federal Reserve from [Drechsel \(2024\)](#). We find that time-series variation in the PCI stems mostly from industrial actions, tax rate changes, and political pressure on the Fed.

What are the implications of price conflict for the macroeconomy? Based on local projection estimates on 130 years of quarterly U.S. data, we document that price conflict changes are associated with large and statistically significant contemporaneous and dynamic effects on realized changes of prices of goods and services. That is, if conflict is high then the *absolute value* of price changes is high. We also find that price conflict changes are associated with a future decline in real GDP growth, stock returns, real wages, and an

increase in unemployment.

The divergence in the responses of quantities and prices following a price conflict shock suggests that we are likely capturing a supply-side disturbance. Suppose that price conflict indeed behaves like a negative supply shock: it reduces the supply of inputs (e.g. labor), leading to higher unemployment and lower aggregate production—which is what we find. Excess demand pushes prices up while real wages fall—which is also what we document. General inflation may be either positive or negative, depending on the relative force of the real wage demand and price inflation channels. This is also Proposition 3 in [Lorenzoni and Werning \(2023b\)](#): price and wage inflation may have the opposite sign if quantities are at their “natural” level. For our purposes, the direction of the inflation response does not matter as long as prices move at all. Importantly, our conflict measure is inherently sign-invariant. A positive innovation in the PCI implies that conflict is up, but we do not necessarily know whether it is due to e.g. the employer or the employee-led aspirations. Moreover, the origin of a conflict “shock” may come from different sources in different years. Thus, whether some positive change in the PCI is inherently inflationary or deflationary is ex-ante ambiguous. However, what is clear is that any shock causes prices to change in *some* direction. Thus, a refined restatement of the Rowthorn conjecture could be the following: conflict is price fluctuations.

Finally, to understand whether our conflict measure has homogeneous effects over space, we estimate the regional impacts of changes in the PCI on regional inflation. Using state-level data on non-tradable and tradable sector CPI inflation from [Hazell et al. \(2021\)](#), we document rich heterogeneity in the regional effects of conflict shocks. Understanding the drivers of this heterogeneity is a fruitful avenue for future research. Interestingly, the effects are mostly concentrated in tradable-good inflation, while the impacts on non-tradable inflation are more muted. This finding is in line with the principle of national price setting because prices of tradable goods are likely to be set by firms uniformly across space with regional characteristics playing a smaller role.

Literature Our paper is most clearly related to the literature that links inflation to disagreement or conflict among stakeholders over relative prices. Building on the canonical [Rowthorn \(1977\)](#) conjecture, [Lorenzoni and Werning \(2023a,b\)](#) have revived the interest in this research question by providing a general theoretical treatment. Other important recent contributions include, among others, [Wildauer et al. \(2023\)](#), [Beaudry et al. \(2023\)](#), [van der Ploeg and Willems \(2024\)](#), [Guerreiro et al. \(2024\)](#), and [Afrouzi et al. \(2024\)](#). The challenge for this literature is that it is almost entirely theoretical. The contribution of my paper is to provide first-pass empirical support and validation to this line of work. The

measures produced in this paper can also facilitate calibration and parameterization of existing theoretical frameworks.

This paper is also contributing to the literature on empirical macro-history (Jordà et al., 2016; Knoll et al., 2017; Ramey and Zubairy, 2018; Jordà et al., 2019; Kelly et al., 2021; Caldara and Iacoviello, 2022; Gabriel, 2023; Amaral et al., 2024). Several studies have focused specifically on the origin of inflation through the prism of long historical data. Caldara et al. (2024a) introduce a novel index of shortages (of materials, labor, energy, etc) and show that shortages can generate persistent inflationary effects. Caldara et al. (2024b) show that that heightened geopolitical risk foreshadows inflationary pressures.

Finally, this paper contributes to the literature that leverages text as data (Loughran and McDonald, 2016; Gentzkow et al., 2019; Ash and Hansen, 2023). Our particular emphasis is on a novel application of advanced LLMs and GenAI tools. GenAI, in particular, has proven to be highly effective in increasing workflow efficiency for researchers and individuals in various contexts, offering substantial productivity benefits when used to automate micro-tasks (Korinek, 2023; Ash et al., 2024). For example, even without model fine-tuning, off-the-shelf retail GenAI models have been shown to predict stock price movements (Lopez-Lira and Tang, 2024). Fetzer et al. (2024) use AI to build a novel measure of input-output production networks across many years and countries. Geiecke and Jaravel (2024) and Hansen et al. (2024) use GenAI and LLMs to create synthetic personas to conduct qualitative interviews at scale and to simulate professional economic forecasters, respectively, thus providing low-cost alternatives to traditional methods with no obvious sacrifice in accuracy.

Our contribution relative to the above literature strands is to leverage state-of-the-art advances in LLMs and GenAI to provide new measurements and validation for the conflict theory of price fluctuations.

2 Theoretical Background

We first provide a simple theoretical background for our empirical analysis. Following Lorenzoni and Werning (2023a), we can formalize inflation as follows:

$$\pi_t = \pi_t^w = \lambda(g_t - f_t) \quad (1)$$

where g_t and f_t are the aspirations of workers and firms, respectively, π_t is price inflation, π_t^w is wage inflation, and λ is a constant that is a function of deep parameters.

Now take the absolute value of both sides of (1):

$$\tilde{\pi}_t = \tilde{\lambda} C_t \quad (2)$$

where $\tilde{\pi}_t \equiv |\pi_t|$, $C_t \equiv |g_t - f_t|$, and $\tilde{\lambda} \equiv |\lambda|$. Similarly for wage inflation.

The measure C_t is a general form of directionless conflict or disagreement over relative prices. Any deviation of C_t from zero implies price fluctuations of some form: either positive or negative, i.e. inflationary or deflationary. Clearly, if there is no conflict ($C_t = 0$), then there are no price fluctuations and $\tilde{\pi}_t = 0$.

The objective of this paper can now be seen more clearly as two-fold. First, we want to provide a novel, accurate measurement of C_t . Second, we want to test whether the relationship in (2) holds statistically in U.S. time-series data over the past 160 years.

3 Measuring Price Conflict with GenAI

In this section we discuss the data and the approach to measuring price conflict.

3.1 The New York Times Digital Archive

Our primary news text database is the New York Times (NYT) digital article archive. The compilation can be obtained from archive.nytimes.com. The dataset spans 1853-present and we have obtained digital access to the headline and (where available) leading paragraph of every article from every year. We discard the early years due to lower quality and focus on the 1860-2023 period throughout the rest of the analysis. The approach of using NYT as a primary news source has at least two advantages. First, the NYT covers major national, domestic news. Our empirical analysis will use aggregate, nationwide macro-historical data. Thus, a national newspaper fits our empirical strategy because any uncovered incidents of price conflict are more likely to matter for the aggregate economy. Second, this newspaper does not exclusively cover economic news. As a result, any incidence of price conflict is likely to be salient enough for the general-interest outlet to cover it.

3.2 Why Generative AI tools?

What are the reasons behind the choice to leverage LLMs and GenAI to build an index of price conflict? There are two simple answers: time and money. First, the speed of processing of huge amounts of textual data is incomparably lower for the machine

than man. Let us consider some simple, rough estimates. Our dataset comprises, on average, 60,000 articles per year. For each article, we have information on the publication day, the headline, and the leading paragraph. How long would it take for a human to give judgement on whether a particular article and lead paragraph combination exhibit evidence of price disagreement? Suppose the answer is 3 minutes. Then, to process 160 years of data with 60K articles (some years have more) per year would require 55 years of uninterrupted work for a single person. It takes our model 1 day.

Second, the financial cost of human labor to finish the above task would be astronomical — around \$14.4 million under the assumption of a \$30 per hour wage rate. Running one prompt on the full sample cost us under \$300 on OpenAI’s flagship GPT-4o-mini model. The enormous savings have enabled us to run numerous additional tests and robustness exercises that would have been impossible otherwise. As such, ours is a clear-cut example of how “micro-task automation” can facilitate economic research (Korinek, 2023). However, there is a risk that AI yields negative social value through a manifestation of the Grossman and Stiglitz (1980) paradox (Acemoglu, 2024). Thus, active human involvement and audit of AI-produced outcomes is still paramount.

3.3 General Methodology

We leverage advances in machine learning and large language models (LLMs) to extract relevant contextualized information about price conflict from the NYT archive. Specifically, we employ the OpenAI’s flagship GPT-4o class of models via the OpenAI’s Application Programming Interface (API). The GPT-4o generation of models is among the most capable LLMs at the moment and also behind web tools such as the current ChatGPT. Yet, rather than accessing the web-interface, sending articles to the underlying model directly via parallelized API calls allows the LLM to read thousands of articles from the newspaper archive simultaneously.

3.4 Prompt Engineering

A critical element of our methodology is prompt construction. We have pre-selected a non-random sample of hundreds of articles across years that corresponded to famous incidents of distributive conflict such as large union strikes. As a placebo, we also collected a number of articles that relate to non-price conflict such as wars. We have iterated over the prompt with the goal of matching our own priors over the chosen articles most of the time. It turns out that three points are noteworthy. First, simpler and more direct prompts are more desirable. This observation is related to the classic over-fitting problem: there

is a clear trade-off between providing necessary information for learning and persona shaping and over-fitting the model. Second, the model performs remarkably well with clear-cut situations, i.e. when there are obvious mentions of price conflict such as tariffs or union strikes.

Third, and most importantly, the model often performs as well if not better than humans on cases that are objectively unclear. To illustrate what is meant by this, we make available the article headlines that were used in prompt generation as well as our own and model’s justifications. Readers are welcome to read and classify those articles as conflict and non-conflict based on their own judgment. Overall, we argue that our model can do as well if not better than a skilled human in all cases that are clear-cut and in the vast majority of the more dubious ones.

Our strategy consists of several separate steps to avoid overloading the models with too many tasks at the same time. First, we use what we refer to as a “baseline prompt” to detect those articles that discuss economic conflicts over prices and wages. Second, we analyze only the conflict articles again with a “topic prompt” to determine which precise conflict topic was discussed in them.

Baseline prompt Each prompt consists of two basic parts. A system part which assigns a persona to the LLM instance, and the main part which contains the article and the task. First, the system part reads: *“You are a professor of economic history at a top US research university. You study disagreement over prices or wages between stakeholders.”* This system prompt helps focus the model on the right thematic direction.

Second, the main part of the baseline prompt reads: *“Does the excerpt mention disagreement or conflict between stakeholders over prices or wages in the United States? If it does, please explain why in one sentence. If it does not or if the text contains insufficient information, please only reply with ‘No’.”* Interestingly, we validated by reading through examples classified by the model that the suggestion to explain its decision in one sentence seems to make the detection of conflicts more accurate and thought-through. We thus feed every article headline and leading paragraph into the model, initiate the same prompt, and store a binary answer: unity if conflict is detected (and explained why) and zero otherwise. As a result, for every year in the sample we obtain the count of detected conflict cases. The time series of this count is essentially our primary aggregate index. We use GPT-4o-mini to detect economic conflict articles with the baseline prompt because it is accurate, fast, and cost efficient. We later employ the costlier model GPT-4o and find no material differences from the baseline. For linguistic, non-mathematical tasks like ours, the two models generally produce indistinguishable results.

