Sentiment and Uncertainty about Regulation*

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Abstract

The U.S. government issues thousands of regulations a year. Regulations can create significant economic and social benefits, but poorly designed or excessive regulations may generate substantial adverse effects on the economy. In this study, we construct measures of sentiment and uncertainty about regulation in the U.S. over time and examine their relationships with macroeconomic performance. We construct the measures using lexicon-based sentiment analysis of an original news corpus, which covers 505,811 news articles related to regulation from seven leading U.S. newspapers. As a result, we build monthly indexes of sentiment and uncertainty about regulation from January 1985 to August 2020. To further explore what types of regulatory policy drive the connection between regulation and macroeconomic outcomes, we also construct categorical indexes for 15 regulatory policy areas. Our impulse response estimates indicate that a negative shock to sentiment about regulation is associated with large, persistent drops in future output and employment, while increased regulatory uncertainty reduces output and employment temporarily. Also, economic outcomes respond differently to sentiment and uncertainty shocks about different regulatory policy areas.

Keywords: Regulation, text analysis, NLP, sentiment analysis, uncertainty

JEL Codes: E2, E3, K2, O4

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1 Introduction

The COVID-19 pandemic has disrupted daily lives and business operations. As part of the policy responses to the pandemic, the U.S. government has taken various regulatory actions. These regulatory responses include interstate and foreign quarantine, state and local "shelter-in-place" orders, the emergency use authorization of medical products, and temporary relaxations of certain regulatory requirements. While the primary objective of these regulations is to contain the spread of coronavirus and protect public health, they also affected many business activities and generated substantial economic impacts.

The U.S. government issues thousands of regulations a year. Some of these are in response to crises, such as the current pandemic, while others have evolved over time to address longer term goals. Regulations can address market failures to reduce or eliminate negative externalities and improve efficiency of resource allocation, creating significant economic and social benefits. However, poorly designed or excessive regulations may impose "regulatory burden" on the economy, which can potentially generate substantial adverse effects on aggregate economic outcomes. How regulation affects the economy is thus an important question for both researchers and policymakers and particularly relevant today.

In this study, we construct measures of sentiment and uncertainty about regulation in the U.S. over time and examine their relationships with macroeconomic performance. We construct the measures using text analysis of news data, which cover 505,811 news articles related to regulation from seven leading U.S. newspapers from January 1985 to August 2020. The overall trend of these articles suggests increasing news attention to regulatory policy, stressing the need to investigate the contents of regulation-related news. We then use lexicon-based sentiment analysis methods to evaluate two dimensions of the news corpus: the general sentiment (i.e., positive and negative tone) and the degree of uncertainty expressed in the news about regulation. As a result, we build monthly indexes of sentiment and uncertainty about regulation from 1985 to 2020. In addition to the aggregate indexes, we also categorize relevant news articles into 15 regulatory policy areas and construct categorical indexes that measure sentiment and uncertainty around specific policy areas in the news.

Using our regulatory indexes, we estimate impulse responses of key macroeconomic variables to shocks in sentiment and uncertainty about regulation, following the monthly vector autoregression (VAR) models in Baker et al. (2016). We have three key findings. First, the impulse response estimates suggest that a negative shock to sentiment about regulation is associated with large, persistent drops in future output and employment, while a regulatory uncertainty shock reduces output and employment temporarily. This indicates that news sentiment about regulation may be a more appropriate measure reflecting the connection between regulation and macroeconomic outcomes than uncertainty about regulation. Second, the impulse responses to sentiment shocks about regulation remain after controlling for measures of general news sentiment or economic policy uncertainty, implying that our sentiment measure contains some unique information that may be valuable for predicting future economic activity. Third, economic outcomes respond differently to sentiment and uncertainty shocks about different regulatory policy areas. Specifically, we find that negative sentiment shocks in the regulatory areas of transportation, environment and natural resources, and energy reduce output and employment, and increased uncertainty about labor and workplace regulation have negative, long-lasting effects on output and employment.

Economic research has well documented that sentiment measuring subject attitudes toward current and future economic conditions has strong predictive power for many macroeconomic outcomes (Bram and Ludvigson, 1998; Carroll et al., 1994; Benhabib and Spiegel, 2019). Survey-based measures of economic sentiment are most widely used in empirical studies, which include the Michigan Consumer Sentiment Index and the Conference Board's Consumer Confidence Index. However, these measures are often subject to limitations due to small sample sizes covered in surveys and low data frequency. As a result, recent studies have begun to discover sentiment measures with high-frequency information in the news. News-based economic sentiment measures are found to be strongly correlated with survey-based measures and help explain aggregate economic fluctuations (Shapiro et al., 2020; Fraiberger, 2016).

The development of news-based measures is partially a result of the advance in text analysis during recent years. Research using text as data has introduced economists to advanced natural language processing (NLP) techniques (Gentzkow et al., 2019). As a popular field of NLP, sentiment analysis is used to extract, quantify, and analyze the semantic orientation of a document, such as customer reviews, social media, survey responses, and news articles. In addition to a mere polar view of sentiment (i.e., positive or negative), sentiment analysis can be applied to broader sentiment classifications such as emotional states (e.g., happiness, fear, and anger), subjectivity, confidence, and uncertainty.

As a type of sentiment, uncertainty has a long history in economic research, including a literature explicitly focused on policy uncertainty (for example, Rodrik (1991); Hassett and Metcalf (1999); Pastor and Veronesi (2012)). Similar to the sentiment literature, text-based measures of policy uncertainty have gained rapid development and increasing attention recently. A key contribution is made by the news-based economic policy uncertainty (EPU) index developed by Baker et al. (2016). Numerous studies have been published subsequently to develop similar measures for other countries (Arbatli et al., 2017; Cerda et al., 2016) and specific policy areas such as trade policy and monetary policy (Caldara et al., 2020; Husted et al., 2019). This research generally finds that increased policy uncertainty reduces business investment and employment growth, raises precautionary savings, and increases stock price volatility (Baker et al., 2016; Bloom et al., 2018; Gulen and Ion, 2016; Caldara et al., 2020; Julio and Yook, 2016). Comparatively, uncertainty surrounding regulatory policy remains largely unexplored.

Just as measures of economic sentiment and uncertainty reveal information about current and future economic activity, our work suggests that news-based measures of sentiment and uncertainty about regulation may provide important information for understanding the effects of regulatory policy on aggregate economic outcomes. Therefore, our study also connects to the literature studying the aggregate economic effects of regulation, which has mostly focused on the volume or restriction of regulation (Coffey et al., 2020; Dawson and Seater, 2013). We thus present a new direction of studying the economic impact of regulation.

Our study has several practical implications. First, although it's hard to draw any conclusion on the causal effects of regulatory sentiment and uncertainty on macroeconomic activity based on the VARs, the dynamic relationships we show in this paper suggest that an improvement in the regulatory system that increases public confidence and reduces uncertainty in government interventions may help minimize unnecessary regulatory burden on the economy. Second, news sentiment and uncertainty around certain regulatory policy areas appear to have particularly strong links with macroeconomic performance. Policymakers in those areas should explicitly consider both incremental and cumulative economic effects of their regulations and increase transparency and clarity of the regulations. Third, up-to-date indexes of regulatory sentiment and uncertainty can provide forward-looking information about economic conditions. This information may help businesses better anticipate payoffs and make optimal hiring and investment decisions.

In the next section, we discuss the data we use in this study, including text data of news articles and economic data used in the VAR analysis. In section 3, we describe our approach to identify the news articles related to regulation and the evidence of increasing media attention to regulation since 1985. Section 4 presents the regulatory sentiment and uncertainty indexes, including the sentiment analysis method we use to construct the indexes, some descriptive analysis of the indexes, and the impulse responses of macroeconomic variables to sentiment and uncertainty shocks. In section 5, we describe the categorical indexes that measure news sentiment and uncertainty in 15 regulatory policy areas and their varied roles in the impulse responses of macroeconomic outcomes. Section 6 concludes the findings and outlines some future work we are planning for this study.

2 Data

Our initial news corpus includes 853,286 news articles that contain the keyword "regulat*" or "deregulat*" (e.g., "regulation", "regulator", "deregulation") from seven U.S. newspapers published between January 1985 and August 2020. The seven newspapers are Boston Globe, Chicago Tribune, Los Angeles Times, New York Times, USA Today, Wall Street Journal, and the Washington Post.[1] We access to the full texts and metadata through ProQuest's TDM Studio, which provides a comprehensive collection of historical and current newspapers in a machine readable format.

Since the keyword "regulation" and its variations can be used in many contexts other than referring to government regulatory policy,[2] we conduct further analysis to refine the data set by defining a dictionary of regulatory noun chunks from the titles of all rules considered by federal agencies from 1995 to 2019. The data of rule titles are obtained from the federal government's semiannual Unified Agenda of Regulatory and Deregulatory Actions reports. The reports provide uniform data on regulatory and deregulatory actions that agencies plan to issue in the near and long-term future. The Unified Agenda reports published over 190,000 actions in total between 1995 and 2019, which reduce to 38,868 unique rules. Section 3 details our approach to define the dictionary and identify the news contents related to regulatory policy. As a result, our final news data set includes relevant sections from 505,811 news articles.

In the VARs, we use the same economic variables as those in Baker et al. (2016). Those include monthly data on employment, effective federal funds rate, and industrial production from FRED Economic Data, and S&P 500 index. In addition, we add the Michigan Consumer Sentiment Index, VIX, the EPU index of Baker et al. (2016), and the news sentiment index of Shapiro et al. (2020) into the monthly VARs for robustness checks.

[1] Data for USA Today and the Washington Post are only available from January 1987.

[2] For example, the term "regulation" and its variations are often used in the context of sports. A February 7, 2019 article in USA Today says: "As you watch the NFL or any baseball game and see every replay tortured and analyzed from every angle, have you ever asked yourself, 'You know, we could really use more regulations in sports.'"

3 News Attention to Regulation

In this section, we describe the approach we use to identify regulation-related news articles from the initial news corpus. After taking into account the total number of news articles published in each newspaper, we show evidence that news attention to regulation has been increasing over time.

3.1 Identifying Regulation-Related News

Identifying regulation-related news is challenging for several reasons. While some newspaper databases label news articles by subject categories such as finance, politics, and health care, news articles are rarely labeled as regulatory policy. Also, regulation may be the main theme of an article, but it may also be mentioned only in certain sections of an article that mainly discusses economic or political issues. This makes a standard article-level analysis inappropriate or insufficient to identify news contents related to regulation. A simple search of a limited set of keywords like "regulation" or "regulator" would also return inaccurate results, because those words could be used in various contexts.

To identify the specific news contents related to regulation, we define a dictionary of regulatory noun chunks to assess the context in which the keyword "regulation" or its variations are mentioned in an article. Specifically, we examine the sentence that mention "regulat*" or "deregulat*" and its neighbor sentences (i.e., a sentence before and after the regulatory sentence). If any of the three sentences contain one or more regulatory noun chunks defined in our dictionary, then we consider these sentences as regulation-related news. An article can have multiple regulatory sentences, depending on the extent to which regulation is the focus of the article, and all these sentences and their neighbor sentences compose the regulatory section of the article. Specifically, we conduct this assessment in a three-step process.

First, we obtain noun chunks from the titles of all unique rules published in the Unified Agenda reports from 1985 to 2019. Noun chunks are "base noun phrases" identified using the

NLP library spaCy. For example, the rule title "Test Procedures for the Analysis of Trace Metals Under the Clean Water Act" is associated with a list of four noun chunks: ["Test Procedures", "the Analysis", "Trace Metals", "the Clean Water Act"]. We then clean the noun chunks by removing special characters, removing leading articles (i.e., "the", "a", and "an" at the beginning of a noun chunk), and lemmatizing the tokens of the noun chunks. The above example thus becomes ["test procedure", "analysis", "trace metal", "clean water act"]. We only keep the cleaned noun chunks with two or more tokens, because a single-token noun chunk such as "analysis" has too broad meaning to suggest any relevance to regulation. We iterate this process over all unique rule titles and eventually generate a list of unique n-token noun chunks ($n \geq 2$). This list includes over 37,000 noun chunks and serves as the base for our dictionary.

Next, we preprocess the texts of all news articles in our initial data set. This includes segmenting sentences of an article, extracting the sentence that mentions "regulat*" or "deregulat*" (indexed i) and its neighbor sentences (indexed $i-1$ and $i+1$), and lemmatizing the tokens in the sentences. We then search each of the n-token noun chunks from the first step in the extracted sentences using regular expression operations. If the three consecutive sentences ($i-1$ to $i+1$) contain one or more of the noun chunks, then these sentences are included in the regulatory section of the article.

As the third step, we conduct human checking and correction of the noun chunks that occurred in the articles. Because the list of the n-token noun chunks automatically generated from the rule titles still includes some general terms that are mentioned frequently in the news articles but not necessarily related to regulatory policy (e.g., "same time", "first quarter", "other country"), we go through the noun chunks that occurred in the news articles most frequently (i.e., with 100 occurrences or more) and manually filter out those general terms.[3] After removing the general terms from the results, there remains 11,103 unique noun chunks that occurred in 505,811 news articles, meaning that each of these articles contains

[3]For filtering out the general terms, two coders went through the list of noun chunks and marked general terms independently, compared their results, and the discussed to solve the discrepancies.

a regulatory section. These noun chunks form our dictionary of regulatory noun chunks, which are also used for building our categorical indexes as discussed in Section 5. Appendix A lists 100 regulatory noun chunks with most occurrences in the articles.

Our sentiment analyses in the remainder of the paper are based on the corpus of the regulatory sections in the 505,811 news articles.