Topic prompt In order to categorize each conflict incident into price- or stakeholder-based groups, we focus on the set of articles that the model replied with unity to before. We use GPT-4o for the arguably more challenging task to group these conflicts into precise subcategories. In an additively-separable way, we ask the model to categorize articles with the following subsequent prompt: *“The excerpt possibly mentions disagreement or conflict between stakeholders over prices or wages in the United States. Which of the following categories fits best?”*

Motivated by existing theories on conflict inflation, we choose 7 price categories that are, verbatim: *“1. Disagreement over wages, 2. Disagreement over prices of goods or services, 3. Disagreement over real estate prices, 4. Disagreement over central bank interest rates, 5. Disagreement over energy prices, 6. Disagreement over tariffs, 7. Any other topic or insufficient information. Reply only with the associated number ‘1’, ‘2’, ‘3’, ‘4’, ‘5’, ‘6’, or ‘7’.”* Similarly, we have 6 stakeholder/agent categories that are, verbatim: *“1. Disagreement between employees or their unions and employers, 2. Disagreement between consumers and firms, 3. Disagreement between domestic firms, 4. Disagreement between domestic firms and foreign firms, 5. Disagreement between economic stakeholders and the government, 6. Any other topic or insufficient information. Reply only with the associated number ‘1’, ‘2’, ‘3’, ‘4’, ‘5’, or ‘6’.”*

3.5 Temperature Setting

A critical parameter for modern GenAI models is the so-called *temperature* setting. Increasing model temperature generally broadens its creativity and willingness to operate outside the box. For all of our baseline analyses above we had set temperature to 0, which is the global minimum option. Zero temperature forces the model to be as conservative in its reading of text as possible. As such, this generally leads to lower counts of price conflict cases. As a robustness check, we have also raised the temperature setting to 1, which is OpenAI’s default option in many situations. While this extension increases the count of conflict cases in most years by around 10-20%, the *cyclical* patterns and macroeconomic correlations do not change materially. In other words, we find that the temperature setting affects the level (average) but not the cycle of the price conflict measure.

3.6 Post-Filtering for Keywords

One concern is that our prompt detects articles which also contain the word “inflation” and records these as conflict. One can argue that the correlation of our index with headline inflation is not meaningful and occurs by construction. We therefore manually remove all instances where the model flagged an article and that article text had also contained

the words “inflation” or “deflation”. It turns out that none of our baseline results change quantitatively. In other words, an index computed based only on those conflict articles that do not mention the words “inflation” and “deflation” directly is almost identical to the baseline. We will return to this robustness test later in the paper.

In addition to the above, due to the phrasing of our research question, it is possible that LLMs mistake military or physical conflict for disagreement about prices. In other words, *conflict* is a sharp keyword that helps pointing the model in the desired direction. On the other hand, the same keyword obviously applies to many other, unrelated, circumstances. To address this concern, we remove all instances where the model flagged an article with price conflict and that article text had also contained the words “military” or “war”. Our measures and results do not change materially.

3.7 Advantages of LLMs over Word Counting

The keyword filtering step above highlights a crucial advantage of our LLM-based approach over the more traditional but simple computational linguistics tools. For example, it is a literature standard to employ word-counting tools in various economic and financial applications (Baker et al., 2016; Hassan et al., 2019). However, detecting price conflict is very nuanced and word-counting methods would likely significantly under-deliver in terms of identifying subtle contexts. Moreover, since we remove the words such as “inflation” and “deflation” from the final index, word-counting methods would fail to capture conflict-related articles unless those keywords appeared explicitly.

3.8 Robustness: The Economist Digital Archive

One could argue that external validity is an issue for our analysis since we only leverage The New York Times archive. As a robustness, we have also employed the historical archive from The Economist magazine, with the sample running from 1890 until 2020. Unfortunately, accessing the actual texts from The Economist is not possible, and only simple keyword counting tools are currently available. This corroborates why the NYT archive—coupled with advanced LLMs—is a much better approach. Nevertheless, it may still be useful to use alternative dataset, albeit the measurement tool is somewhat inferior. Thus, with the help of our LLM model, we construct a novel dictionary of some 70 words (unigrams) and two-word (bigrams) combinations that relate to conflict or disagreement on prices or wages.

4 The Price Conflict Index (PCI): 1860-2023

We now proceed with measuring and defining our baseline index of price conflict. Let $c_{i,t}$ be a binary indicator that takes the value of 1 if the article i in year t is identified by the LLM as containing discussions of price conflict. Our baseline, aggregate index of price conflict is defined as follows:

$$C_t = \frac{\sum_i^{N_t} c_{i,t}}{N_t} \quad (3)$$

where N_t is the number of articles in a given year. Our measures therefore take into account any trends in the number of articles over time.

Figure 1 plots our baseline quarterly Price Conflict Index (PCI) C_t . It shows the percentage of all NYT articles every quarter that contain a case of price or wage disagreement. The measure is highly dynamic, volatile, but not excessively noisy. It has several interesting local peaks such as the 1890s, 1940s, and 1970s—all episodes of significant price fluctuations such as high tariffs, the Depression or WWII, and the pre-Volcker inflation decade.

4.1 Conflict and Actual U.S. Price Changes

The main research question of our paper is whether disagreement about relative prices is associated with actual, realized price movements. To this end, we obtain the historical time-series of U.S. GDP implicit price deflator and wages from Ramey and Zubairy (2018) and Jordà et al. (2016). We use linear interpolation to obtain quarterly measures from the annual ones, whenever necessary. Specifically, we computed the *absolute value* of year-on-year changes in the quarterly GDP price deflator inflation. We will refer to this measure as $|\pi|_t$, henceforth, and to inflation as π_t . Thus, we are interested in capturing any price changes, and not simply positive price changes (inflation) as discussed earlier in Section 2. We will further refer to real wages as w_t .

Figure 2 plots the measures of price fluctuations, $|\pi|_t$, and real wages, w_t , along with C_t . We can notice a very strong contemporaneous correlation between $|\pi|_t$ with C_t . The pairwise correlation coefficient is 0.43 and statistically significant at the 1% level. Moreover, the correlation between w_t (in levels) with C_t is -0.57%. Figure 3 makes this connection even clearer with yearly scatterplots of C_t , π_t , w_t . From panel (a) we see that at low levels of C_t price changes of any sign are minimal. As C_t grows, there are more instances of years with either very positive or very negative realizations of π_t . In panel (b), we see clearly that C_t and w_t are strongly negatively associated. Thus, at first glance it appears that if

conflict is high then price fluctuations (of any sign) are high and real wages are low. We will establish this association more formally in the next sections.

Our index performs remarkably well in terms of tracking price fluctuations not only on average and in normal times but also during turbulent episodes. First, we observe noticeable spikes in the conflict and price measures around both World Wars, i.e. 1914-1918 and 1939-1945. As is well documented, military conflicts are inflationary and general price movements are likely to be associated with high price conflict. Second, the index increases right around the Great Depression (1929-1934). During those years, U.S. prices fell by an average of 7% nearly every year. Deflation is captured as an increase in the absolute value of price changes, which could also be correlated with heightened conflict and disagreement. Third, price conflict is high during the Great Inflation era of 1964-1982, which is generally explained as being due to excessive growth in the supply of money which, in turn, can come with conflict and wage-price spirals. Fourth, our index is fairly stable during the Great Moderation (1980s-2007) as the U.S. economy faced a reduced volatility of general economic cycle fluctuations. Finally, it is interesting that our index goes *down* during the recent post-Covid inflation episode that was seemingly predominantly due to food and energy prices (Bernanke and Blanchard, 2023). This potentially suggests that the threat of a spiral was not a concern as of 2023, which is also the conclusion in Lorenzoni and Werning (2023b).

4.2 Decomposing Price Conflict by Price and Stakeholder Type

We now proceed with the decomposition of our baseline index by price and stakeholder categories. We believe that this is a fruitful exercise for at least two broad reasons. First, the original work by Rowthorn (1977) claimed that aggregate surplus in the economy must be divided among the following major parties: the state, foreign suppliers, workers, and capitalists. Alternatively, the same division can be thought of in terms of unit prices: taxes, tariffs, wages, and goods prices or profits. To this end, our decomposition is important for theoretical reasons. Second, it would be useful to nail down the precise channels of the empirical impact of price shocks on the economy. The baseline aggregate index may be too broad and a more nuanced categorization is necessary to inspect the mechanism.

Figure 4 plots the decomposition of the baseline price conflict index into price topics. We discard the final, “other”, category as it mainly captures residual noise in the base index. We collect from the Figure at least four noteworthy observations. First, panels (a) and (b) resemble the baseline index the most. In other words, disagreement about wages and prices of goods and services drives most of the dynamic pattern of the baseline measure. Second, disagreement about interest rates notably spikes during the Paul Volcker

era. Third, disagreement about real estate prices is the highest around the Great Financial Crisis. Finally, while disagreement about tariffs is high only in the early decades of the sample during the McKinley tariff era, there is a noticeable spike around 2016-2020.

Figure 5 plots the five stakeholder-based topical measures. As before, we discard the “other” category. We see that panels (a) and (b) are most closely resembling the baseline index’s time variation. In other words, disagreements between employees and employees and (to a lesser extent) consumers and companies drive aggregate price conflict. Two further interesting observations are noteworthy. First, conflict between stakeholders and the government spikes during the 1970s-1980s—the period of high inflation and the subsequent Volcker dis-inflation. Second, disagreement between domestic firms is globally the highest during the 1890s which corresponds to a wave of union strikes as well as volatility in tariffs. Both observations are intuitive and act as additional validation checks to our decomposition exercise.

Figures 6 and 7 present the separately additive decompositions of the baseline index into price and agent types in the forms of stacked bars. For tractability, for each type we present annual-frequency data over 1860-2023 and quarterly-frequency data over 1950q1-2023q4.

4.3 Case Studies

In this section, we discuss several illustrative cases. Table 1 reports the following information. First, we provide the year, headline, and (if available) snippet of the first paragraph of a NYT article that we picked. Our choice was dictated by well-known incidents such as union strikes, and placebo events such as military conflicts. Third, we report our own judgment on whether an article contains evidence of price conflict. This is shown in the form of a binary indicator that takes the value of unity if the answer is yes and zero otherwise. Fourth and finally, we report the model’s judgement and justification.

We document three general results from the case study analysis. First, in 18 out of 20 cases there is complete alignment between our own (column “Humans”) and the model’s (column “Model”) judgements. One disagreement occurs with case “4”, which we classified as conflict due to the first paragraph mentioning a “steel strike”. However, the model seem to have concluded that there is not enough evidence to suggest that a price conflict occurred. What the article actually mentions is the following key sentence: “if there is no steel strike at midyear, steel demand and production would be off sharply”. Technically, no strike had occurred at the time of writing of that article and the statement was purely hypothetical/speculative. As such, this is a good example of an always inherent residual of disagreement in these article classifications also among trained humans.

Second, the model does remarkably well at identifying clear cases of price conflict. Consider case “5”. An article from 1922 reads: “Rioting breaks out in Railroad Strike . . . union and non-union men of western Maryland line fight in . . .”. The model thinks that this is evidence of a price conflict event and provides the following argument: “Yes, the excerpt mentions disagreement between stakeholders over wages in the United States, as the rioting between union and nonunion men during the railroad strike likely stemmed from disputes over wage levels.” Another interesting example is a hypothetical article “20” that reads “House buyers are unhappy with the level of interest rates on their mortgages after the recent interest rate hike of FED”. The model classifies this as conflict and justifies the decision with the following statement: “Yes, the excerpt mentions disagreement between house buyers and the Federal Reserve over the level of interest rates on mortgages, indicating a conflict over prices in the housing market.”

Third and finally, an interesting question to ask is whether it is possible to mislead the model with situations that relate to other types of conflict such as military or distributional (i.e. wealth or income inequality related). To this end, we also feed through the model some placebo cases. For example, case “3” reads: “The Return of Superpower Conflict . . . What’s different about this diplomatic drama with Russia”. Notice how although the article mentions the word “conflict” explicitly, the model immediately realizes that this statement has nothing to do with our prompt and returns a “No”. Another interesting example is case “9”, which is admittedly very tricky. The article reads “World inflation, as one of the causes of world advance in prices, is discussed in the current issue of The Americas, issued by the National City Bank of New York”. Notice that the article clearly discussed inflation. However, our prompt asks specifically about *conflict* inflation. Thus, the model cleverly decides to return a “No”.

Overall, we believe that the ability of our LLM instance to understand fairly non-trivial economic concepts and correctly identify incidents of price conflict is remarkable. What is perhaps even more impressive is its success at differentiating across flavors of conflict — e.g. military, inequality, prices — and making the right decision almost all of the time. Again, it is very hard to extrapolate from just 20 case studies to over a million of articles that the model will perform well on scale. To this end, we are also performing a large-scale human audit of thousands of articles.