3.2 Increasing News Attention to Regulation

The relative frequency of articles discussing regulation over time can suggest trends in news attention to regulation. We investigate that by building a monthly index of news attention to regulation using an approach similar to Baker et al. (2016)'s approach to building their EPU index. That is, we scale the monthly count of news articles that contain regulatory sections by dividing it by the total number of news articles published in the newspaper in the month, and then standardize the scaled monthly counts and normalize the time series to a mean of 100 from 1985 to 2009. Specifically, the monthly news attention index NA_t is calculated as:

$$NA_t = z_t \frac{100}{\frac{1}{\widetilde{T}} \sum_{t=1}^{\widetilde{T}} z_t},$$

where z_t is the mean of standardized monthly counts over newspapers:

$$z_t = \frac{1}{K} \sum_{i=1}^{K} \frac{x_{it}}{N_{it} \delta_{i,\widetilde{T}}},$$

where $i = \{1, 2, ..., K\}$ denotes the newspaper, $t = \{1, 2, ..., T\}$ denotes the month, x_{it} is the raw count of articles related to regulation in newspaper i in month t, N_{it} is the total number of news articles published in newspaper i in month t, $\delta_{i,\widetilde{T}}$ is the standard deviation of the scaled count $\frac{x_{it}}{N_{it}}$ over the time interval $\widetilde{T}$ for standardization and normalization (i.e., January 1985 – December 2009 in our case).

Figure 1 plots the monthly index of news attention to regulation. The overall trend suggests that regulation has been drawing increasing attention from the media, especially since 1996. In addition, news attention to regulation raised during months of important regulatory developments or historical events that triggered massive regulatory responses. For example, the index shows spikes around the Lehman Brothers bankruptcy in 2008, the passage of Obamacare and the Dodd-Frank Act in 2010, and the 2016 presidential election, and a substantial drop during the month of the 9/11 attack in 2001. Beside the overall increasing trend, the 2016 election is accompanied by particularly elevated news attention to regulation compared to other elections, presumably because deregulation is one of Trump's top political priorities (Dudley, 2020).

The trend in news focus on regulation not only suggests that regulatory policy has become an increasingly popular topic among journalists, but also implies that regulation has become more relevant to their readers, potentially including consumers, workers, and business leaders. This also motivated our study to investigate these news contents and their implications for the macroeconomy.

4 Sentiment and Uncertainty about Regulation

This section starts with a description of the sentiment analysis method we use to estimate the sentiment and uncertainty scores of the regulation-related news articles in our sample. Using the estimated scores, we present our monthly indexes of sentiment and uncertainty about regulation from 1985 to 2020. We then apply the indexes to VAR analyses to examine how macroeconomic variables respond to sentiment and uncertainty shocks about regulation.

4.1 Sentiment Analysis

We use a lexicon-based approach for sentiment analysis. The lexicon-based approach assesses the semantic orientation of a document based on the frequency of words or phrases with a particular semantic orientation that occur in the document. It relies on pre-defined dictionaries of opinionated words, such as a list of positive or negative words. There are many available sentiment dictionaries designed for general purposes and some for specific domains.

We use the 2018 Loughran and McDonald (LM) dictionary (originally developed in Loughran and McDonald (2011)) to assess the sentiment and uncertainty in the regulatory sections of the relevant news articles in our baseline analysis. The LM dictionary was constructed specifically for the domain of finance, using a corpus of corporate 10-K reports (Loughran and McDonald, 2011). Because of its domain relevance, the LM dictionary has been frequently used in economic research (for example, Fraiberger (2016); Calomiris et al. (2020); Ostapenko et al. (2020)). The 2018 version of the dictionary comprises sentiment word lists in several categories, including 2,355 words in the negative category, 354 words in the positive category, and 297 words in the uncertainty category.

However, we also notice that the LM positive and negative word lists are strongly unbalanced, with substantially more negative words than positive words. One reason is that Loughran and McDonald (2011) has a clear focus on the proportion of negative words in 10-Ks for detecting the association between tone and excess returns. They note that finance and accounting research generally finds little incremental information in positive words, and the LM positive word list was created more for completeness than "discerning an impact on tone identification" (Loughran and McDonald, 2011, p.45). While an unbalanced dictionary may not affect our interpretation of the sentiment trend over time, it may bias our sentiment score toward a disproportionately negative tone. For this reason, we also use two other dictionaries to construct the sentiment measure for comparison: the Harvard General Inquirer (GI) dictionary and the Lexicoder Sentiment Dictionary (LSD). The GI dictionary is a general-purpose lexicon originally developed in the 1960s and has been widely used in various disciplines. It covers several broad valence categories, including lists of 2,005 negative words and 1,637 positive words. The LSD is a comprehensive sentiment lexicon combining three pre-existing dictionaries and tailored primarily to political news (Young and Soroka, 2012).[4] The LSD comprises 2,857 negative words and 1,709 positive words.

We use a standard formula to calculate the scores of sentiment and uncertainty about regulation. The sentiment score of an article is the difference between the proportion of positive words and the proportion of negative words in the regulatory section of the article. Similarly, the uncertainty score of an article is the proportion of uncertainty words in the regulatory section of the article. Therefore, a positive sentiment score indicates an overall positive tone in the news about regulation, and a negative score means an overall negative tone. A higher uncertainty score suggests a higher level of uncertainty expressed in the regulation-related news.

Similar to our search of regulatory noun chunks, we use regular expression to count the occurrence of each sentiment word in the preprocessed regulatory section of an article.

4.2 Sentiment and Uncertainty Indexes

Table 1 shows the descriptive statistics of the sentiment scores estimated using the LM, GI, and LSD dictionaries and the uncertainty scores using the LM dictionary. The absolute sentiment score that measures the polarity of a document is clearly dependent on the scope of opiniated words defined in the dictionary. Unsurprisingly, the sentiment measured using the LM dictionary is generally more negative compared with the GI and LSD (Table 1). The LSD generated the most balanced result, with an approximately same number of articles estimated negative and positive. To illustrate how the three dictionaries assess a document differently, Appendix B shows examples of regulatory sections with negative and positive words identified from each dictionary. As shown in Table 1, the uncertainty scores indicate that approximately half of the articles expressed a degree of uncertainty in the sections that discuss regulation. Appendix B also includes the estimated uncertainty scores for the examples.

[4] The three pre-existing dictionaries combined in the LSD are the GI, the Regressive Imagery Dictionary (Martindale, 1975), and the Roget's Thesaurus (Roget, 1911).

To construct the monthly sentiment and uncertainty indexes, we use fixed effects regressions following Shapiro et al. (2020). The specification is:

$$s_j = u_{t(j)} + v_{i(j)} + \epsilon_j,$$

where s_j is the estimated sentiment or uncertainty score for article j, $u_{t(j)}$ is a year-month fixed effect, and $v_{i(j)}$ is a newspaper fixed effect. The estimated coefficients on the year-month fixed effects u_t from this regression are the monthly sentiment or uncertainty index, depending on the dependent variable. One advantage of this approach is that the newspaper fixed effects control for time-invariant heterogeneities across newspapers, which can potentially address the concern of ideological differences among news sources. This is particularly important for our study, because the news sentiment toward government regulation could be largely affected by the political stance of the newspaper.

Figure 2 plots the sentiment indexes estimated using different dictionaries between January 1985 and August 2020. To focus on the trend rather than relative polarity, we normalize the indexes by their means and standard deviations. The three time series demonstrate similar trends over time and are strongly correlated with each other. The correlation between the LM and LSD indexes is 0.8; the correlation between the LM and GI indexes is 0.55; and the correlation between the LSD and GI indexes is 0.71. While the LM index generally displays larger fluctuations than the GI and LSD indexes, all the three indexes suggest that news sentiment about regulation has changed over time. For example, the newspapers in the period of late 1980s and early 1990s appear to express a relatively more negative tone when discussing regulation, while the sentiment largely improved around the mid-1990s and maintained at a stable and high level until the early 2000s. In the following VAR analyses, we present the results using the LM sentiment index, but include the results using the GI and LSD indexes in Appendix C to show robustness.

Figure 3 plots the uncertainty index. In particular, we see more spikes in regulatory uncertainty during recent years. Regulatory uncertainty reached a historical peak in 2010, a year that marks many important events in the regulatory history, including the enactment of Obamacare (March 2010), the Deepwater Horizon oil spill (April 2010), and the passage of the Dodd-Frank Act (July 2010). Other large spikes occurred around the Lehman Brothers bankruptcy in September 2008, the Trump election in November 2016, and the coronavirus outbreak in the U.S. in April 2020.

4.3 Impulse Responses

We then examine how our measures of sentiment and uncertainty about regulation affect future economic activity. We use the monthly VAR model of Baker et al. (2016), through which we estimate how measures of economic activity respond to shocks to sentiment or uncertainty about regulation. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: our regulatory sentiment or uncertainty index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. The VAR includes three lags of all variables. We show impulse responses up to 36 months after the shock.

Figure 4 plots the impulse responses of industrial production and employment to a one-standard-deviation negative shock to the regulatory sentiment index, with point estimates and 90 percent confidence bands. The estimates show that a negative sentiment shock reduces industrial production and employment. The effects on industrial production are statistically significant between 5 and 17 months after the shock and reach the maximum of a 0.36% drop at 13 months post the shock. The shock leads to a statistically significant reduction in employment for a longer time period, lasting up to 26 months after the shock, and the maximum estimated drop is 0.2%.

Figure 5 shows the impulse responses to a regulatory uncertainty shock. The effects of an upward one-standard-deviation shock to regulatory uncertainty are relatively short-lived, compared to the sentiment shock. Industrial production and employment drop by 0.14%

and 0.16%, respectively, in the next month after the shock, but the effects start waning and are not statistically significant after that.

Similar to Baker et al. (2016), we make several modifications to the VAR specification to test the robustness of the results. Those include the VAR with reverse ordering, a bivariate VAR, a bivariate VAR with reverse ordering, dropping the S&P index, including the VIX, including time trends, and including the Michigan Consumer Sentiment Index. Figures 6 and 7 show the results on the sentiment and uncertainty indexes, respectively, suggesting that the estimates of impulse responses to sentiment shocks are robust to the modifications, while the estimates to uncertainty shocks present some variations. In particular, the effects of sentiment shocks on industrial production and employment are nearly unaffected after controlling for the Michigan Consumer Sentiment Index, regardless of the ordering of the Michigan index and our sentiment index (see the bottom two subplots of Figure 6). The Michigan index reflects consumers' confidence in current and future economic conditions. The robust impulse response functions suggest that our measure of news sentiment about regulation reflect at least some unique information about economic activity that is not captured by the general consumer sentiment or other sources of first-moment information.

To investigate this issue further, we also add the general news sentiment index of Shapiro et al. (2020) and the EPU index of Baker et al. (2016) to the VARs. As shown in Figures 8 and 9, most of the impulse response estimates remain after controlling for general news sentiment or economic policy uncertainty. When the general news sentiment index is placed after our sentiment index in the causal ordering, the estimated effects of a regulatory sentiment shock on output and employment are nearly unchanged. When the general news sentiment is placed first in the ordering, the magnitudes of the effects diminish but still remain sizable.

In sum, the impulse response estimates indicate that news sentiment about regulation has a larger and more robust link with aggregate economic activity than uncertainty about regulation. A drop in sentiment about regulation has a significant, persistent effect on future output and employment. The robustness of this effect after controlling for other measures of sentiment and policy uncertainty implies that our measure of sentiment about regulation contains some unique information that may be valuable for predicting future economic outcomes. An increase in regulatory uncertainty may reduce output and employment temporarily, but this effect is smaller in terms of magnitude and presents some variations in robustness checks.

While the application of our sentiment and uncertainty indexes has some interesting implications, these indexes measure information in the news about regulatory policy in general. However, regulation is diverse, involving various policy areas and segments of the economy. In the next section, we discuss disaggregated measures of sentiment and uncertainty by regulatory area.

5 Sentiment and Uncertainty in Regulatory Policy Areas

To discover how news sentiment and uncertainty about regulation differ by policy area and how they connect to economic activity, we build categorical indexes of sentiment and uncertainty for 15 regulatory policy areas. As we continue working to improve the classification accuracy, we present the preliminary indexes and impulse response estimates in this section.

5.1 Categorizing News Articles

To categorize relevant news contents by regulatory area, we rely on the dictionary of regulatory noun chunks described in Section 3.1. Specifically, we use the fact that the regulatory noun chunks are extracted from rule titles and that rules are issued by agencies with specific regulatory authorities. For example, the Environmental Protection Agency generally issues environmental regulations, the Food and Drug Administration issues regulations to protect food safety and health, and the Commodity Futures Trading Commission regulates part of the financial market. Therefore, we categorize agencies by regulatory area according to their authorities and assume that the noun chunks extracted from the rules issued by a given agency are associated with the regulatory area of the agency.

As a result, we specify 15 regulatory areas for the agencies in our sample, including consumer safety and health, national and homeland security, transportation, labor and workplace, environment and natural resources, energy, finance and banking, general business and trade, agriculture and rural development, education and culture, communications, criminal justice, society, international relations, and government operations. Appendix D lists examples of the agencies, their designated areas, and rule titles. After linking regulatory noun chunks back to agencies, the vast majority of the noun chunks (9,649 out of 11,103) in our dictionary are designated with one regulatory area, while a small proportion of the noun chunks appear in multiple rules issued by multiple agencies and thus are associated with multiple regulatory areas.

Since the regulatory section of a news article in our sample contains one or more of the noun chunks, the article can potentially be classified into regulatory areas based on the noun chunks mentioned. The following is an example of the regulatory section in an article (Boston Globe, January 30, 1985):

> Automobile manufacturers are financing a multimillion dollar lobbying campaign aimed at persuading state legislatures to require motorists to buckle up their **seat belts**, a move designed to kill a **federal regulation** requiring the industry to equip vehicles with more expensive **air bags** by 1989. Last year, legislatures in New York, New Jersey and Illinois adopted mandatory **seat belt** laws and legislation already has been filed on Beacon Hill to bring about the same end.

This regulatory section contains four regulatory noun chunks: "seat belt", "federal regulation", "air bag", and "seat belt" (with "seat belt" occurring twice). Among these terms, "federal regulation" is a relatively broad term associated with seven different regulatory areas, whereas "seat belt" and "air bag" are noun chunks specific to the area of transportation in our dictionary. We classify this article into the transportation category, because it is the area linked to most of the noun chunks.