4.4 Human Audit

We have initiated a large-scale audit of thousands of articles with the help of graduate students at the University of Oxford. Six students will individually and independently validate the LLM’s responses by auditing 500 articles each, with a total of 3,000 carefully

checked positive and negative recorded cases of conflict. Results will be available in the next revision of the paper by May, 2025.

5 The Determinants of Price Conflict

In this section we study the drivers of price conflict. To this end, we assemble an array of potential explanatory factors: the monetary base, the labor tax rate, house prices, geopolitical risk, political pressure on the Federal Reserve, the short-term interest rate, fiscal revenues, fiscal expenditures, labor union strikes, inter-state wars around the world, the tariff intensity index, and the oil price. We estimate linear regressions with one- and four-quarter-ahead baseline price conflict index as the dependent variable and the explanatory factors as independent variables. The former represent short-term and the latter more longer-term effects. All regressions are estimated with one regressor at a time.

Figure 8 reports the results in the form of point estimates and 68% and 90% confidence intervals. Each row represents a different explanatory factor. We find that three characteristics are strongly associated with greater incidence of price conflict and disagreement—labor income taxes, union strikes, and political pressure on the Fed. The tariffs index and geopolitical risk are borderline significant. The remaining variables do not seem to contain information to credibly predict movements in price conflict as their effects are statistically insignificant.

6 Macroeconomic Implications of Price Conflict

In this section we proceed with establishing dynamic effects of changes in the price conflict measures on the macroeconomy.

We begin by defining the main independent variable to be used in the rest of the Section. Noticeable autocorrelation of the index C_t complicates identification of price conflict changes on the economy. For our baseline analysis, we therefore do not focus on the *level* of conflict but, instead, construct and utilize price conflict *changes*— \tilde{C}_t —which we define as the first difference of the baseline index C_t . This isolates transitory time-series deviations of price conflict from the more persistent topics. In Section 6.3 we will define an alternative shock measure with an HP-filter. We will also show that our results do not change if we use the level of conflict as the independent variable.

6.1 Historical Macro Data

In order to control for standard macroeconomic variables in our empirical tests, we obtain historical macroeconomic and financial data from several publicly available sources. U.S. real GDP growth, GDP implicit price deflator, and the unemployment rate are from [Ramey and Zubairy \(2018\)](#). Since these time series end in 2016, we prolong them until 2022 with corresponding indices from the FRED database. We obtain the T-bill interest rate and returns on the S&P500 index from [Welch and Goyal \(2007\)](#). Nominal wages are obtained from [Jordà et al. \(2019\)](#). All variables have been de-measured, standardized, and intrapolated to the quarterly frequency if necessary.

6.2 Baseline Evidence from Local Projections

We proceed with estimating the dynamic effects of price conflict shocks on the macroeconomy. Our approach is essentially to take to the data the theoretical relationship in Equation (2). To this end, we run [Jordà \(2005\)](#)-style local projections. Following [Jorda and Taylor \(2025\)](#), we estimate the long difference specification:

$$Y_{t+h} - Y_{t-1} = \delta_h + \beta_h \tilde{C}_t + \gamma'_h \mathbf{X}_t + u_{t+h} \quad (4)$$

where δ_h is a constant, Y_t is an outcome variable in levels, such as prices or real wages, and \tilde{C}_t is the change in the PCI. \mathbf{X}_t is a vector of controls that always includes the lagged dependent and treatment variables and, additionally, real GDP growth, stock returns, the short-term interest rate, and the unemployment rate. u_{t+h} is the error term. We refer to β_h as the impulse response function. To mitigate serial correlation, we include 4 lags of all control variables. In the next section, we explore sensitivity to lag length and show that results do not change if we include up to 16 lags. Confidence bands are computed with the lag-augmentation approach of [Montiel Olea and Plagborg-Møller \(2021\)](#).

Figure 9 reports impulse responses from the baseline local projection specification. Panels (a) and (b) report the dynamic responses of $|\pi|_t$ and w_t to price conflict changes. The relationship is positive and statistically significant for up to 6 quarters in the case of price changes and negative and significant for up to 4 quarters in the case of real wages. The impact is economically large. A 1-standard-deviation price conflict rise increases price fluctuations by around 20% of the dependent variable's standard deviation three quarters in. In words, spikes in conflict are associated with large and persistent increases in fluctuations in prices and deteriorations in real wages—precisely what the conflict theory of inflation predicts.

We also document that positive changes in the PCI lead to negative responses from real GDP growth and stock returns, a positive response from the unemployment rate, and no response from the short-term rate. The combined positive effect on prices and negative effect on quantities implies that price conflict changes behave as “supply-side” disturbances. In this regard, our interpretation of the price conflict measure is also similar to [Beaudry et al. \(2023\)](#).

6.3 Generative AI Sensitivity Analysis and Robustness

Our finding of a dynamic association of price conflict changes with price fluctuations could be complicated by several issues.

Model Temperature Our baseline price conflict index is computed conditional on the global temperature parameter set to 0 (zero). This implies the highest possible degree of conservatism in the reading of documents. Now, we set temperature to unity, which is often the default setting for many OpenAI models. Results are reported in panel (a) of Figure 10. The dependent variable is the absolute value of the GDP deflator changes. Changing the temperature appears immaterial.

Prompt Construction Recall that the price- and agent-based decompositions of the baseline indicator are additively-separable and include the residual “other” category. One approach to correct for potential measurement error in the baseline measure is to remove the “other” categories and define *refined* indicators as C_t minus the price- or agent-based “other” topical category. We label the resulting robust indices as C_t^1 and C_t^2 , respectively, first difference them and use as main regressors in the baseline projection the same way as before. Panel (a) of Figure 10 shows that our result is quite robust to these alternative approaches.

Filtering Out Keywords As mentioned earlier in the paper, it is concerning if we obtain our results mechanically. In other words, if the LLM algorithm simply identifies articles that mention “inflation” or “deflation” explicitly then our local projection results are not useful. To this end, we manually remove all cases when the LLM identifies price conflict *and* the article includes either “inflation” or “deflation” in the headline or the first paragraph. Panel (b) of Figure 10 shows that our results do not change. Importantly, basic word-counting of these terms would most likely fail this test completely. In addition, we also remove all articles that contain the word “military” or “war” to address the possibility

that our models capture military, as opposed to price, conflict. Results do not change as well.

No System Prompt Recall that we pre-initiate our query with a persona-shaping prompt which directs the LLM into the area of economic research. We now run the same baseline prompt over the whole sample but without the system prompt. Generally, having a system prompt increases the count of conflict cases in most years, everything else equal. However, the business cycle patterns and correlations remain quantitatively unaffected as shown on panel (b) of Figure 10.

The Economist External validity of our results could be questioned if our findings do not extend to other news outlets. Thus, we have also constructed an alternative price conflict measure using the digitized archive of The Economist and keyword counting tools, as explained before. Panel (b) of Figure 10 shows that the impulse response does not change.

6.4 Econometric Sensitivity Analysis and Robustness

In this section, we address several issues related to the econometric arm of our analysis.

Time Sample It is possible that our results are driven by the early years of the sample, when volatility of price conflict fluctuations was high, or by the post-Volcker era. To address this issue, we run the baseline local projection on the 1919q1-2022q4 and 1890q1-1980q1 sub-samples. Panel (c) of Figure 10 demonstrates that our result survives time truncation.

Inflation in level The main dependent variable in our baseline analysis is the absolute value of price changes, i.e. $|\pi|_t$. We now consider inflation in levels, i.e. π_t . Panel (c) of Figure 10 shows that our results do not change.

No controls We also consider a local-projection specification without any additional controls, i.e. the vector X_t . Panel (c) of Figure 10 shows that our conclusions are not materially affected.

Lag Length As mentioned before, serial correlation of the dependent variable and of the shock measure could pose econometric problems. While we include 4 lags of all regressors in the baseline, we can potentially do more given the length of our time series.

We therefore re-run the baseline projection with 8 and 16 lags. Panel (d) of Figure 10 shows that lag selection does not affect our findings.

Alternative Shock Specifications Recall that the baseline treatment variable is constructed by first-differencing the PCI measure. We now consider an alternative approach to what constitutes the price conflict *shock*: HP-filtering the index instead of first-differencing it (Ravn and Uhlig, 2002). Panel (d) of Figure 10 shows that our result is also robust to alternative definitions of the price conflict shock.

To conclude, we have run an array of sensitivity checks and robustness tests. None of our tests have materially affected the main result of the paper: price conflict is contemporaneously and dynamically associated with price fluctuations.

6.5 Evidence from Topical Indices

We now proceed with the presentation of dynamic effects of our topical indices on the macroeconomy. We first-difference each categorical index, use them as treatment variables, include the same controls, and use the same lag structure.

Figure 11 reports the results from local projections for the decomposition by price topic. We document—based on panels (a) and (b)—that disagreement on wages and on prices of goods and services have the most sustained—economically and statistically speaking—effects on price changes. The impact of other topical indices is relatively mild and/or very short-lived. Figure 12 presents impulse responses for the stakeholder-based decomposition of the baseline price conflict indicator. From panel (a) we observe that disagreement of employees vs employers has positive effects on aggregate price changes that last for around 5 quarters.

We conclude that the impact of aggregate price conflict on price fluctuations is largely driven by disagreements on the prices of goods or services, wages, and by conflicts between workers and employers. In this sense, our empirical finding supports the canonical wage-price spiral theory and suggests that price conflict and spirals could be related.

7 Price Conflict and State-Level Inflation

Does price conflict have homogeneous effects across space? To understand if different U.S. regions respond differently to the same change in C_t , we obtain state-level inflation data from Hazell et al. (2021). We consider both tradable and non-tradable sector CPI

inflation. Local projections are now estimated state by state with the same long-horizon and lag specifications as before.

Figure 13 plots the maps of U.S. states with the color of each state representing the impact of \tilde{C}_t on $Y_{t+4} - Y_{t-1}$, i.e. the horizon is 4 quarters. The top panel, which presents the results for tradable-sector inflation, showcases rich heterogeneity in the responses that are predominantly positive but can range from -0.06 to 0.19 in terms of standard deviations of the dependent variable. About half of the state-level impulse response functions are significant for up to 2 quarters (not shown). The bottom panel of the figure, on the other hand, shows results for non-tradable sector inflation. Here, the estimates are mostly negative and can range from -0.11 to 0.17.

The impacts of price conflict shocks are not only heterogeneous across space but they also transmit differentially across tradable and non-tradable sectors. We find that the impacts are statistically and economically significant only for the tradable sector, and not for the non-tradable goods. This findings support a national price setting view of conflict-driven price fluctuations. Prices of tradable goods are set by firms homogeneously across space with persistent regional characteristics playing a minute role. To the extent that our conflict measure is national, and disagreement over relative prices is a driver of general inflation, firms react to the dynamic of aggregate conflict by adjusting tradable-good prices while non-tradable inflation is driven by more local forces. Understanding the drivers of regional heterogeneity in the effects of price conflict on local inflation is a fruitful avenue for future research. Moreover, constructing regional, state-level measures of price conflict is an important next step for this research agenda.

8 Conclusion

We provide the first, comprehensive, macro-historical empirical test of the Rowthorn (1977) conjecture that inflation is driven by conflict and disagreement on relative prices by economic stakeholders. We apply state-of-the-art tools from Generative AI to automatically “read” the digitized archive of the New York Times and construct a novel, quarterly measure of price conflict that spans 1860-2023. We investigate the drivers of price conflict and establish dynamic effects of changes in the price conflict measure on the macroeconomy in general and price changes in particular. Our results are robust and withstand a large set of LLM-related and econometric robustness checks. Decomposing our baseline index by price- or agent-based category reveals that aggregate conflict is mostly driven by disagreement on wages and on prices of goods and services as well as conflict between employees and employers. Thus, we empirically corroborate the wage-price spiral view

of price fluctuations.