In longer regulatory sections, it is common that there are many regulatory noun chunks that are linked to multiple areas. In that case, we define the dominant area of an article as the most common area across all regulatory noun chunks in the regulatory section. Mathematically, suppose there are n noun chunks in the regulatory section (duplicated noun chunks are counted multiple times), $\mathbf{a}^p_{m\times 1}$ denotes a $m \times 1$ vector for the pth noun chunk, where the qth element of the vector $a^p_q = 1$ if the pth noun chunk is associated with the qth area ($q = \{1, 2, \ldots, m\}$), and otherwise $a^p_q = 0$. We add the vectors for all noun chunks:

$$\sum_{p=1}^{n} \mathbf{a}^p_{m\times 1} = \mathbf{b}_{m\times 1}.$$

Then the dominant area is q_{max} such that $b_{q_{max}} = \max_{1\leq q\leq m} b_q$. In some instances, there are multiple dominant areas for an article.

Appendix E plots article counts by dominant area, showing that finance and banking is the regulatory area that has drawn the most news attention, followed by environment and natural resources regulation. While our dominant area approach intends to capture the primary regulatory areas discussed in the relevant text of a news article, we implement alternative approaches to link articles to areas of noun chunks as robustness checks and also plan to use other approaches such as unsupervised learning (e.g., topic modeling) to categorize articles. Next, we construct categorical sentiment and uncertainty indexes using the articles classified into each regulatory area.

5.2 Categorical Indexes

We use the same approach to construct the categorical indexes as we did for the aggregate sentiment and uncertainty indexes. Specifically, for a given regulatory area, we create the indexes by fitting the fixed effects regression to the estimated sentiment or uncertainty scores of the articles classified into the area.

Figures 10 and 11 plot the categorical sentiment and uncertainty indexes over time. There are substantial variations in the measured sentiment and uncertainty about different regulatory areas. For example, the sentiment about environmental and natural resources regulation largely improved in the 1990s, a decade beginning with the passage of the 1990 Clean Air Act amendments. The sentiments around finance and banking regulation and general business and trade regulation comoved closely over time, with large drops around recessions. In contrast, regulatory uncertainty around those two areas raised substantially during and post recessions.

5.3 Impulse Responses

We conduct the VAR analyses for the categorical indexes using the same economic variables as described in Section 4.3. In some regulatory areas, we find particularly strong linkage between our sentiment and uncertainty measures and future economic outcomes. Figures 12 and 13 show the impulse responses of output and employment to a negative sentiment shock for each regulatory area. We find that a sentiment shock about regulations concerning transportation, environment and natural resources, and energy reduces future output and employment. The point estimates of the reductions in industrial production are generally between 0.2% and 0.4%, and the estimates of employment reductions are 0.1% – 0.2%. The effects are also very persistent, some of which remain statistically significant in 36 months after the shock. The responses of aggregate economic activity to shocks in these three regulatory areas are perhaps not surprising, as environmental, transportation, and energy regulations are important types of regulations that affect various industries. We also see that a sentiment shock related to general business and trade regulation is associated with a peak reduction of 0.14% in employment about one year post the shock (Figure 13), indicating that sentiment about business and trade regulations may influence firms' decision to hire.

Similar to the aggregate regulatory uncertainty, responses of economic activity to categorical regulatory uncertainty shocks are either not statistically significant or short-lived in the estimated impulse response functions (Figures 14 and 15). An exception is labor and workplace regulation, for which an uncertainty shock is associated with measurable and persistent drops in both output and employment, which present no sign of diminishing even in 36 months after the shock. While previous studies such as Baker et al. (2016) find adverse effects of uncertainty around financial regulation on the economy, our results only show transitory drops in output and employment after a uncertainty shock to financial and banking regulation.

6 Conclusion and Future Work

In this study, we examine how the sentiment and uncertainty about regulation expressed in the news changed over time and affected aggregate economic activity. We identify an original corpus of regulation-related news from seven leading U.S. newspaper, which shows that news attention to regulation has been increasing since 1996. We then use lexicon-based sentiment analysis of the relevant news text to construct monthly indexes of sentiment and uncertainty about regulation from January 1985 to August 2020.

Using monthly VARs, we estimate how aggregate economic indicators respond to regulatory sentiment and uncertainty shocks. The impulse response functions suggest that a negative sentiment shock about regulation is associated with persistent drops in future output and employment, while a regulatory uncertainty shock only has transitory effects. Notably, the responses to sentiment shocks largely remain after controlling for existing measures of general news sentiment and policy uncertainty, which suggests that our measure of sentiment about regulation may capture some unique information about the economy.

To further explore what types of regulatory policy drive the connection between regulation and macroeconomic outcomes, we construct categorical indexes of sentiment and uncertainty for 15 regulatory policy areas. Our preliminary estimates of impulse responses using the categorical indexes suggest that sentiment shocks to transportation, environment and natural resources, and energy regulations have large and persistent effects on future output and employment. In addition, increased uncertainty around labor and workplace regulation also has long-lasting adverse effects on output and employment, regardless of the lack of findings on persistent effects of aggregate regulatory uncertainty shocks in our analysis.

As we continue working to complete this study, we plan to refine our approach of using regulatory noun chunks to classify news articles to improve the accuracy of the categorical indexes. We will also adopt other methods such as machine learning (e.g., topic modeling, as a method of unsupervised learning) to define regulatory policy areas as comparisons to our baseline approach. In a later stage, we would like to extend the study to industry-specific news and industry-level economic analysis. That would help further explain the mechanisms through which regulation affects the macroeconomy.

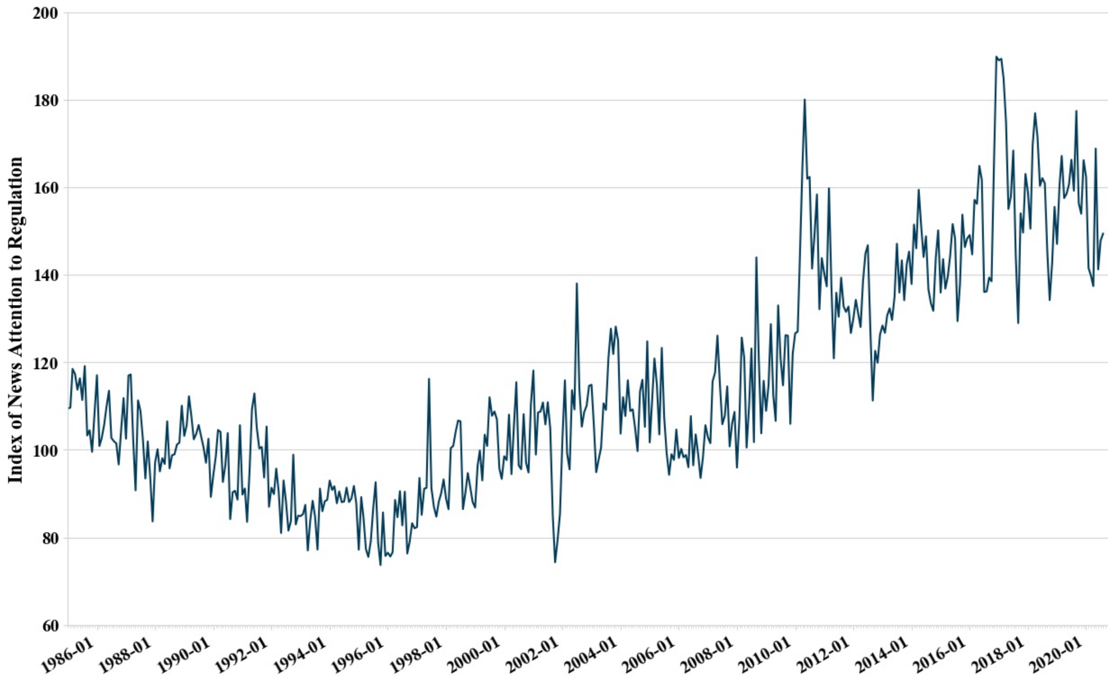
Tables

Table 1: Descriptive Statistics of Estimated Sentiment and Uncertainty Scores

	Sentiment Score			**Uncertainty Score**
	LM	**GI**	**LSD**	**LM**
Mean	-2.06	1.03	-0.07	0.74
Standard deviation	2.58	4	3.43	0.95
Minimum	-27.5	-30.77	-35.71	0
Maximum	13.33	30.77	26.32	20.45
Number of articles with negative scores	367,549	172,691	224,333	N/A
Number of articles with positive scores	60,975	284,223	220,295	274,052
N	505,811	505,811	505,811	505,811

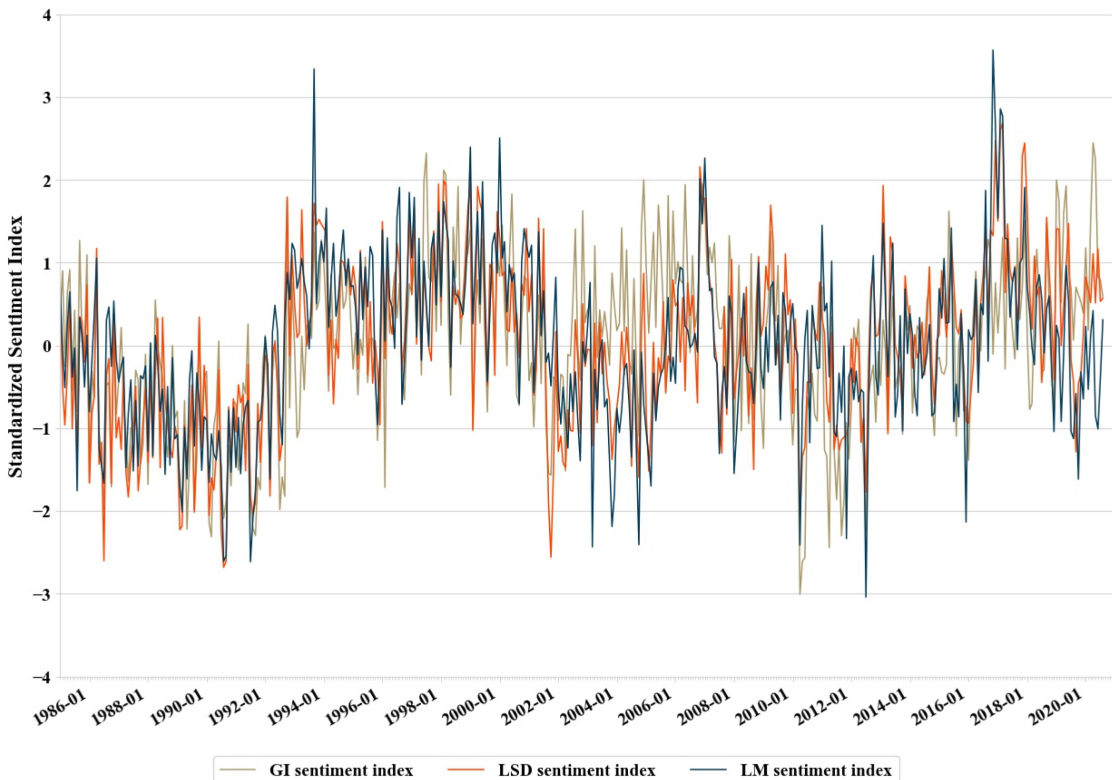
Figures

Figure 1: Monthly Index of News Attention to Regulation
(January 1985 – August 2020)



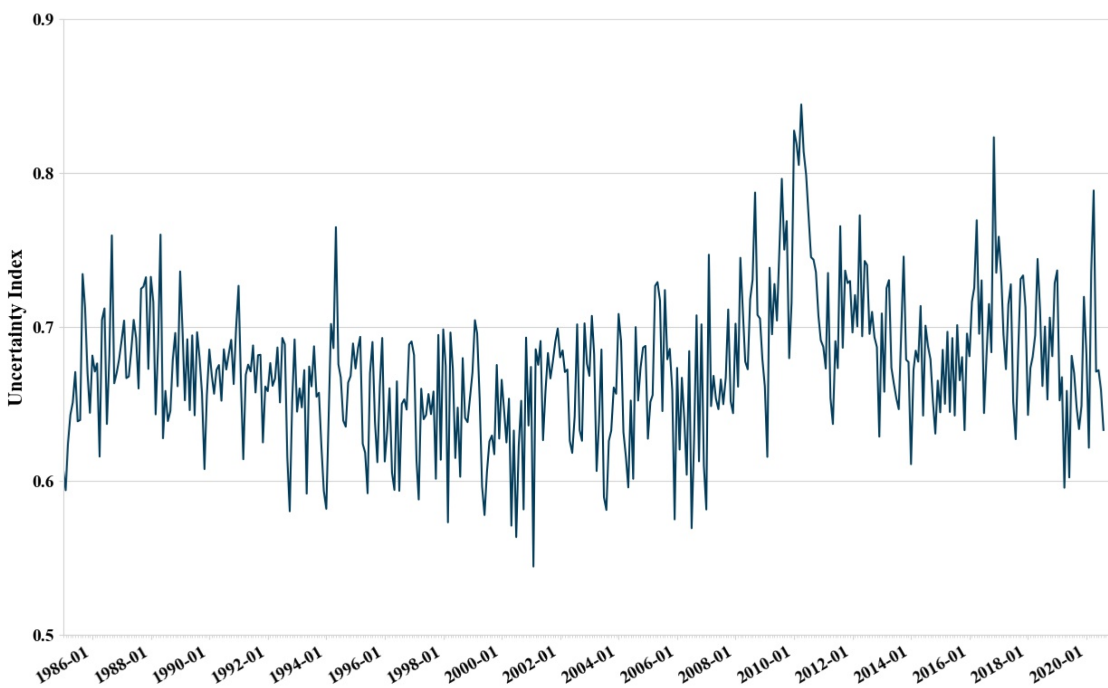
Notes: The index is normalized to mean 100 from January 1985 through December 2009. The index is calculated and plotted using data from seven U.S. newspapers including Boston Globe, Chicago Tribune, Los Angeles Times, New York Times, USA Today, Wall Street Journal, and the Washington Post. Data for the Washington Post are available from January 1987, and data for USA Today are available from April 1987.

Figure 2: Monthly Indexes of News Sentiment about Regulation
(January 1985 – August 2020)



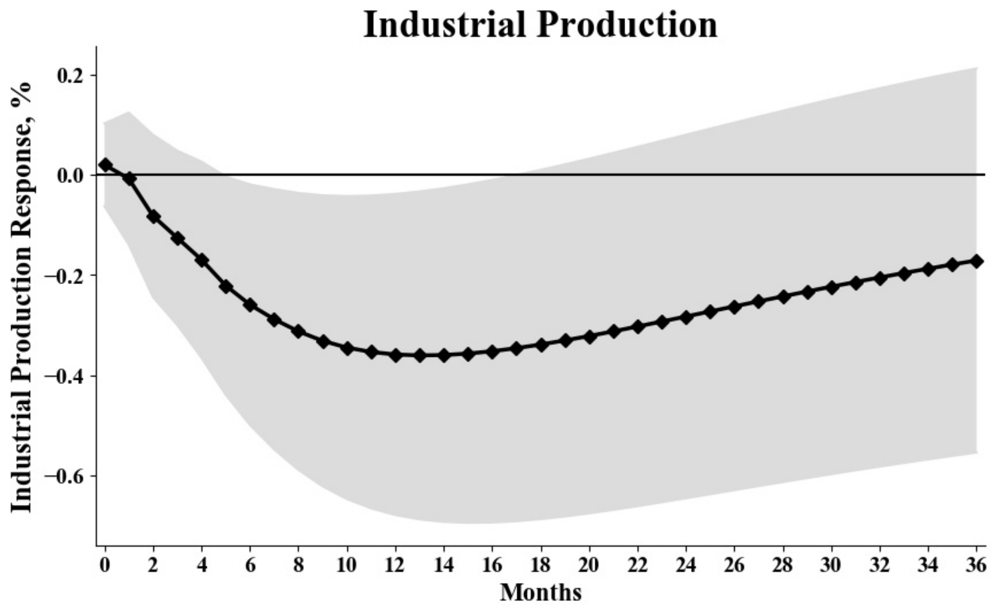
Notes: The figure plots three sentiment indexes estimated using the Loughran and McDonald (LM) dictionary, the General Inquirer (GI) dictionary, and the Lexicoder Sentiment Dictionary (LSD), respectively. All indexes are normalized to have mean equal to zero and standard deviation equal to one.

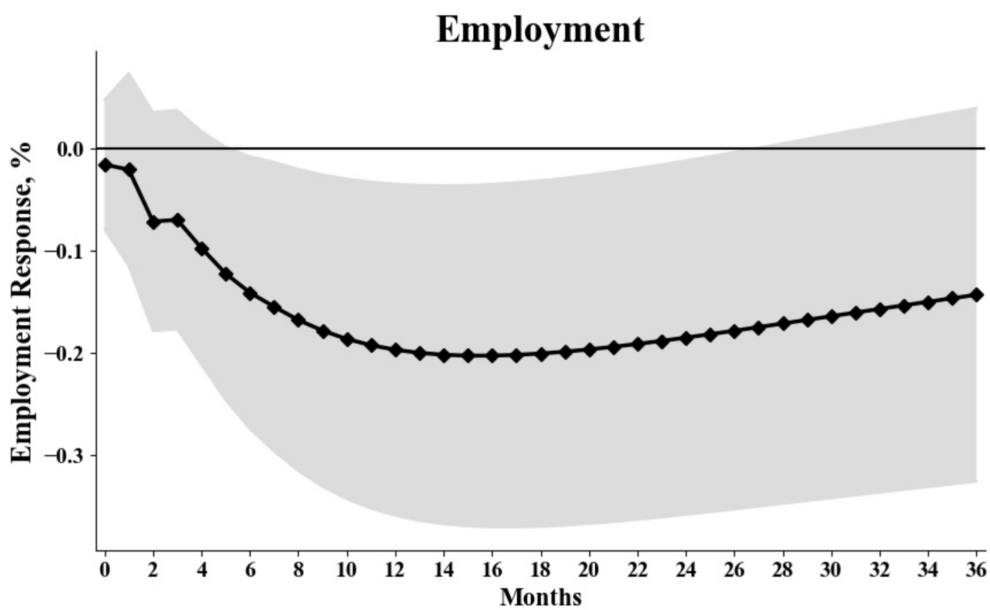
Figure 3: Monthly Index of Regulatory Uncertainty
(January 1985 – August 2020)



Notes: The figure plots the regulatory uncertainty index estimated using the Loughran and McDonald (LM) dictionary.

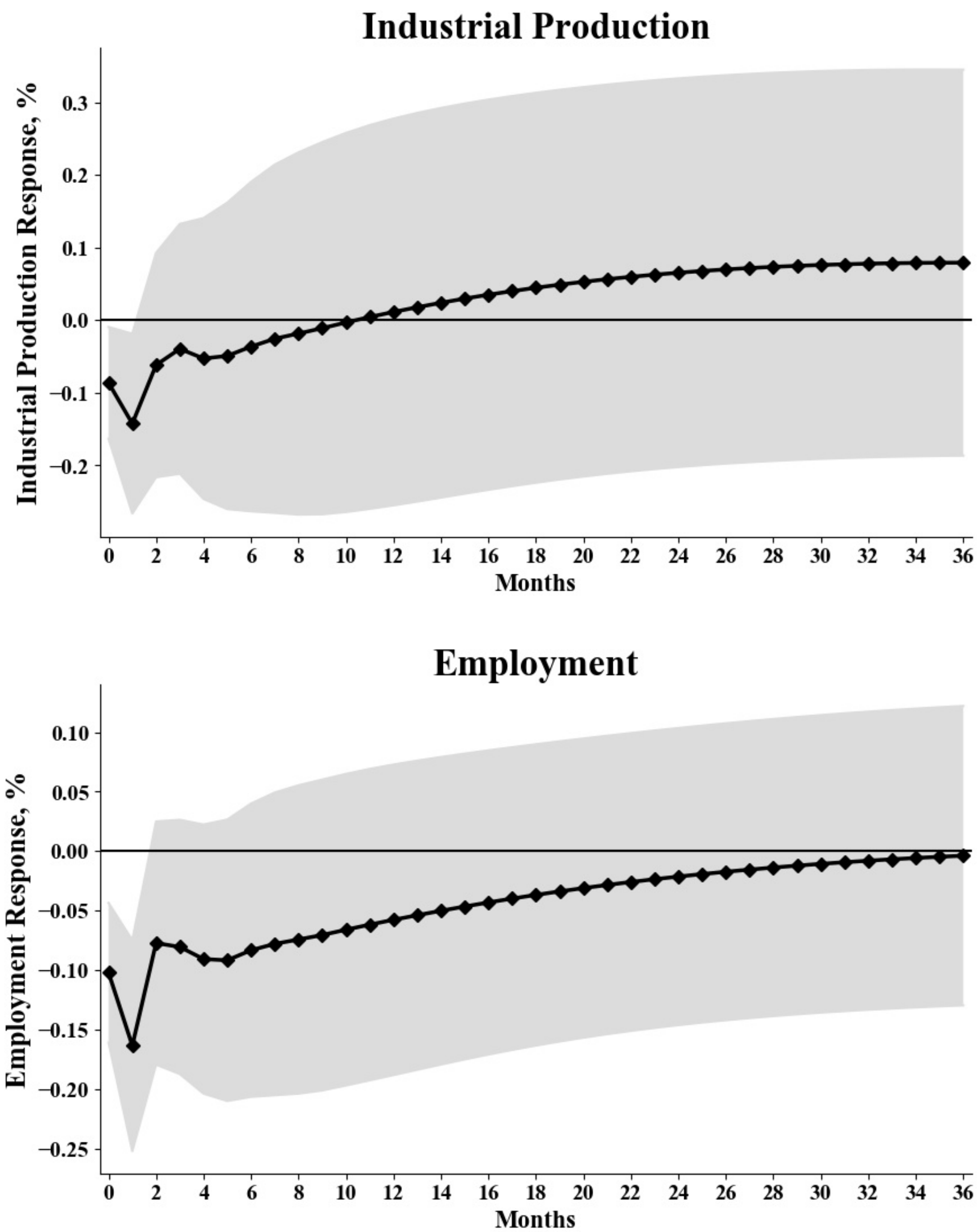
Figure 4: Impulse Responses to a Sentiment Shock about Regulation (Monthly VAR)





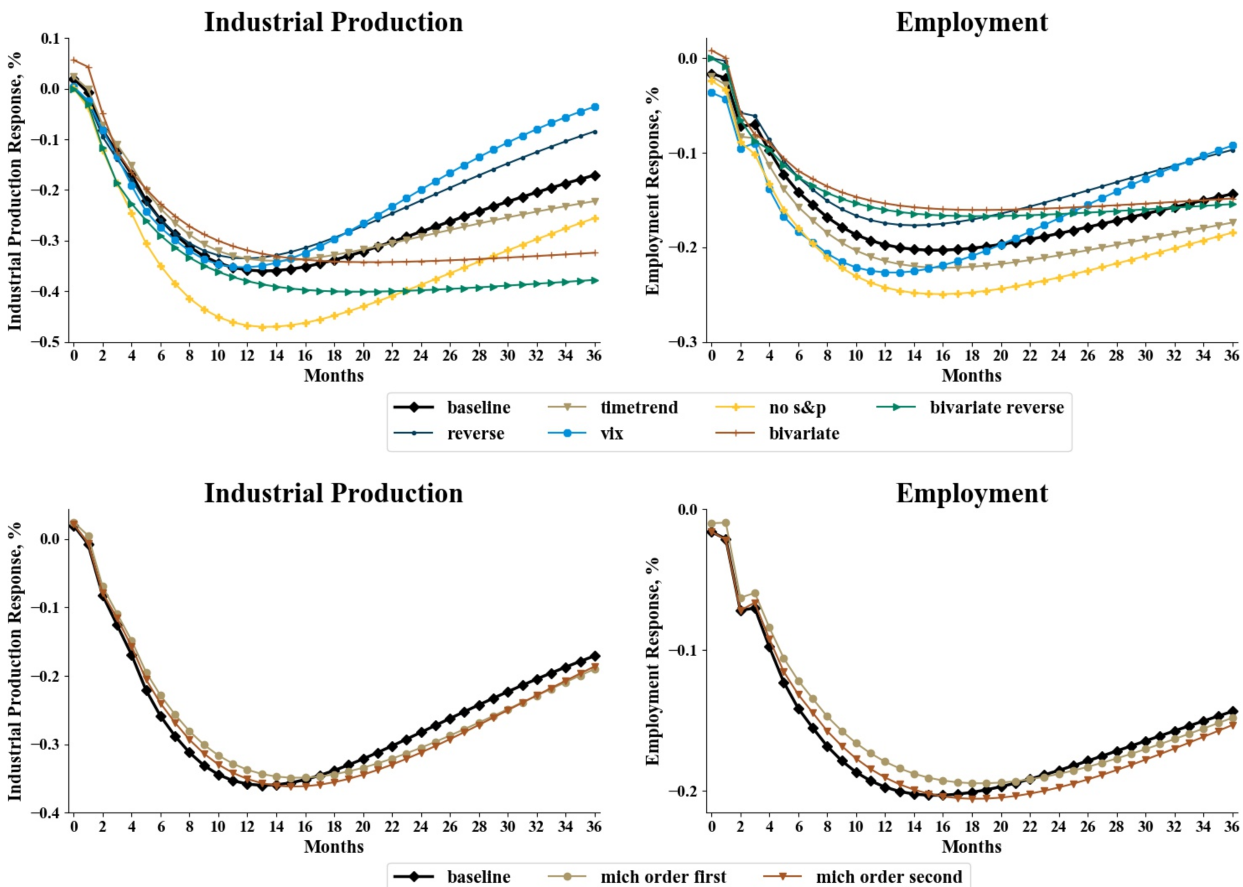
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation negative shock to sentiment about regulation. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

Figure 5: Impulse Responses to an Uncertainty Shock about Regulation
(Monthly VAR)



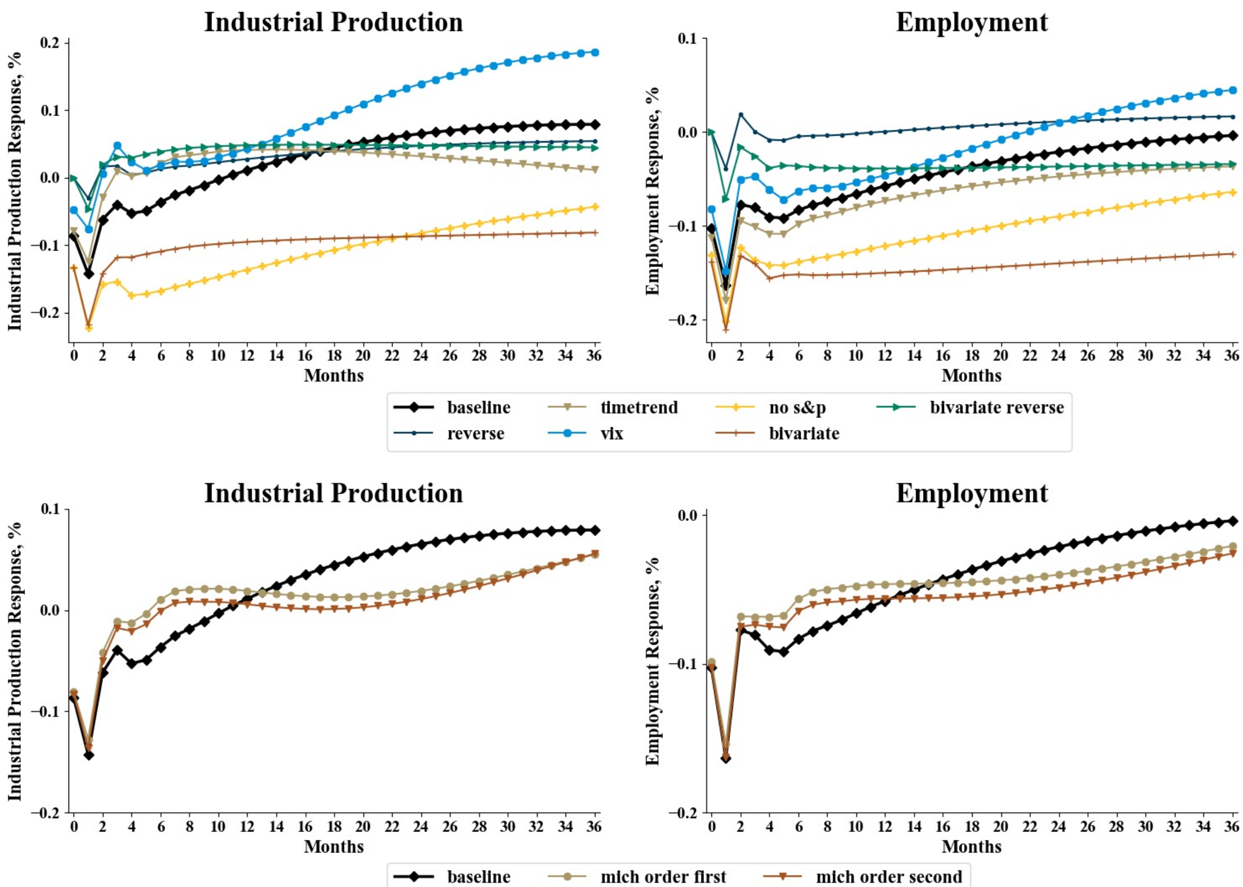
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation upward shock to uncertainty about regulation. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory uncertainty index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