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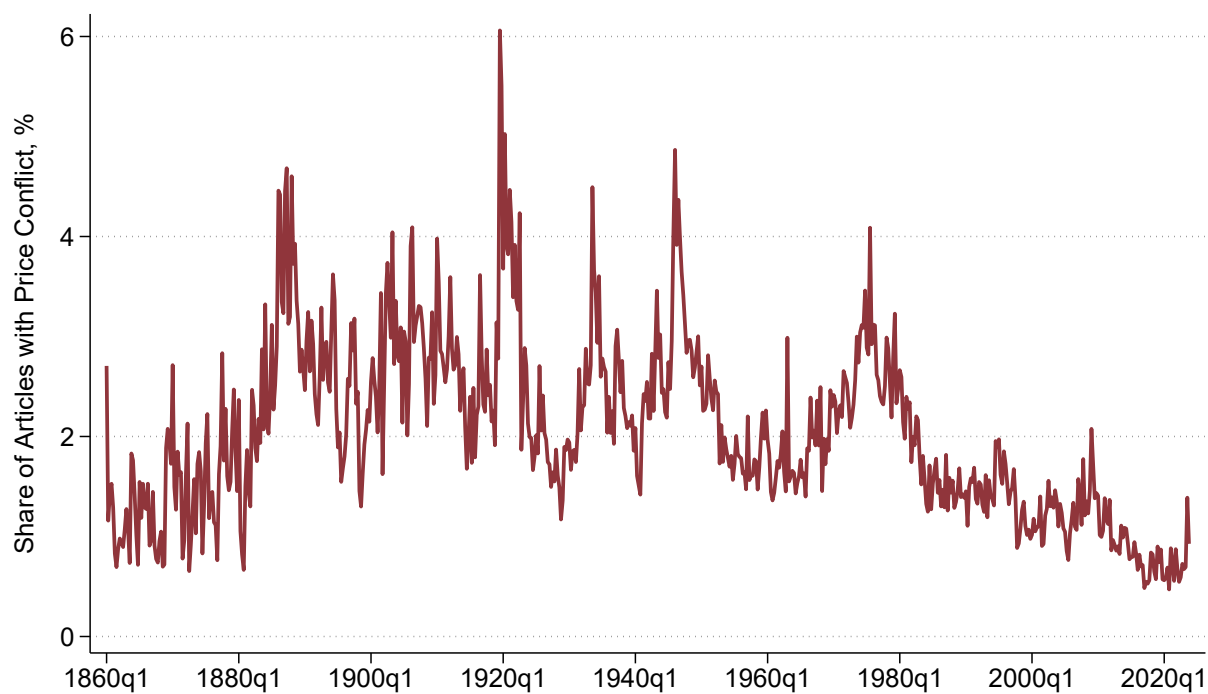
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Figures and Tables

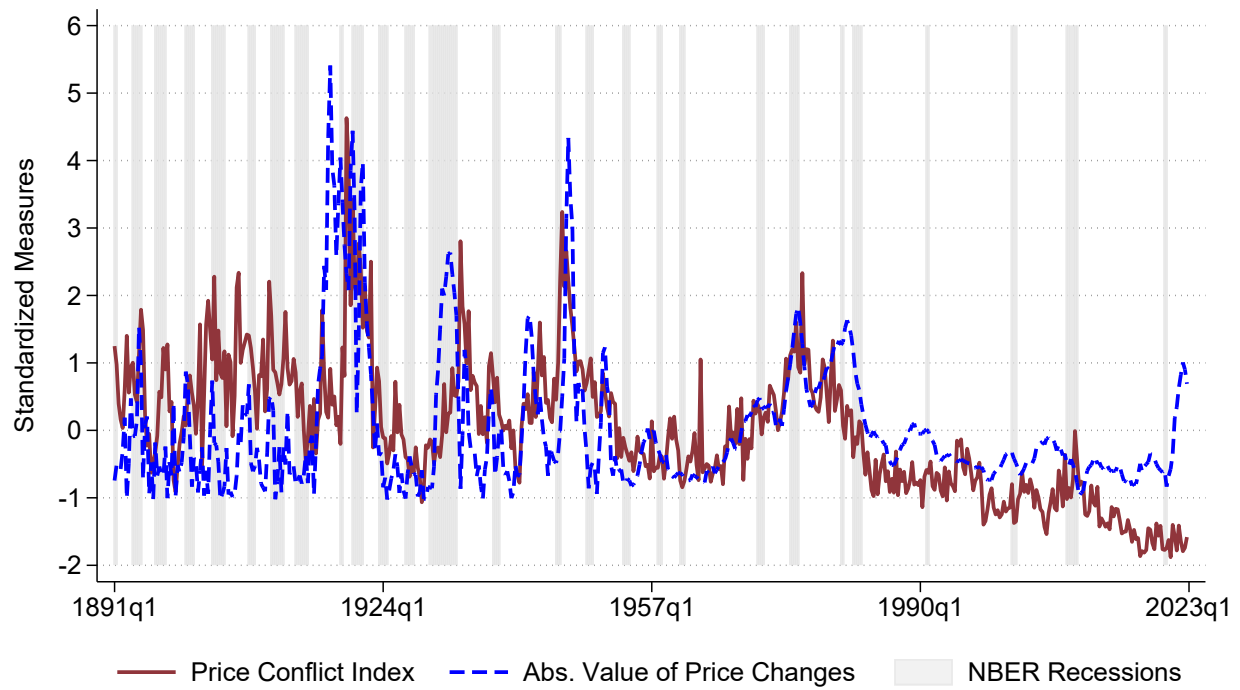
Figure 1: The Price Conflict Index



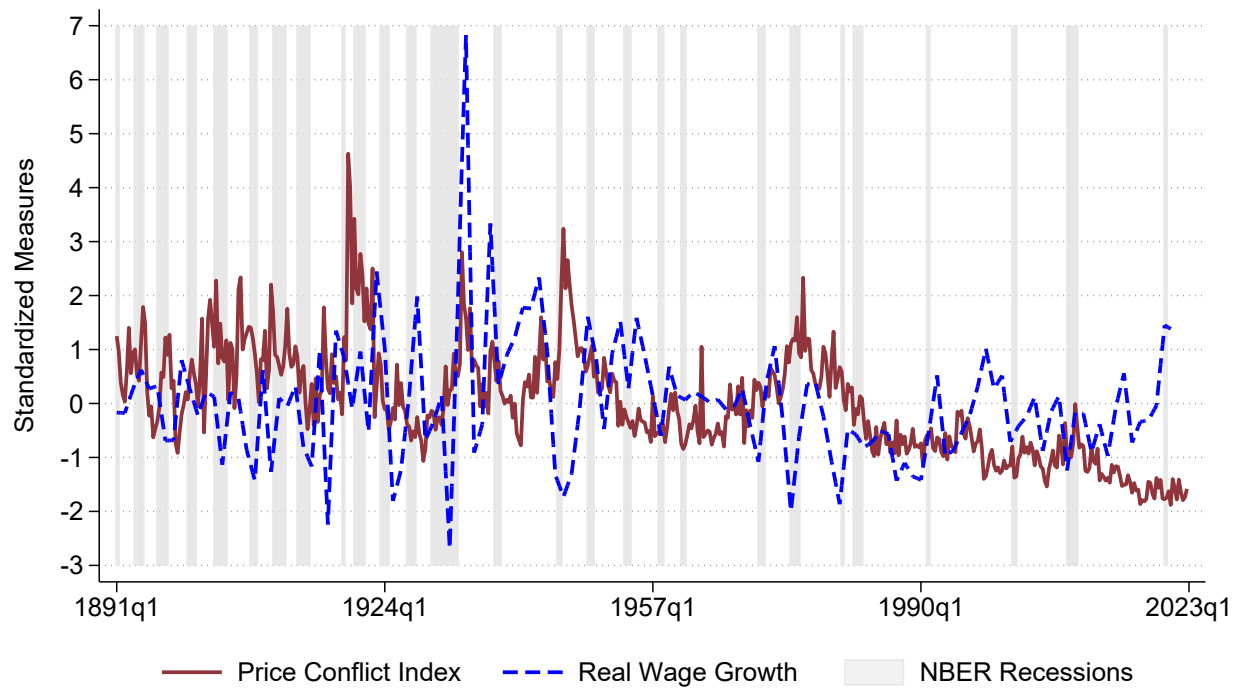
Notes: The baseline index of price conflict C_t . Source: [Jamilov \(2025\)](#).

Figure 2: Conflict and Prices

(a) Prices of Goods and Services



(b) Real Wages



Notes: The baseline price conflict index, C_t , and the absolute value of U.S. GDP deflator inflation (top panel) and real wages (bottom panel). All variables have been standardized.