Figure 6: Impulse Responses to a Sentiment Shock about Regulation
(Monthly VAR, Robustness Checks)



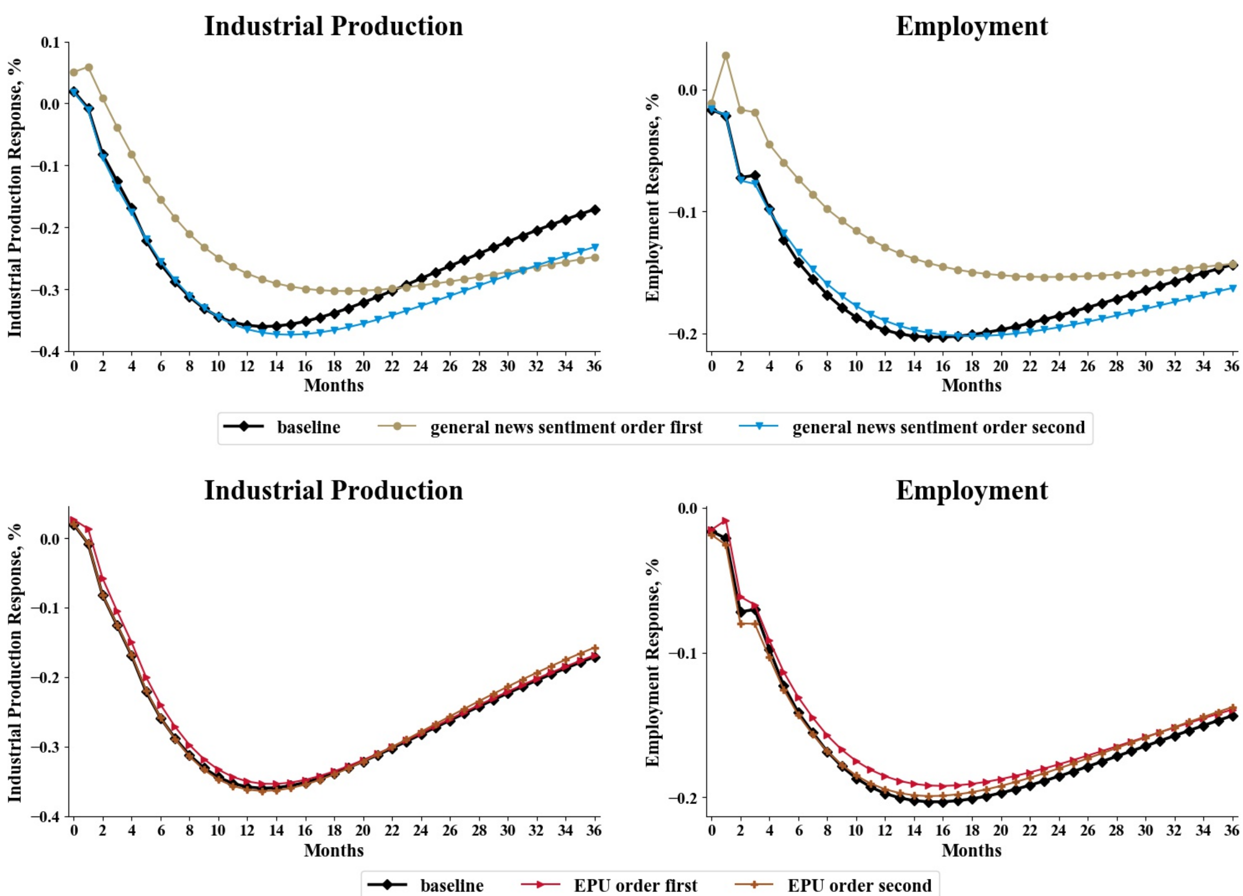
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation negative shock to sentiment about regulation, with several modifications to the baseline specification. The modifications include reverse ordering, a bivariate VAR, a bivariate VAR with reverse ordering, dropping the SP index, including the VIX, including time trends, and including the Michigan Consumer Sentiment Index.

Figure 7: Impulse Responses to an Uncertainty Shock about Regulation
(Monthly VAR, Robustness Checks)



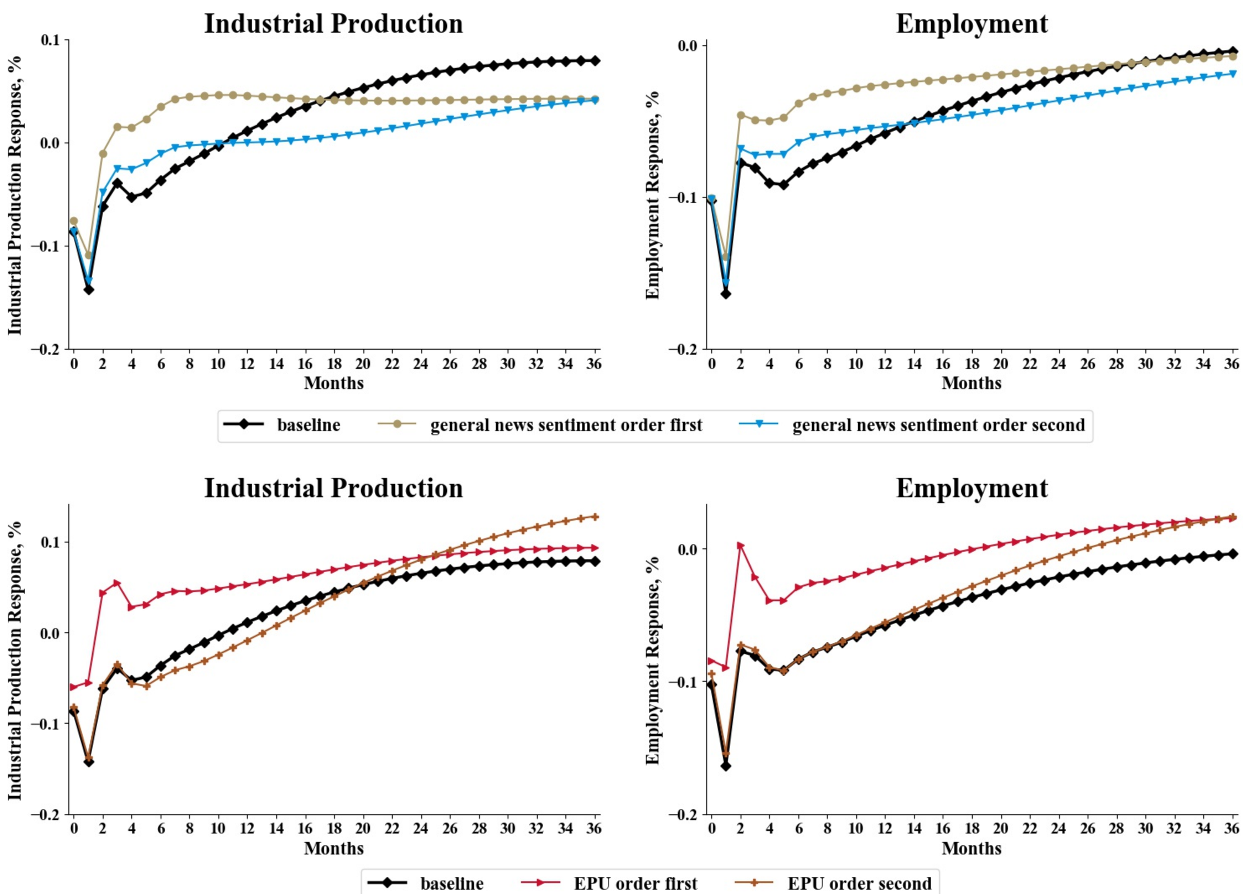
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation upward shock to uncertainty about regulation, with several modifications to the baseline specification. The modifications include reverse ordering, a bivariate VAR, a bivariate VAR with reverse ordering, dropping the SP index, including the VIX, including time trends, and including the Michigan Consumer Sentiment Index.

Figure 8: Impulse Responses to a Sentiment Shock about Regulation
(Monthly VAR, Adding General News Sentiment or EPU)



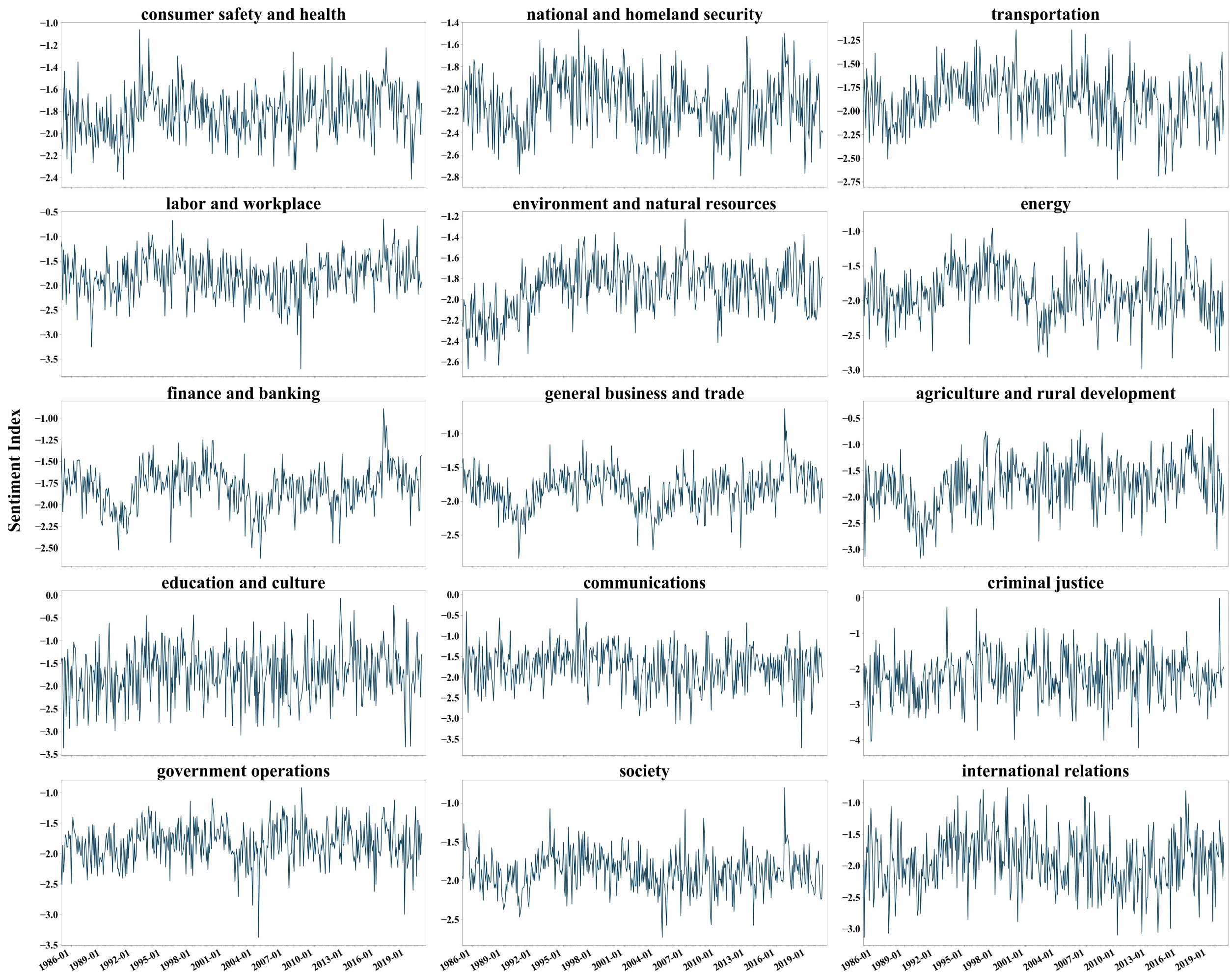
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation negative shock to sentiment about regulation, after adding the news sentiment index of Shapiro et al. (2020) or the EPU index of Baker et al. (2016).