Figure 3: Conflict and Prices

(a) Prices of Goods and Services



(b) Real Wages

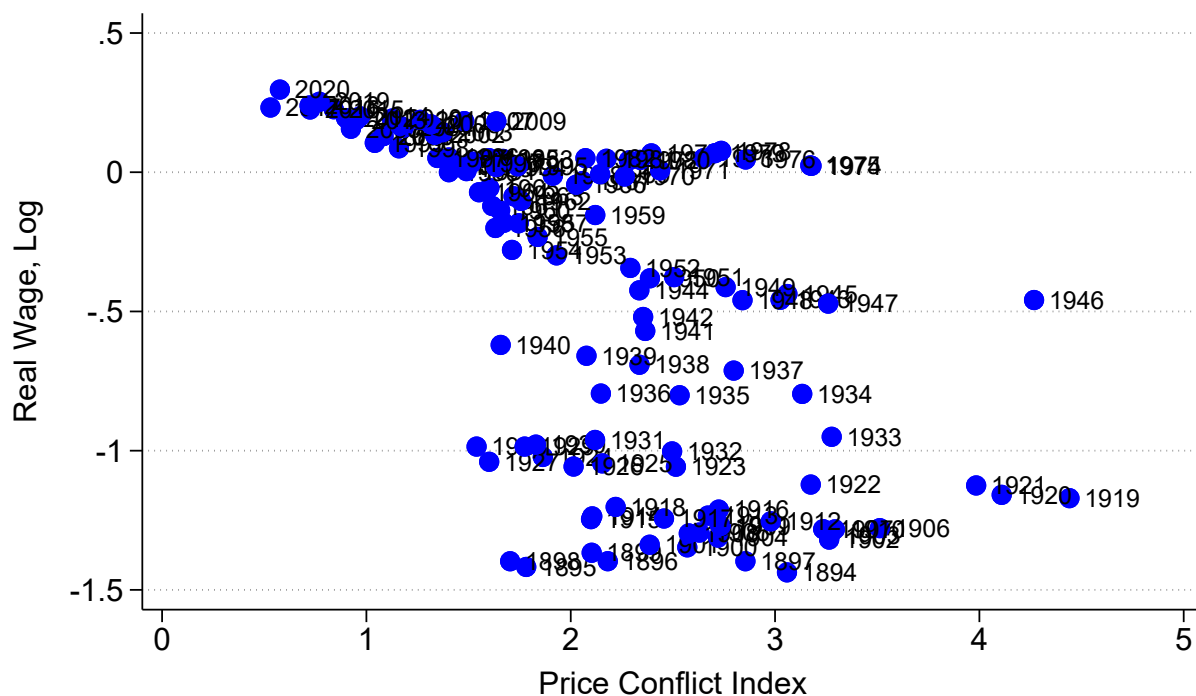
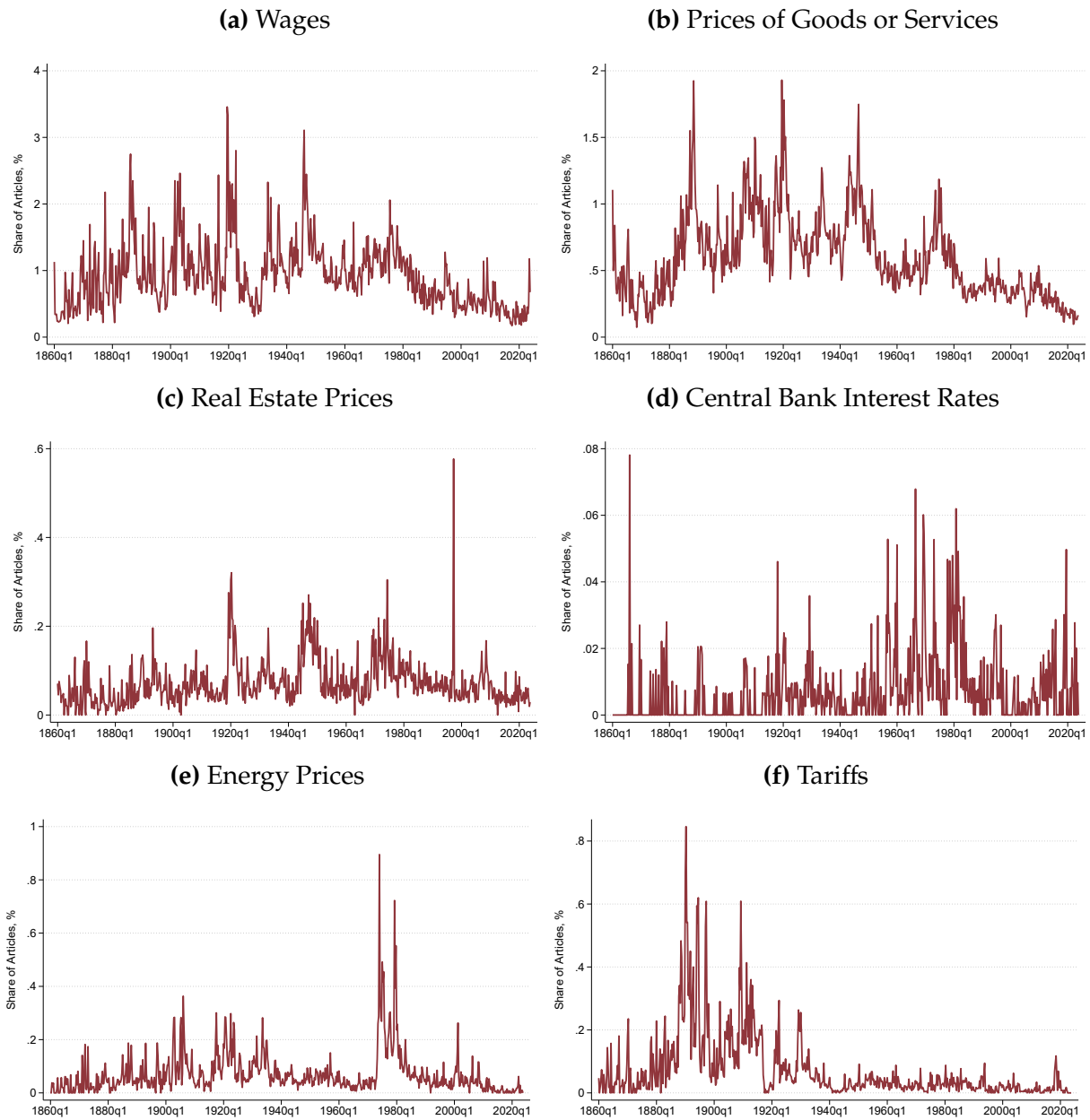
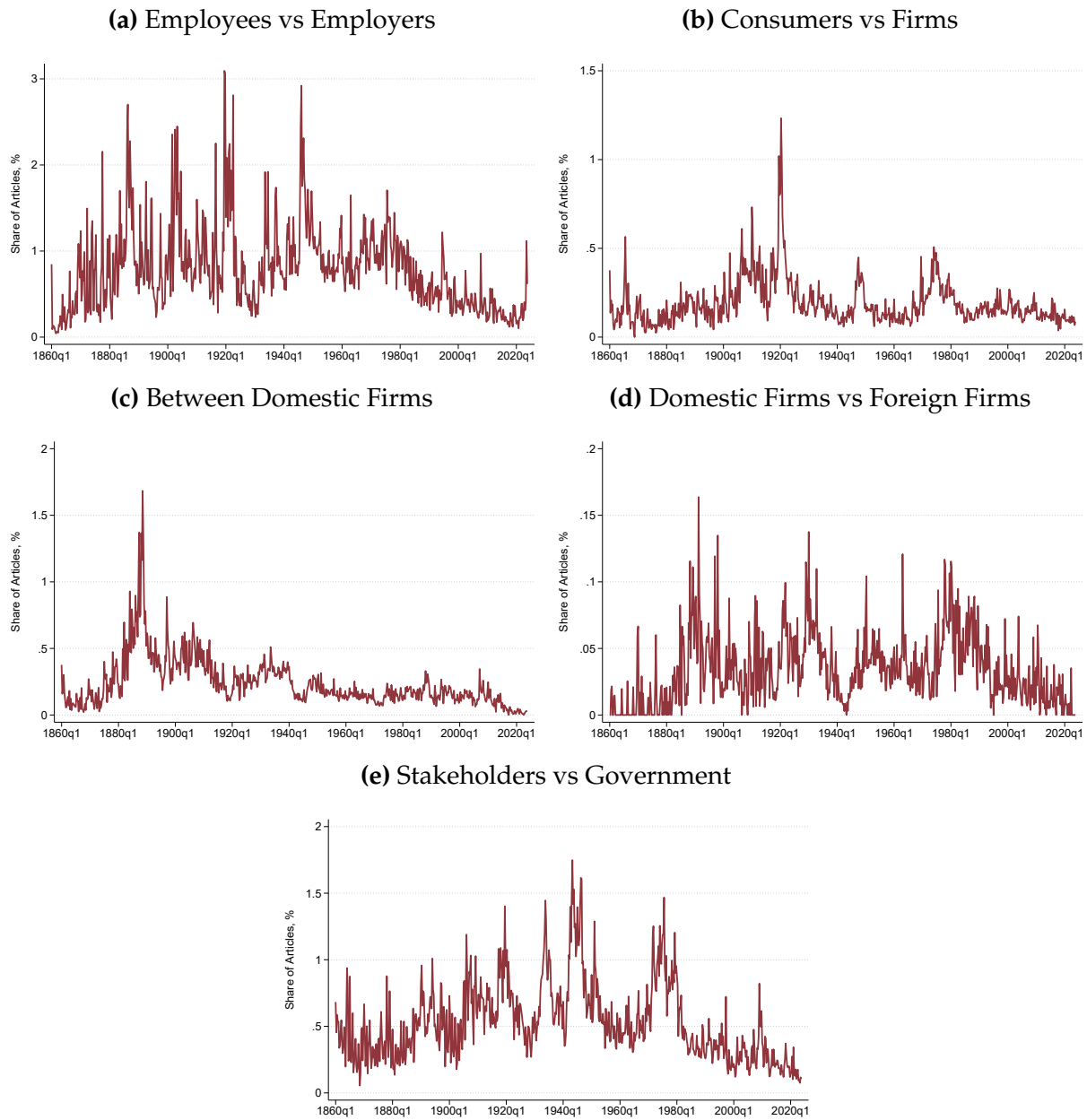


Figure 4: Price Conflict Index by Price Type



Notes: Decomposition of the price conflict index by price category.

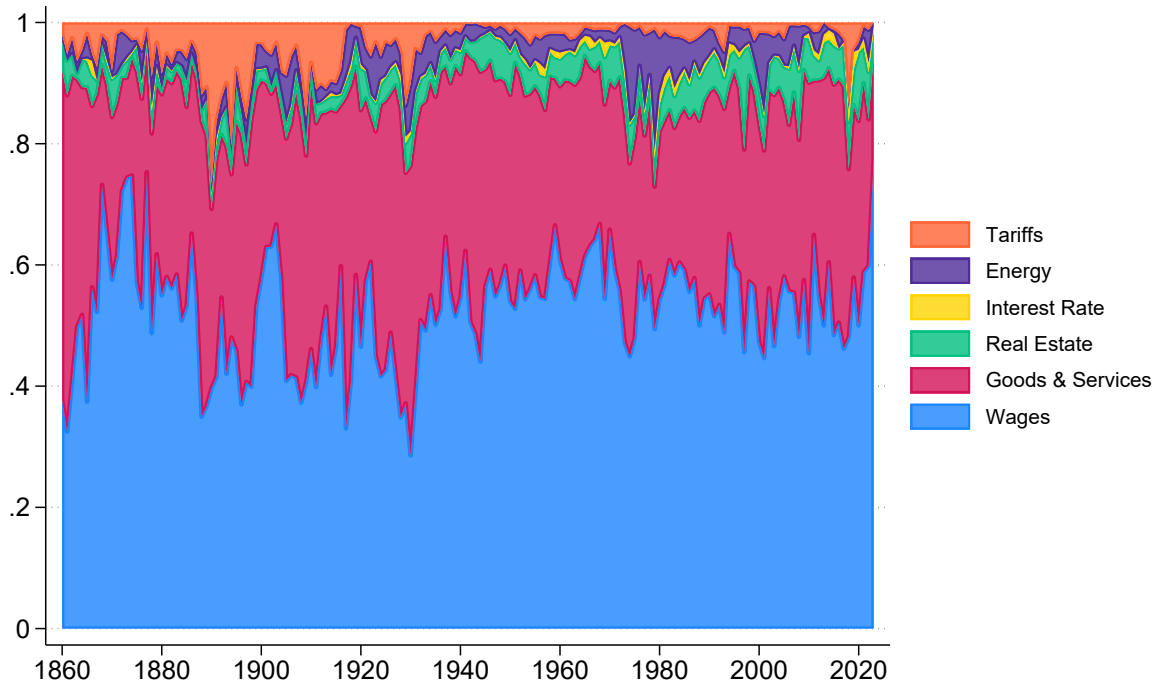
Figure 5: Price Conflict Index by Stakeholder Type



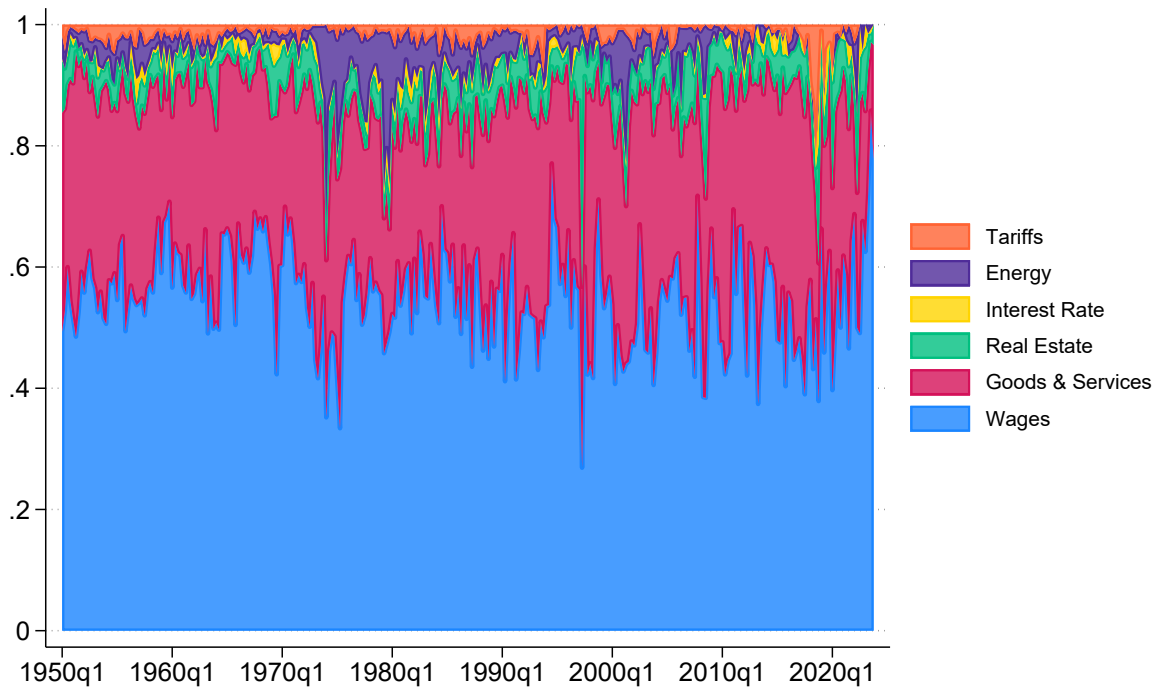
Notes: Decomposition of the price conflict index by agent category.

Figure 6: Index Decomposition by Price Type

(a) Annual over 1860-2023



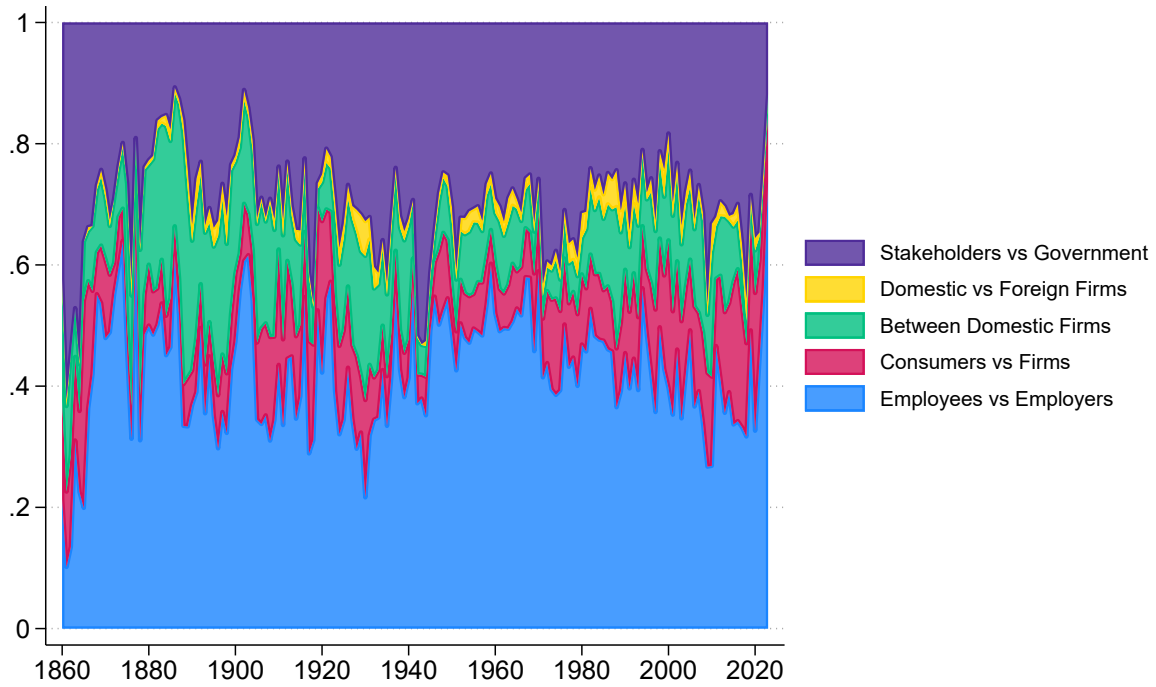
(b) Quarterly over 1950q1-2023q4



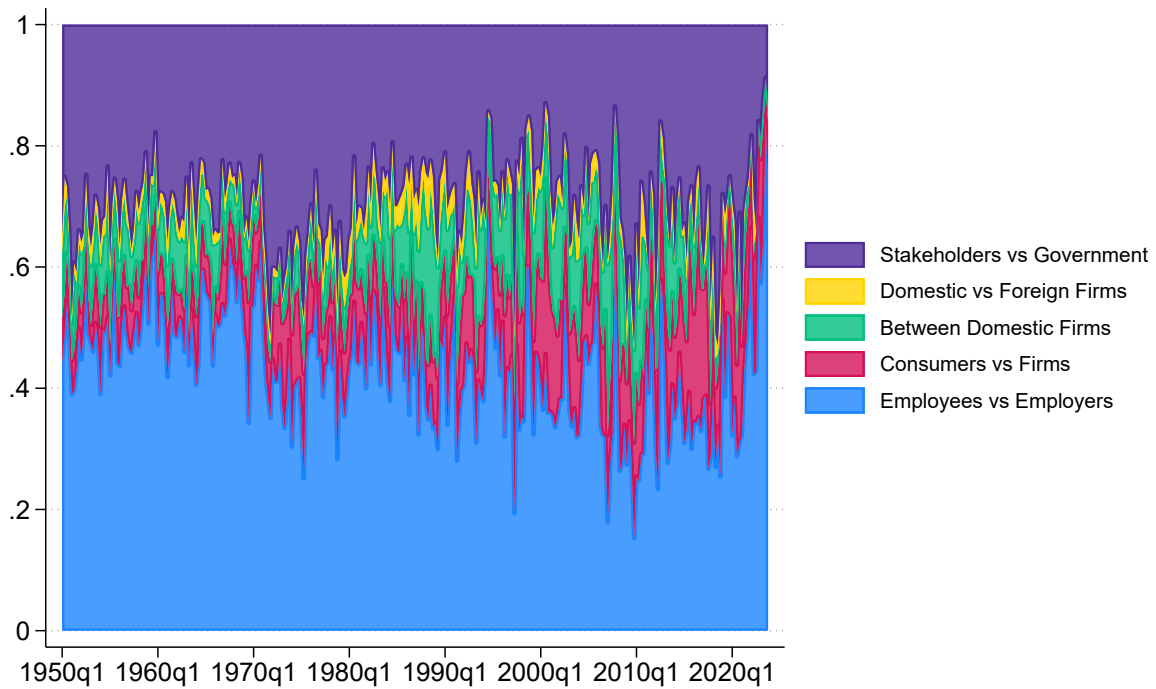
Notes: Historical decomposition of the price conflict index by price category.

Figure 7: Index Decomposition by Agent Type

(a) Annual over 1860-2023

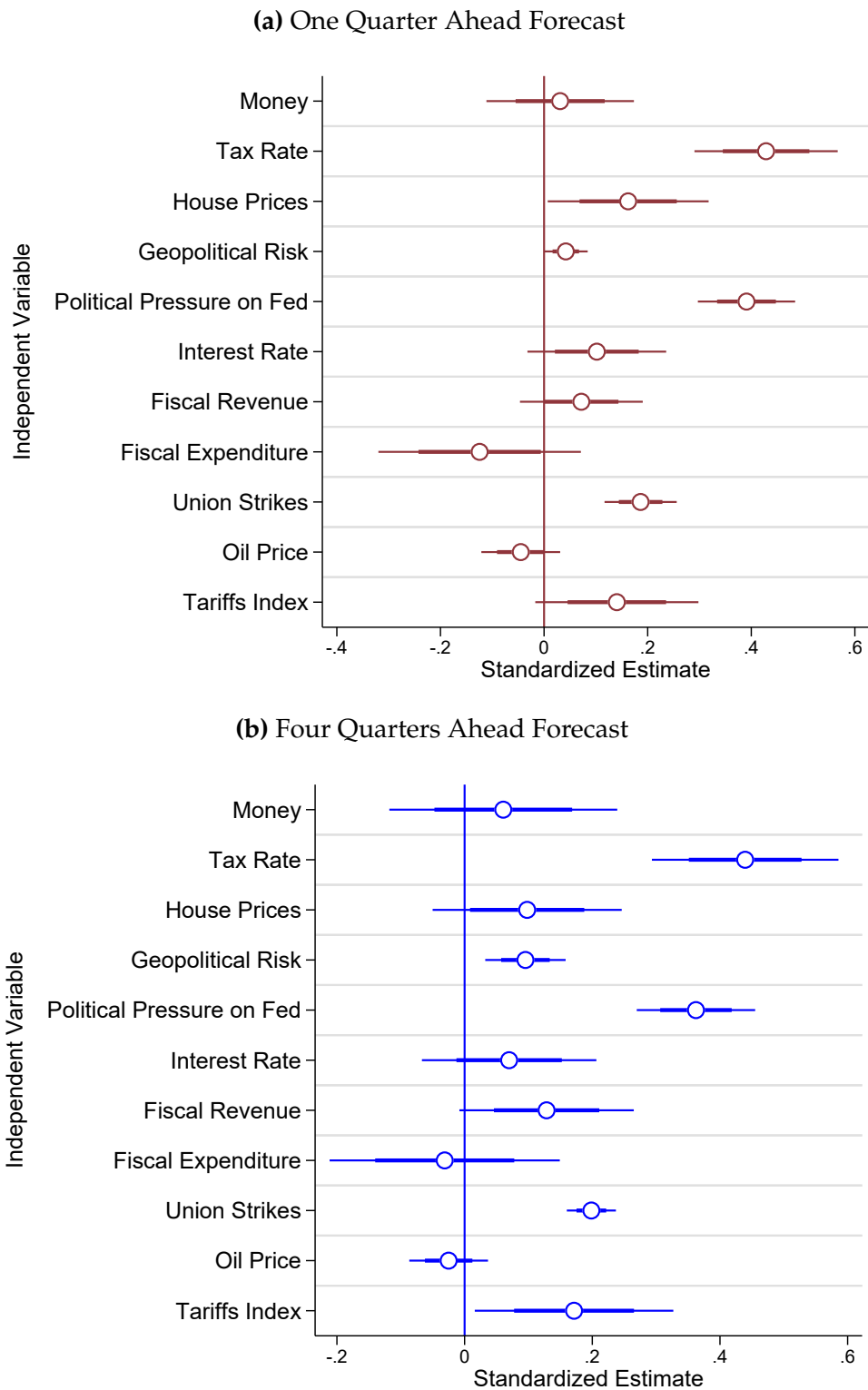


(b) Quarterly over 1950q1-2023q4



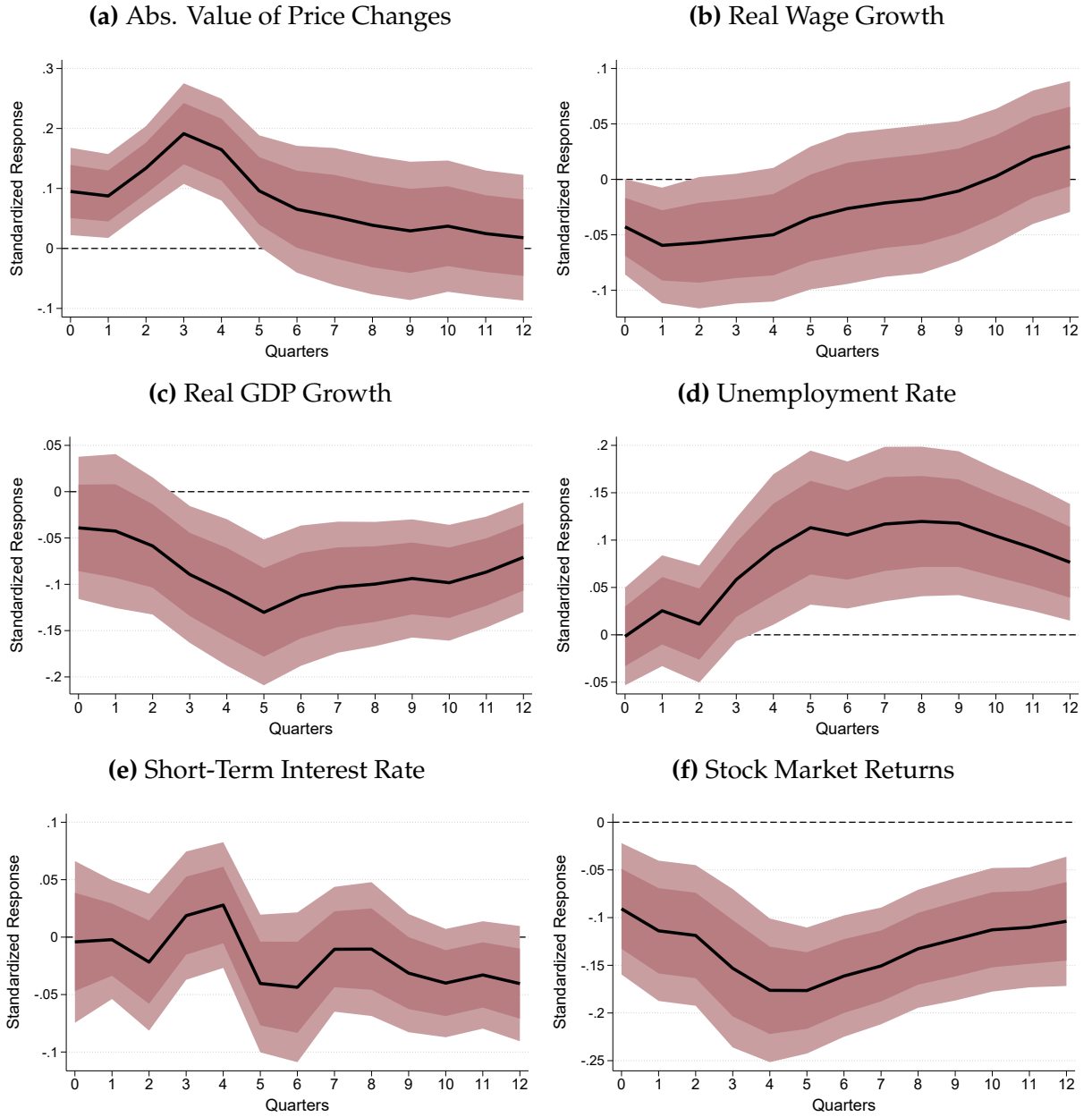
Notes: Historical decomposition of the price conflict index by agent category.