Figure 9: Impulse Responses to an Uncertainty Shock about Regulation
(Monthly VAR, Adding General News Sentiment or EPU)



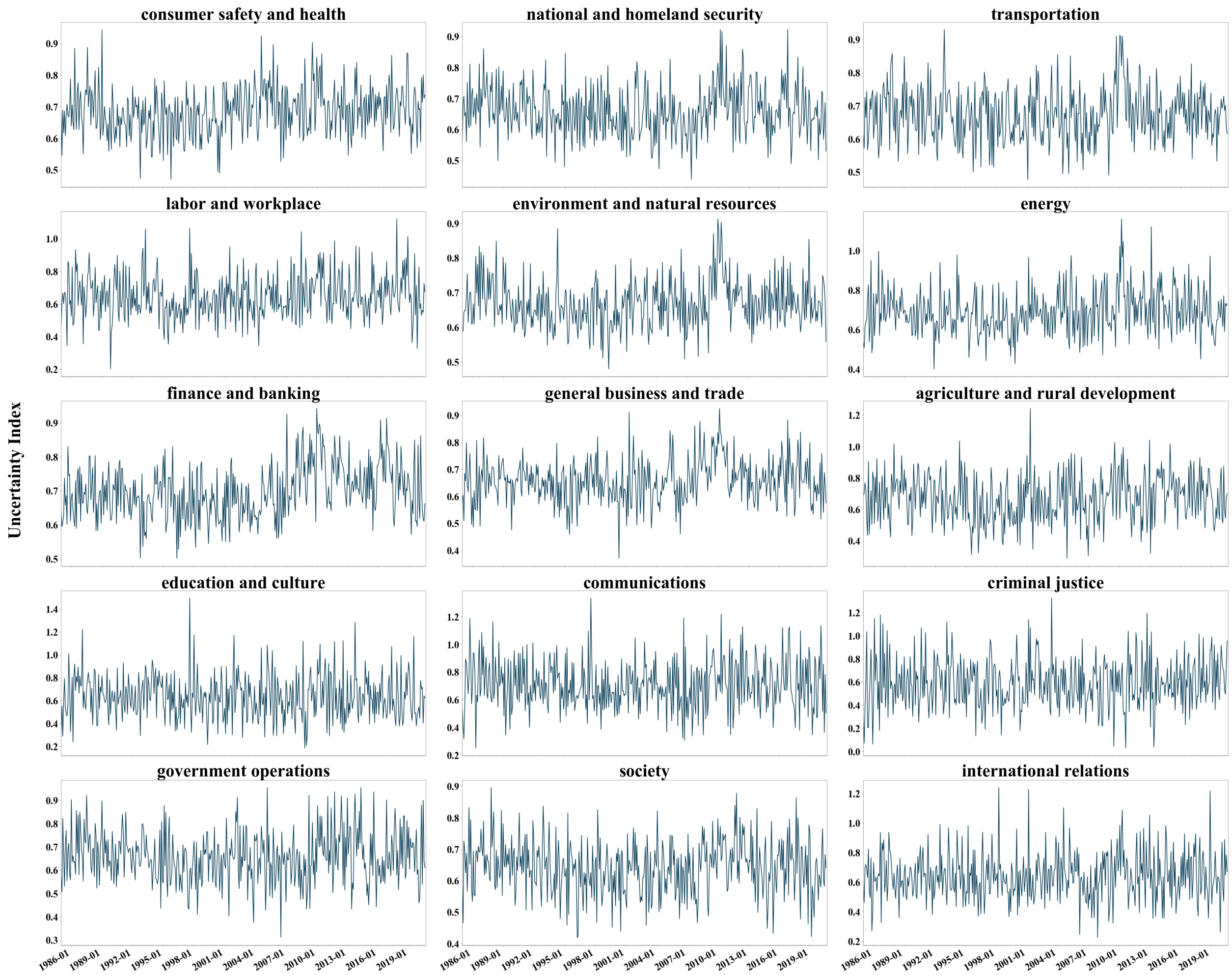
Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation upward shock to uncertainty about regulation, after adding the news sentiment index of Shapiro et al. (2020) or the EPU index of Baker et al. (2016).

Figure 10: Monthly Sentiment Index By Regulatory Policy Area
(January 1985 – August 2020)



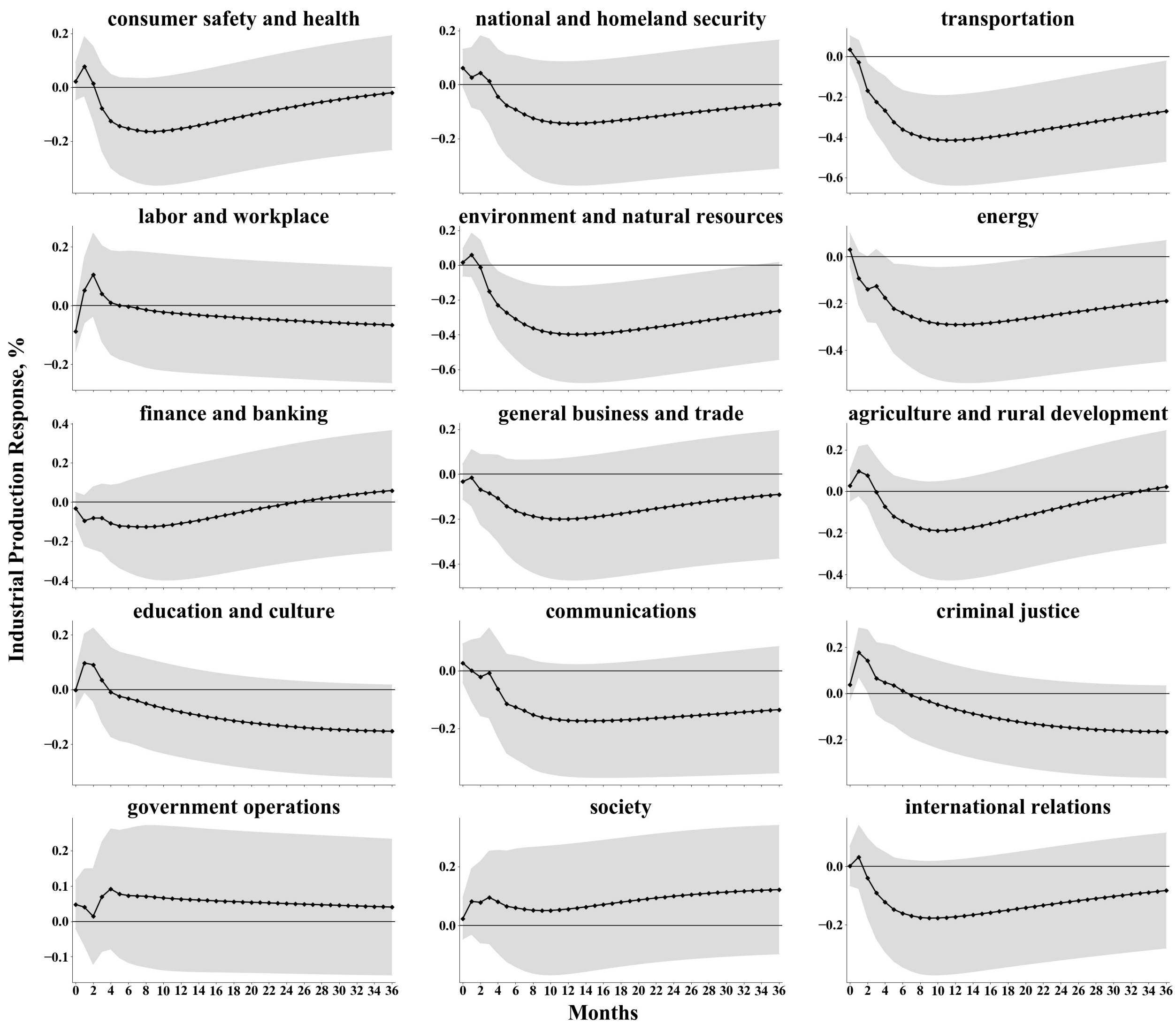
Notes: The figures plot the sentiment indexes estimated using the Loughran and McDonald (LM) dictionary for each regulatory policy area.

Figure 11: Monthly Uncertainty Index By Regulatory Policy Area
(January 1985 – August 2020)



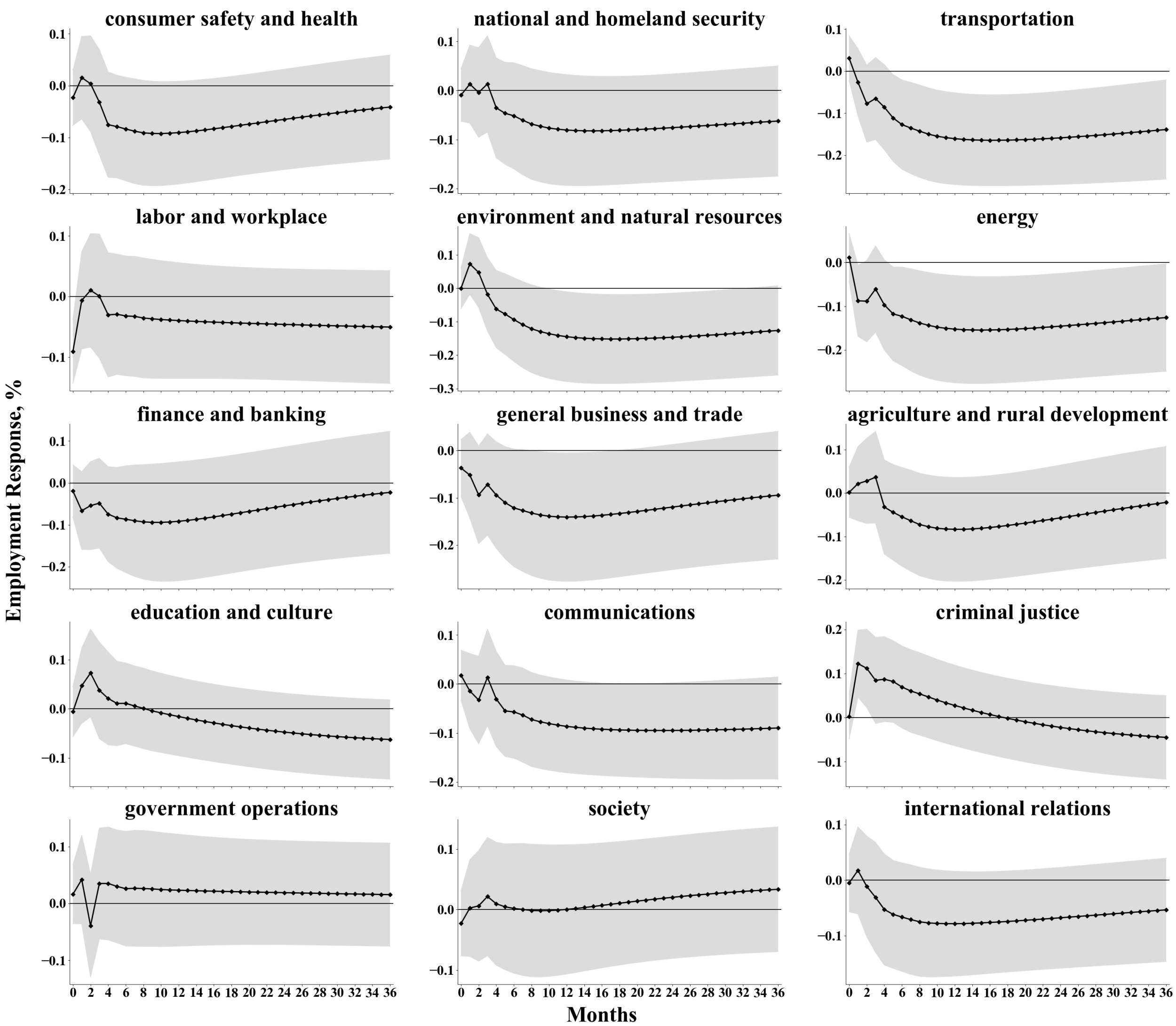
Notes: The figures plot the uncertainty indexes estimated using the Loughran and McDonald (LM) dictionary for each regulatory policy area.

Figure 12: Industrial Production Responses to a Sentiment Shock By Regulatory Area (Monthly VAR)



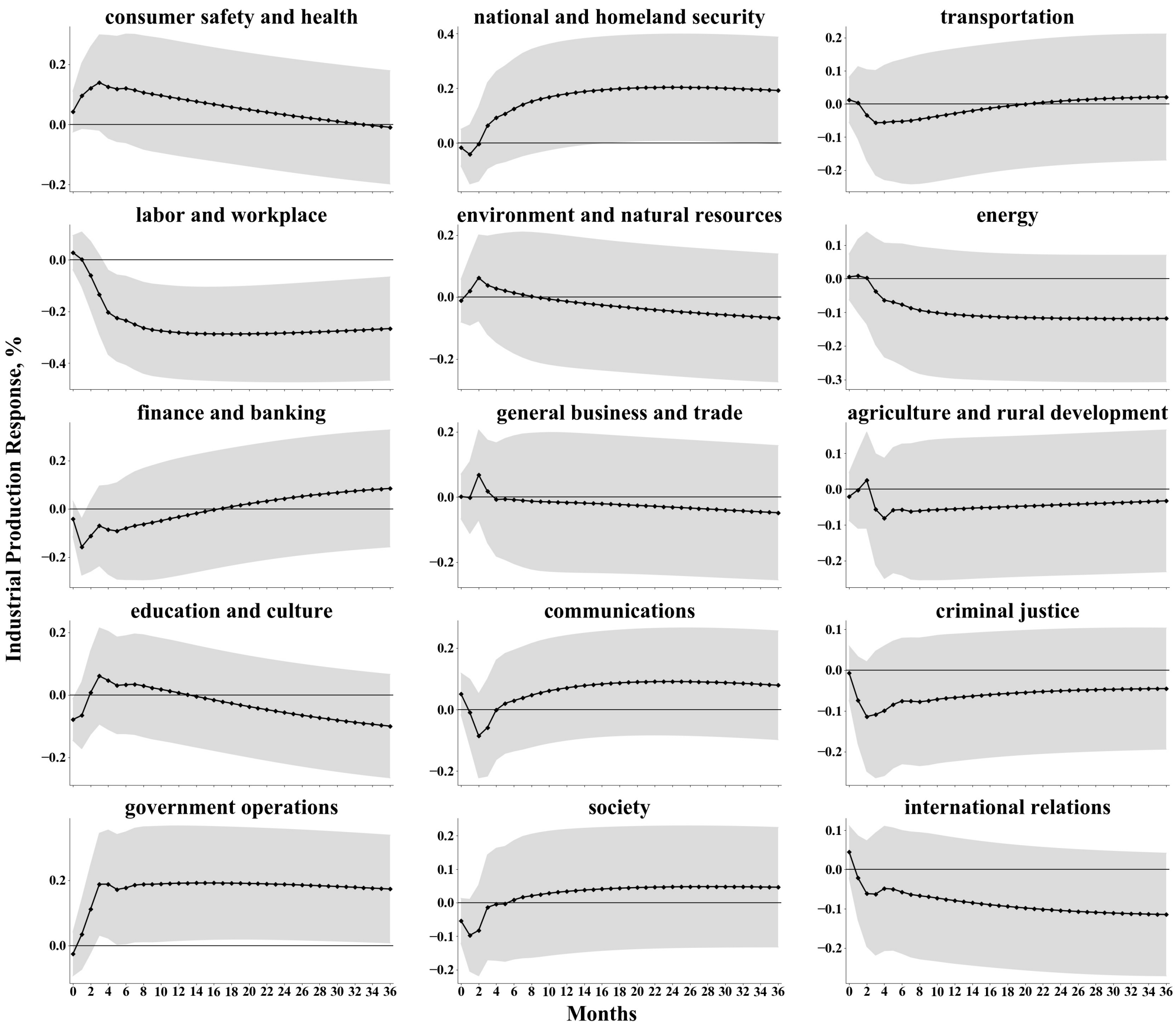
Notes: The figures plot VAR-estimated impulse responses of industrial production to a one-standard-deviation negative sentiment shock for each regulatory policy area. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