Figure 8: Understanding the Drivers of Price Conflict



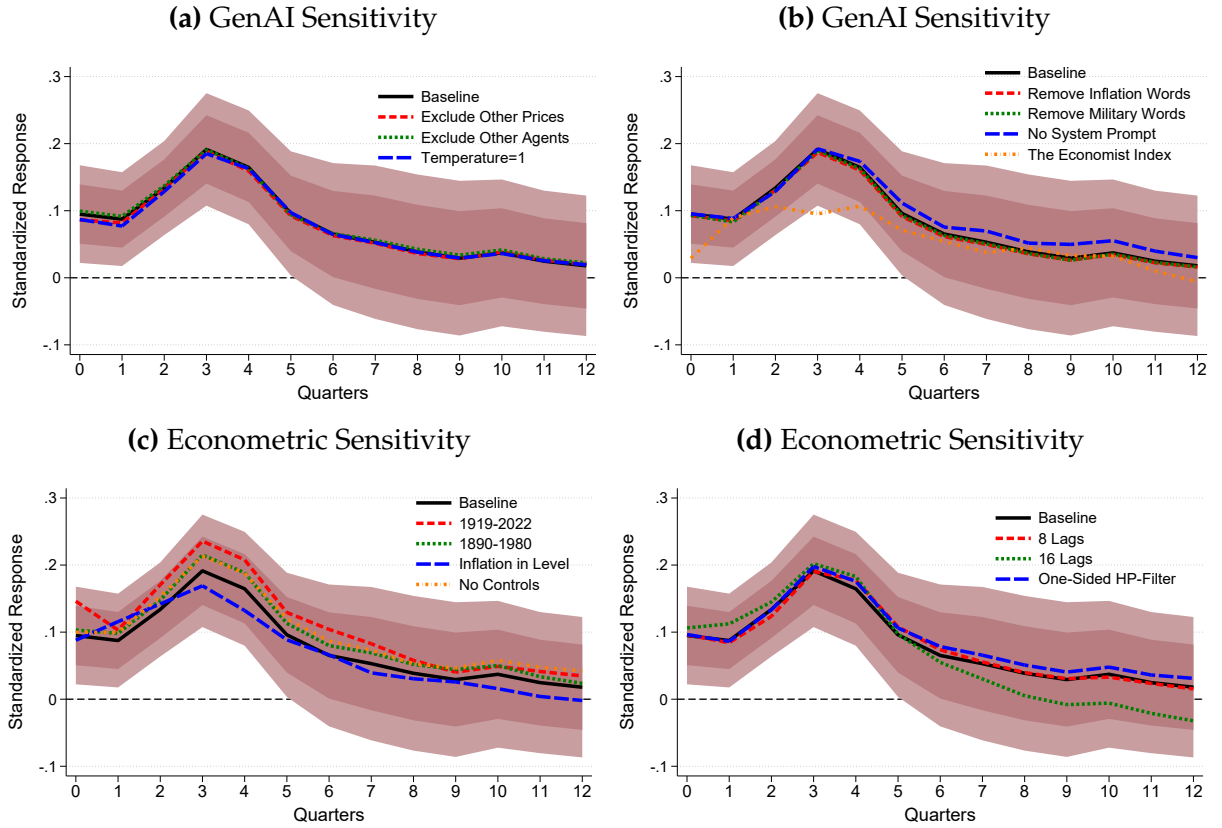
Notes: Estimates from linear regressions where one- (top panel) and four- (bottom panel) quarter-ahead price conflict is the dependent variable and explanatory factors are the independent variable. Explanatory factors are added one-by-one and are represented in each row. Estimates are standardized.

Figure 9: Macroeconomic Effects of Price Conflict Changes



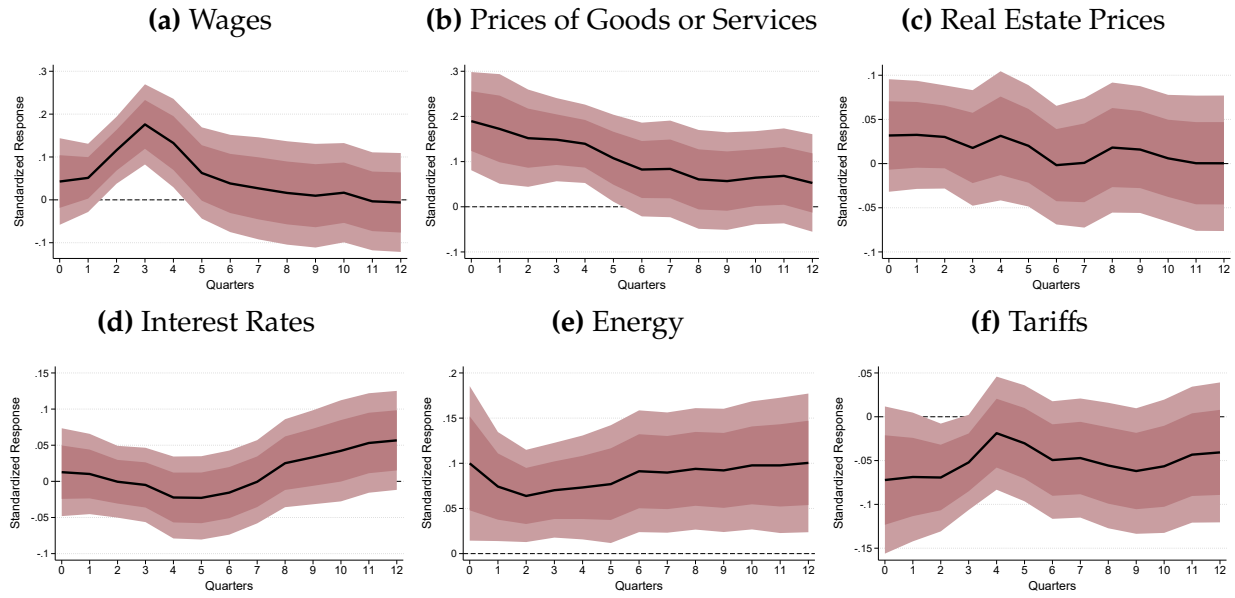
Notes: Results from local projections of macroeconomic aggregates on price conflict. Independent variable is the first-difference of the baseline price conflict index, \tilde{C}_t . Shaded areas are 68% and 90% confidence bands. Standard errors are robust to serial correlation and heteroskedasticity.

Figure 10: Robustness and Sensitivity Analysis



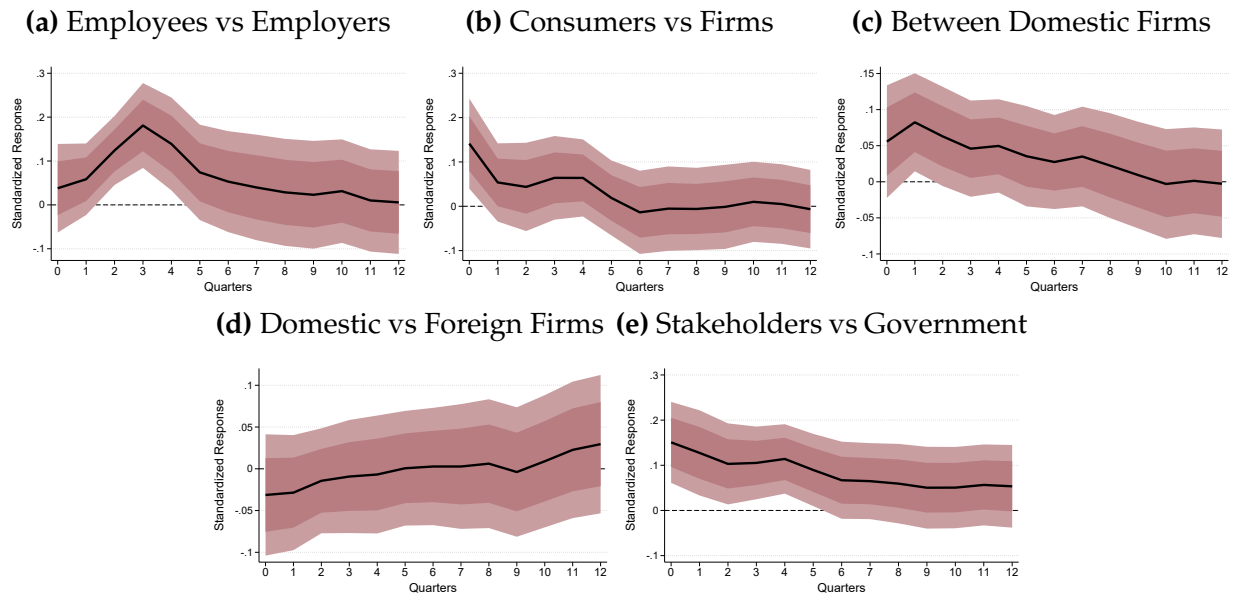
Notes: Dependent variable is the absolute value of GDP implicit price deflator inflation. Shaded areas are 68% and 90% confidence bands. Standard errors are robust to serial correlation and heteroskedasticity.

Figure 11: Impulse Responses by Price Topic



Notes: Dependent variable is the absolute value of GDP implicit price deflator inflation. Independent variables are topical indices of conflict. Shaded areas are 68% and 90% confidence bands. Standard errors are robust to serial correlation and heteroskedasticity.