Figure 13: Employment Responses to a Sentiment Shock By Regulatory Area (Monthly VAR)



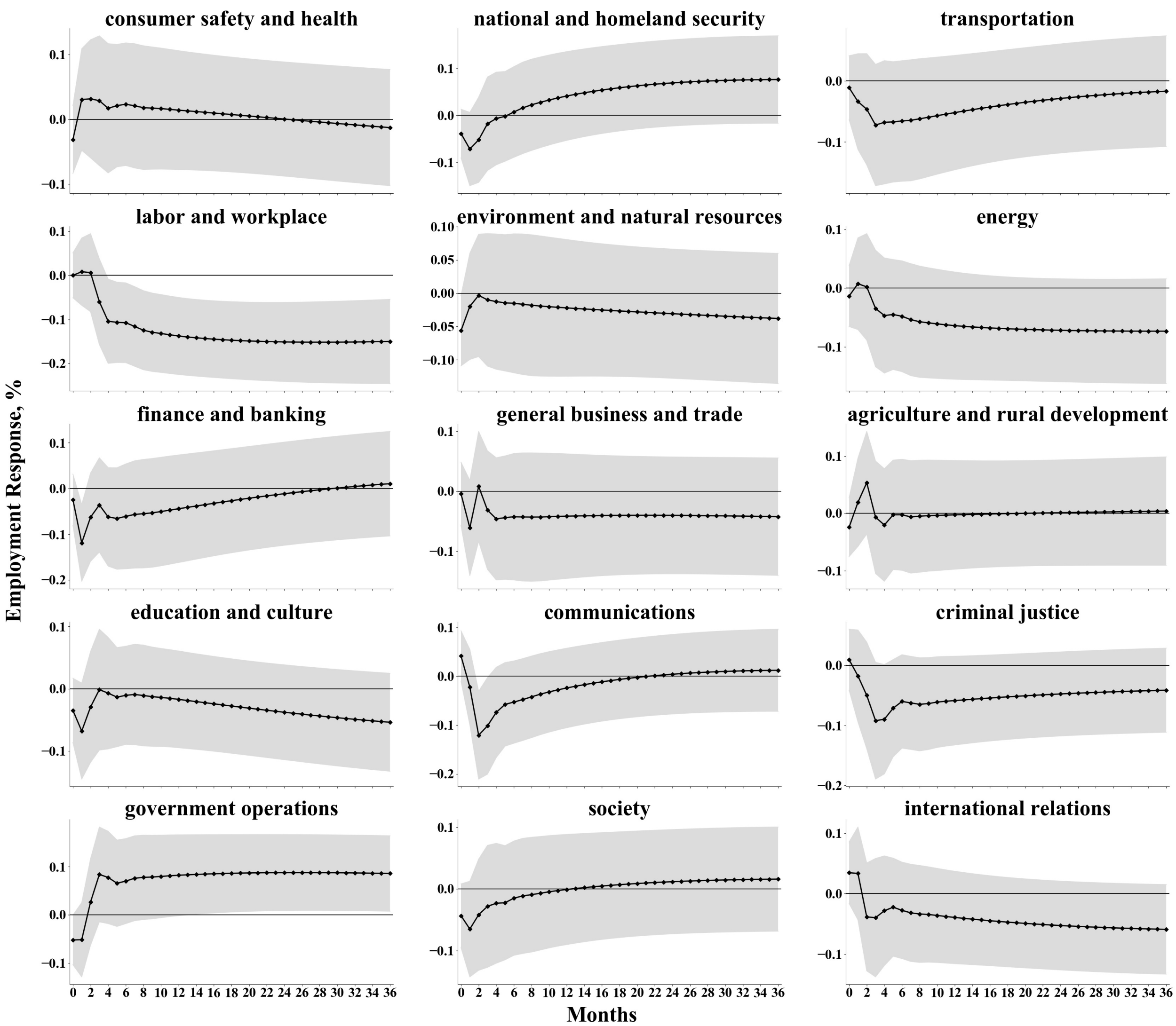
Notes: The figures plot VAR-estimated impulse responses of employment to a one-standard-deviation negative sentiment shock for each regulatory policy area. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

Figure 14: Industrial Production Responses to an Uncertainty Shock By Regulatory Area (Monthly VAR)



Notes: The figures plot VAR-estimated impulse responses of industrial production to a one-standard-deviation upward uncertainty shock for each regulatory policy area. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory uncertainty index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

Figure 15: Employment Responses to an Uncertainty Shock By Regulatory Area (Monthly VAR)



Notes: The figures plot VAR-estimated impulse responses of employment to a one-standard-deviation upward uncertainty shock for each regulatory policy area. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory uncertainty index, the log of S&P500 index, the federal funds rate, log employment, and log industrial production. VARs are fit to monthly data from January 1985 to August 2020. Gray areas show 90 percent confidence bands.

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Appendices

A The Most Common Regulatory Noun Chunks in News Articles

{'new regulation': 30585, 'federal regulation': 22506, 'health care': 18483, 'real estate': 17589, 'federal reserve': 16926, 'new rule': 16314, 'federal government': 15698, 'attorney general': 15021, 'government regulation': 14007, 'interest rate': 12281, 'food and drug administration': 12254, 'hedge fund': 12142, 'natural gas': 11636, 'state regulation': 11343, 'nuclear regulatory commission': 10972, 'mutual fund': 10545, 'financial institution': 10353, 'small business': 10199, 'environmental protection agency': 10166, 'public health': 8928, 'federal law': 8848, 'state law': 8715, 'financial service': 8120, 'insurance company': 8095, 'executive director': 7777, 'propose regulation': 7262, 'federal agency': 7241, 'federal deposit': 6804, 'federal energy regulatory commission': 6749, 'clean air': 6609, 'state department': 6566, 'fannie mae': 6436, 'state official': 6178, 'credit card': 5768, 'greenhouse gas': 5666, 'task force': 5597, 'freddie mac': 5402, 'hold company': 5111, 'brokerage firm': 5088, 'safety regulation': 5018, 'law enforcement': 4972, 'health insurance': 4936, 'regulatory change': 4778, 'life insurance': 4482, 'rate increase': 4478, 'consumer protection': 4462, 'air quality': 4453, 'regulatory body': 4383, 'nursing home': 4365, 'economic growth': 4348, 'nuclear power plant': 4312, 'propose rule': 4281, 'local government': 4197, 'general counsel': 4151, 'national bank': 4099, 'public hearing': 4078, 'air pollution': 4021, 'regulatory requirement': 3929, 'regulatory system': 3916, 'public comment': 3859, 'joint venture': 3821, 'set aside': 3800, 'insider trading': 3603, 'government agency': 3577, 'credit union': 3531, 'commodity futures trading commission': 3477, 'capital requirement': 3415, 'air bag': 3342, 'regulation a': 3335, 'high speed': 3308, 'carbon dioxide': 3247, 'enforcement action': 3203, 'security firm': 3165, 'federal home loan bank': 3160, 'tax cut': 3157, 'health plan': 3135, 'executive officer': 3134, 'market share': 3124, 'state agency': 3095, 'u.s government': 3062, 'regulatory reform': 3005, 'commercial bank': 2986, 'initial public offering': 2914, 'executive order': 2898, 'land use': 2872, 'electric utility': 2862, 'regulatory review': 2855, 'inspector general': 2833, 'self regulation': 2818, 'public utility': 2775, 'court decision': 2763, 'drinking water': 2742, 'high cost': 2676, 'u.s department': 2662, 'money laundering': 2634, 'fuel economy': 2625, 'start up': 2608, 'accounting firm': 2605, 'national security': 2597, 'regulatory burden': 2580}

Notes: The above shows 100 most common regulatory noun chunks that occurred in the news articles in our sample. The number indicates the occurrence of the noun chunk across all news articles. The noun chunks are lemmatized.

B Examples of Regulatory Sections

Example 1 (Wall Street Journal, 1993-06-22):

Property and casualty insurers would have to meet stringent capital requirements under a proposal likely to be adopted by insurance regulators. The standards, similar to those now in place for life and health insurers, would require property and casualty insurers to have sufficient capital to meet the riskiness of their investments and operations. Failure to meet the requirements would mean regulators could either seize a troubled insurer or order operational changes. The property and casualty market, alone, involves annual premiums totaling $500 billion. Under the proposal, each insurer must report to what extent it exceeds or falls below its minimum-capital threshold. Insurance regulators released a draft of the rules at a conference for state insurance commissioners here. "We are entering the home stretch of one of the most important improvements in insurance regulation," said Virginia Insurance Commissioner Stephen Foster, chairman of the National Association of Insurance Commissioners. Regulators will vote on whether to adopt the proposal in December. The rules, if passed, would go into effect next year and the results would be available to the public in the spring of 1995. Insurance experts say it's unlikely that regulators will make major changes in the proposal before voting on it. The effort comes at a time when Congress is concerned about whether states are up to the job of overseeing insurance companies. The company wants to prove that the idea is administratively possible, said Roger Joslin, State Farm's treasurer. Under the plan, State Farm can still trade securities but cannot withdraw from the account or convert safe assets into riskier ones without approval of the trustee and state insurance regulators.

Regulatory noun chunks: ['capital requirement', 'minimum capital', 'insurance regulation', 'major change', 'insurance company']

Sentiment:

LM negative words: ['stringent', 'concerned', 'risky', 'seize', 'troubled']

LM positive words: ['improvement']

LM sentiment score: -1.4085

GI negative words: ['casualty', 'capital', 'pass', 'casualty', 'stringent', 'capital', 'fall', 'capital', 'casualty', 'involve', 'make', 'risky', 'approval (with negation)', 'mean', 'seize', 'order']

GI positive words: ['health', 'sufficient', 'meet', 'pass', 'meet', 'home', 'important', 'improvement', 'company', 'premium', 'expert', 'make', 'major', 'company', 'security', 'safe', 'asset', 'credit', 'meet', 'order']

GI sentiment score: 1.4085

LSD negative words: ['casualty', 'riskiness', 'casualty', 'casualty', 'unlikely', 'concerned', 'riskier', 'approval (with negation)', 'failure', 'seize', 'troubled']

LSD positive words: ['sufficient', 'adopted', 'improvements', 'foster', 'adopt', 'experts', 'effort', 'safe', 'assets', 'credit']

LSD sentiment score: -0.3521

Uncertainty:

LM uncertainty words: ['riskiness', 'possible', 'risky', 'could']

LM uncertainty score: 1.4085

Example 2 (Wall Street Journal, 2010-06-22):

House and Senate Democrats are under pressure to complete their overhaul of financial regulations before President Barack Obama meets with world leaders this weekend, setting up a scramble to iron out differences on a range of complicated provisions. The discussions cover issues from bank regulation to consumer protection. They seek to find a balance that may appease the few centrist Republicans willing to support the bill, while also keeping liberal Democrats happy. Lawmakers are also close to a deal that would place a new consumer-financial protection bureau within the Federal Reserve, scrapping an original White House proposal to create a standalone agency. The change, which closely follows language adopted by the Senate in May, would likely not appease business groups, which oppose the creation of any new consumer-protection regulator with broad powers. Lawmakers are divided over whether it would have power over auto dealerships. Lawmakers on Monday did reach a deal that would limit the amount of fees banks are allowed to charge retailers for processing debit cards. The conference committee of congressional negotiators seeking to resolve differences between the House and Senate versions of the bill plans to work through the consumer-protection issues on Tuesday, the Volcker Rule on Wednesday, and derivatives regulation on Thursday. The timing could slip if lawmakers need more time to resolve disputes.