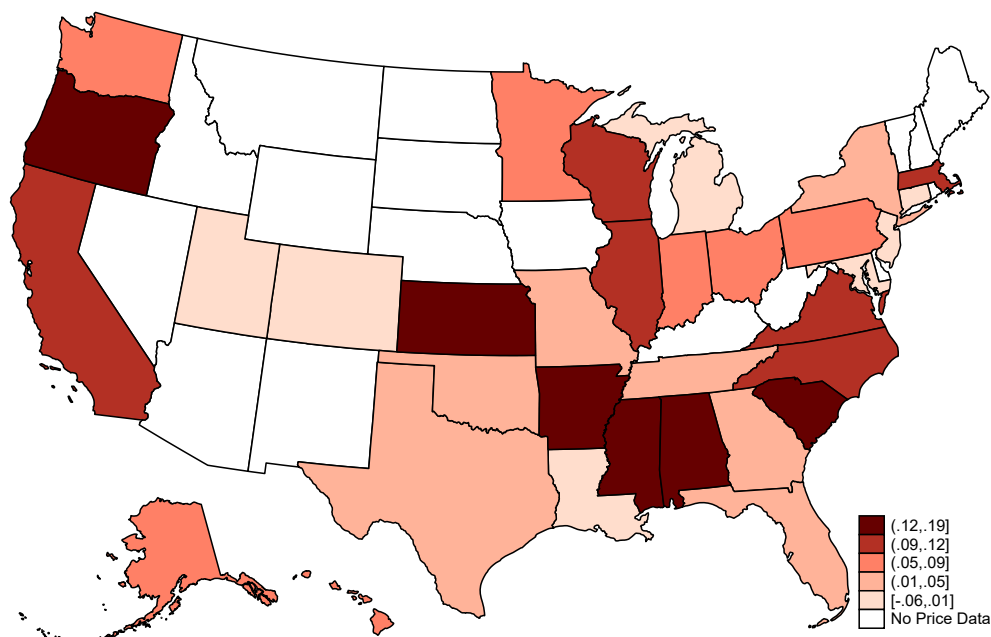
Figure 12: Impulse Responses by Agent Topic



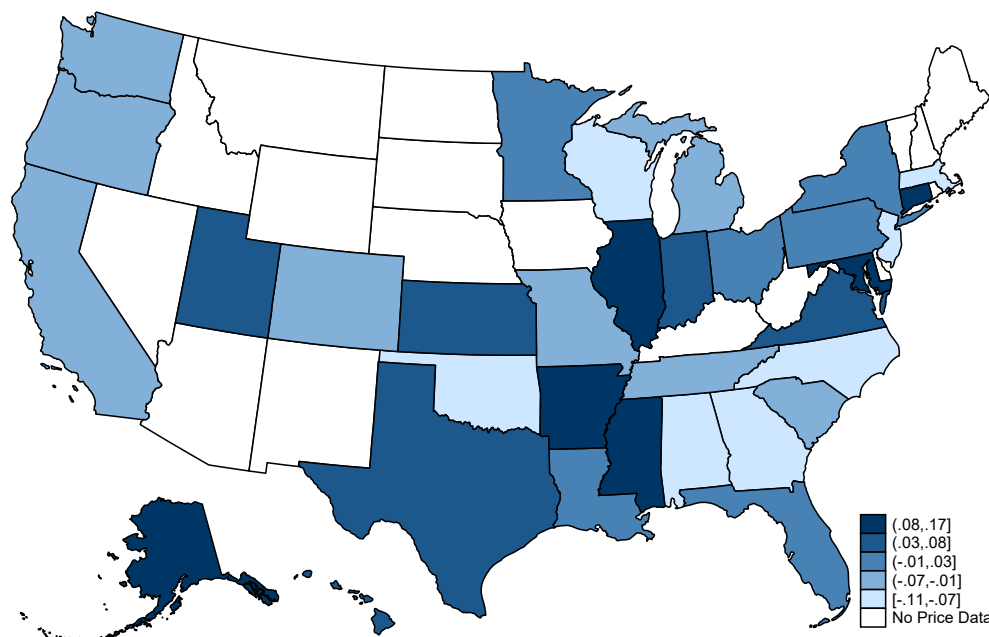
Notes: Dependent variable is the absolute value of GDP implicit price deflator inflation. Independent variables are topical indices of conflict. Shaded areas are 68% and 90% confidence bands. Standard errors are robust to serial correlation and heteroskedasticity.

Figure 13: The Impact of Price Conflict on Regional Inflation

(a) Tradable Inflation



(b) Non-Tradable Inflation



Notes: Results from local-projection estimates of regional inflation on the PCI for the horizon of 4 quarters. The dependent variables are state-level tradable (top panel) and non-tradable (bottom panel) CPI inflation from [Hazell et al. \(2021\)](#). The independent variable is the baseline PCI measure.

Table 1: Case Studies

Identifier	Year	Headline	Detailed Snippet	Humans	Model	Model Justification
1	1945	WASHINGTON SEES LUBLIN DIFFICULTY; Recognition of New Government in Poland Would Conflict With Present Course	The action of the Lublin Committee of National Liberation in proclaiming itself the Provisional Government of Poland has placed the newly reorganized State Department ...	0	0	No
2	2023	Economists Pin More Blame on Tech for Rising Inequality	Recent research underlines the central role that automation has played in widening disparities.	0	0	No
3	2023	'The Return of Superpower Conflict'	What's different about this diplomatic drama with Russia.	0	0	No
4	1959	STEEL PRODUCTION HEADS FOR MARK; Record of 65,000,000 Tons Foreseen in First Half if Level Is Continued MIDYEAR DIP POSSIBLE If a Strike Is Averted, as Seems Unlikely; Demand Probably Will Fall'	It was clear last week that if there is no steel strike at midyear, steel demand and production would be off sharply in July and August. But last week steel mills were steaming toward a six-month record in steelmaking.	1	0	No
5	1922	RIOTING BREAKS OUT IN RAILROAD STRIKE; Union and Non-Union Men of Western Maryland Line Fight in Hagerstown	Headline: RIOTING BREAKS OUT IN RAILROAD STRIKE; Union and Non-Union Men of Western Maryland Line Fight in Hagerstown —	1	1	Yes, the excerpt mentions disagreement between stakeholders over wages in the United States, as the rioting between union and non-union men during the railroad strike likely stemmed from disputes over wage levels.
6	1997	Companies End Strike	Headline: Companies End Strike — First paragraph: Union representing 2,000 striking elevator-maintenance workers has signed contract with two of more than 40 maintenance companies that it has been striking against since Oct 31; International Brotherhood of Electrical Workers Local 3 signs agreement with Kent Elevator and Atlantic Elevator (S) —	1	1	Yes, the excerpt mentions disagreement between stakeholders over wages in the United States, as it discusses the union representing elevator-maintenance workers signing a contract with maintenance companies after a strike.

Continued on the next page

Table 1: Case Studies

Identifier	Year	Headline	Detailed Snippet	Humans	Model	Model Justification
7	1851	COTTON.—Some of the Southern papers are discussing and recommending a scheme for enhancing the value of Cotton. The plan is to form a company, with a capital of \$20,000,000, to receive all the Cotton produced in the United States and sell it, guaranteeing to the owner eleven cents a pound, and withholding it from the market whenever it will not bring that price	Headline: COTTON.—Some of the Southern papers are discussing and recommending a scheme for enhancing the value of Cotton. The plan is to form a company, with a capital of \$20,000,000, to receive all the Cotton produced in the United States and sell it, guaranteeing to the owner eleven cents a pound, and withholding it from the market whenever it will not bring that price —	1	1	Yes, the excerpt mentions disagreement between stakeholders over prices in the United States as some Southern papers are discussing and recommending a scheme to enhance the value of cotton by guaranteeing a specific price, which may not align with the market forces or individual sellers' preferences.
8	1870	WASHINGTON.; The Tariff on Pig Iron—Protests Against the Reduction—Counterfeit Seven-Thirties—The Legal-tender Cases—Ohio and the Fifteenth Amendment	Headline: WASHINGTON.; The Tariff on Pig Iron—Protests Against the Reduction—Counterfeit Seven-Thirties—The Legal-tender Cases—Ohio and the Fifteenth Amendment — First paragraph: The action of the Ways and means Committee in reducing the tariff on pig iron from \$9 to \$7 per ton has brought out a savage howl from pig iron producers, though scarcely any of them aver that they cannot still make pig from at a good profit. — World inflation, as one of the causes of world advance in prices, is discussed in the current issue of The Americas, issued by the National City Bank of New York.	1	1	Yes, the excerpt mentions disagreement between pig iron producers and the Ways and Means Committee over the reduction of the tariff on pig iron, indicating a conflict over prices in the United States.
9	1917	CURRENCY OF WORLD; Increases from \$13,680,000,000 to \$24,660,000,000 Between Years of 1913-1917.	World inflation, as one of the causes of world advance in prices, is discussed in the current issue of The Americas, issued by the National City Bank of New York.	0	0	No
10	1914	WAR SPIRIT STIRS BERLIN TO FRENZY	A semi-official statement says that Germany has made it known to the European capitals, notably Paris and St. Petersburg, that she regards the conflict between Austria and Servia as the concern of those two States alone, and it, therefore, must be localized.	0	0	No

Continued on the next page

Table 1: Case Studies

Identifier	Year	Headline	Detailed Snippet	Humans	Model	Model Justification
11	1984	WHY INFLATION REMAINS LOW	Remarkably, in the face of the economy's continued rapid growth, the stubbornly high inflation that blighted the American economy for more than a decade has dissipated, and a vast majority of the nation's economists see little reason for it to return for as far as they can predict into the 1980's. Prices continue to rise, of course, but at lower rates than the country has seen since the 1960's. Some experts say the United States may have entered a long-lived period of disinflation in which a broad range of prices would increase at a rate significantly slower than in the past.	0	0	No
12	2020	Why the New Coronavirus's Economic Hit Could Be Worse Than SARS	As Chinese stocks plunge and health experts worry about a pandemic, analysts increasingly see the Wuhan coronavirus as a huge threat to the global economy.	0	0	No
13	1896	THE TARIFF IN THE SENATE; No Expectation that the House Bill Will Pass. A WIDE DIVERSITY OF IDEAS List of Amendments Growing Daily – A General Overhauling of the Schedules is Probable.	Headline: THE TARIFF IN THE SENATE; No Expectation that the House Bill Will Pass. A WIDE DIVERSITY OF IDEAS List of Amendments Growing Daily – A General Overhauling of the Schedules is Probable. —	1	1	Yes, the excerpt mentions a wide diversity of ideas and a general overhauling of the schedules related to the tariff in the Senate, indicating disagreement among stakeholders over trade policies that could impact prices and wages in the United States.
14	1896	WILL OPPOSE THE BOND BILL.; Silverites in a Majority on the Senate Committee – Action on Tariff		1	0	No
15	1913	TARIFF DIVIDING ENGLISH UNIONISTS; But London Times Says Only 17 Are in Favor of Bonar Law's Food Tax Policy	proposals of food taxation opposed by Unionist Party in Parliament	0	0	No

Continued on the next page

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Identifier	Year	Headline	Detailed Snippet	Humans	Model	Model Justification
16	1902	RAILROAD STRIKERS STAY OUT.; Ultimatum Announced by Northern Pacific Rejected by Men.	Headline: RAILROAD STRIKERS STAY OUT.; Ultimatum Announced by Northern Pacific Rejected by Men. —	1	1	Yes, the excerpt mentions disagreement between stakeholders over wages in the United States, as the railroad strikers rejected an ultimatum announced by the Northern Pacific regarding their wages.
17	1972	Anti-Inflation Plan Backed	Headline: Anti-Inflation Plan Backed — First paragraph: Natl Fed of Ind Business reports poll of its members finds that 91% support Nixon Adm's plan to combat inflation by restraining wages and prices —	1	1	Yes, the excerpt mentions disagreement between stakeholders over prices or wages in the United States as it highlights the support of the Nixon Administration's plan to restrain wages and prices, indicating a potential conflict between labor and business interests.
18	1989	As Berlin Wall Totters Symbolically, Europeans Brace for Economic Impact'	As thousands of East Germans continue to pour into West Germany from Czechoslovakia, the European Community is beginning to ponder the prospect of something the West has demanded for 28 years: the demolition of the Berlin wall, built in 1961 to keep East Germans from fleeing to the West. In effect, by allowing	0	0	No
19	2016	End a Potential Conflict of Interest at City Hall	Mark Peters, the head of an agency involved in a corruption inquiry, should recuse himself.	0	0	No
20	2023	House buyers are unhappy with the level of interest rates on their mortgages after the recent interest rate hike of Fed.	Headline: House buyers are unhappy with the level of interest rates on their mortgages after the recent interest rate hike of Fed. —	1	1	Yes, the excerpt mentions disagreement between house buyers and the Federal Reserve over the level of interest rates on mortgages, indicating a conflict over prices in the housing market.