Regulatory noun chunks: ['consumer protection', 'consumer protection', 'volcker rule', 'consumer protection', 'debit card', 'consumer financial protection bureau', 'federal reserve']

Sentiment:

LM negative words: ['oppose', 'dispute', 'complicated', 'close']

LM positive words: ['happy', 'resolve', 'resolve']

LM sentiment score: -0.4444

GI negative words: ['divide', 'appease (with negation)', 'oppose', 'deal', 'limit', 'charge', 'need', 'dispute', 'iron', 'close', 'deal']

GI positive words: ['protection', 'appease', 'willing', 'support', 'liberal', 'happy', 'resolve', 'protection', 'protection', 'deal', 'allow', 'resolve', 'complete', 'meet', 'deal', 'protection', 'create']

GI sentiment score: 2.6667

LSD negative words: ['divided', 'appease (with negation)', 'oppose', 'limit', 'charge', 'disputes', 'complicated', 'scrapping']

LSD positive words: ['protection', 'balance', 'appease', 'support', 'keeping', 'happy', 'resolve', 'protection', 'adopted', 'creation', 'protection', 'allowed', 'resolve', 'protection', 'create']

LSD sentiment score: 3.1111

Uncertainty:

LM uncertainty words: ['may', 'could']

LM uncertainty score: 0.8889

Example 3 (New York Times, 2016-11-10):

Republican control of Washington sets the stage for a sweeping shift in economic policy. Mr. Trump has proposed a fairly standard set of conservative prescriptions, such as lower taxes and less regulation, with one notable departure: a promise to reduce trade with other nations. The centerpiece of Mr. Trump's plans is a major overhaul of the federal tax code. An analysis by the nonpartisan Committee for a Responsible Federal Budget estimated that

Mr. Trump's plans would increase the federal debt by $5.3 trillion over the next decade, and raise the ratio of debt to gross domestic product to 105 percent. Mr. Trump also has promised to reduce federal regulation. Business groups argue that the Obama administration has impeded economic growth by significantly expanding regulation in areas including environmental and worker protections. He has specifically promised to reverse some new environmental rules, such as the climate change regulations on power plants. Earlier this year, he also proposed the "dismantling" of the Dodd-Frank Act, which overhauled federal regulation of the financial industry in the aftermath of the 2008 financial crisis. The act created the Consumer Financial Protection Bureau, a likely target for Republican legislators. He also has threatened a variety of sanctions against American companies that move manufacturing jobs overseas, although the legality of such measures is unclear. Republicans who broadly agree with Mr. Trump on taxes and regulation may have greater reservations about his views on trade. The party has long supported increased trade among nations.
Regulatory noun chunks: ['economic growth', 'consumer financial protection bureau', 'change regulation', 'federal regulation', 'dodd frank act', 'federal regulation']
Sentiment:
LM negative words: ['argue', 'impede', 'threaten', 'against', 'aftermath', 'crisis']
LM positive words: ['great']
LM sentiment score: -2
GI negative words: ['argue', 'impede', 'threaten', 'against', 'unclear', 'crisis', 'tax', 'low', 'raise']
GI positive words: ['protection', 'support', 'create', 'company', 'promise', 'great', 'promise', 'major', 'notable', 'promise']
GI sentiment score: 0.4
LSD negative words: ['argue', 'impeded', 'threatened', 'against', 'unclear', 'crisis', 'debt', 'debt', 'gross']
LSD positive words: ['protections', 'supported', 'created', 'protection', 'agree', 'frank', 'notable', 'responsible']
LSD sentiment score: -0.4
Uncertainty:
LM uncertainty words: ['unclear', 'may']
LM uncertainty score: 0.8

Example 4 (Boston Globe, 1998-10-25):
"We don't know whether it will be feasible to lower emissions 75 percent by 2005, but we will participate in the effort." On sludge, or the muck left over when wastewater is drained, Shaheen's plan builds on the ongoing efforts at the Department of Environmental Services to more tightly regulate mercury in the waste, some 18,600 tons of which are spread on farmland annually as fertilizer. The department is moving to adopt a new standard for how much mercury may be in the sludge, and is considering – as per Shaheen's plan – an even tighter standard.
Regulatory noun chunks: ['environmental service', 'new standard']
Sentiment:
LM negative words: ['waste']

LM positive words: []
LM sentiment score: -1.0204
GI negative words: ['know (with negation)', 'lower', 'waste', 'even']
GI positive words: ['feasible', 'consider', 'even']
GI sentiment score: -1.0204
LSD negative words: ['wastewater', 'drained', 'waste']
LSD positive words: ['feasible', 'effort', 'efforts', 'adopt']
LSD sentiment score: 1.0204

Uncertainty:
LM uncertainty words: ['may']
LM uncertainty score: 1.0204

Example 5 (The Washington Post, 2001-04-05):

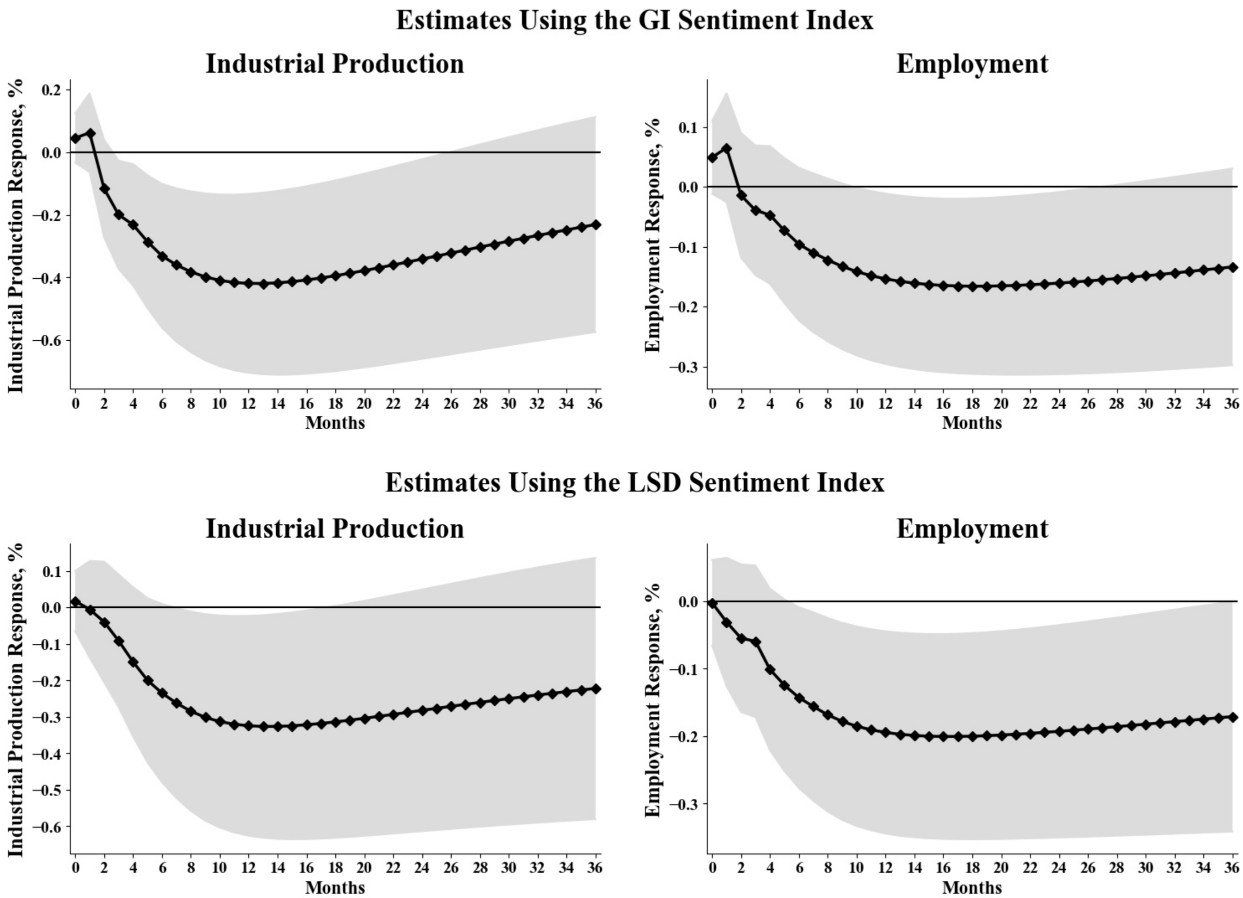
All recreational boats will be limited to one bushel of hard crabs and three dozen soft or peeler crabs per day. The new limits were implemented after the Chesapeake Bay Commission's Bi-State Blue Crab Advisory Committee decided last year that fishing regulators should reduce crab harvests by 15 percent over three years to increase spawning stock. In recent years, crab harvests have dipped near all-time lows throughout the region. They pointed out that other factors – including recreational crabbers, environmental damage and predatory fish – also contribute to diminishing crab populations. Those factors, the watermen said, should also be addressed when local regulators devised new limits. The commercial crabbers' reaction to the new limits varied from disappointment to relief. He suggested that the panel's new limits are too tough on the commercial crab industry. "These regulations are just getting piled on us one after the other," said Conway, of Crisfield. "If society wants to eliminate the waterman, then these regulations are a very efficient way of doing it." The shortening of the crabbing season drew more complaints from watermen than did the lowering of pot limits.

Regulatory noun chunks: ['recreational boat', 'chesapeake bay', 'advisory committee', 'environmental damage']

Sentiment:
LM negative words: ['complaint', 'disappointment', 'damage', 'predatory', 'diminish']
LM positive words: ['efficient']
LM sentiment score: -2.1277
GI negative words: ['eliminate', 'limit', 'hard', 'limit', 'low', 'limit', 'get', 'limit', 'too', 'complaint', 'limit', 'limit', 'disappointment', 'point', 'damage']
GI positive words: ['efficient', 'just', 'relief', 'contribute']
GI sentiment score: -5.8511
LSD negative words: ['eliminate', 'limited', 'hard', 'limits', 'limits', 'limits', 'too', 'tough', 'complaints', 'limits', 'limits', 'disappointment', 'damage', 'predatory']
LSD positive words: ['efficient', 'recreational', 'relief', 'recreational']
LSD sentiment score: -5.3191

Uncertainty:
LM uncertainty words: ['suggest', 'vary']
LM uncertainty score: 1.0638

C Impulse Responses Using the GI or LSD Sentiment Indexes

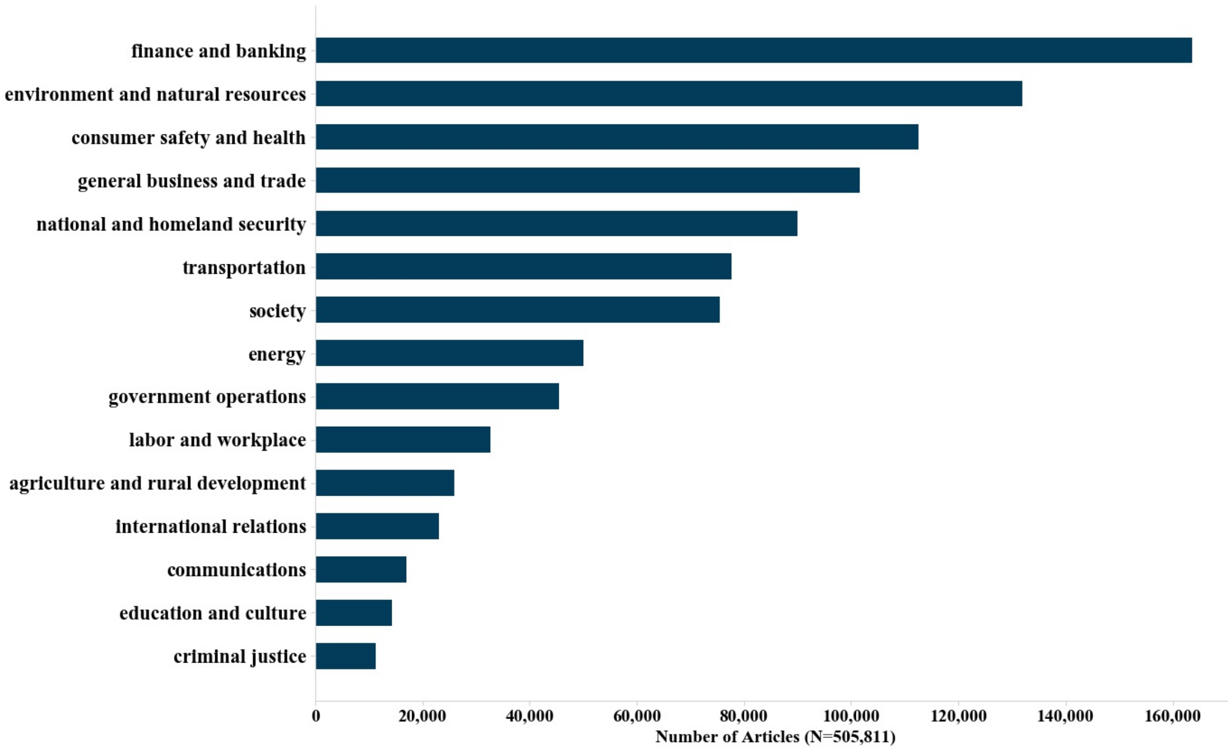


Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation negative shock to sentiment about regulation, using the sentiment index estimated from the General Inquirer (GI) dictionary or the Lexicoder Sentiment Dictionary (LSD). Gray areas show 90 percent confidence bands.

D Examples of Agencies, Regulatory Areas, and Rule Titles

Agency	Department	Regulatory Area	Rule Title
Agricultural Marketing Service	Department of Agriculture	agriculture and rural development	National Organic Program
Federal Communications Commission	N/A	communications	Streamlining the Commission's Rules and Regulations for Satellite Application and Licensing Procedures (IB Docket No. 95-117)
Centers for Medicare & Medicaid Services	Department of Health and Human Services	consumer safety and health	Deduction of Incurred Medical Expenses (Spenddown) (HCFA-2020-F)
Bureau of Prisons	Department of Justice	criminal justice	Volunteer Community Service Projects
Office of Elementary and Secondary Education	Department of Education	education and culture	Improving Basic Programs Operated by Local Educational Agencies
Energy Efficiency and Renewable Energy	Department of Energy	energy	Energy Efficiency Standards for Room Air Conditioners
Office of Air and Radiation	Environmental Protection Agency	environment and natural resources	National Volatile Organic Compounds (VOC) Emission Standards for Consumer Products; Amendments
Commodity Futures Trading Commission	N/A	finance and banking	Review of Commission Disclosure Requirements Concerning Commodity Pool Operators
Small Business Administration	N/A	general business and trade	Certificate of Competency
General Services Administration	N/A	government operations	Nondiscrimination on the Basis of Race, Color, National Origin, and, Where Applicable, Sex
Agency for International Development	N/A	international relations	Administration of Grants and Cooperative Agreements
Employment and Training Administration	Department of Labor	labor and workplace	Airline Deregulation: Employee Benefit Program
Bureau of Citizenship and Immigration Services	Department of Homeland Security	national and homeland security	Employment Verification by Employers That Are Members of a Multi-Employer Association
Office of Fair Housing and Equal Opportunity	Department of Housing and Urban Development	society	Economic Opportunities for Low- and Very-Low-Income Persons (FR-2898)
Federal Aviation Administration	Department of Transportation	transportation	Objects Affecting Navigable Airspace

E Frequencies of Articles By Regulatory Area



Notes: The figure plots the number of news articles classified into each regulatory policy area in our sample.