Sentiment and Uncertainty about Regulation*

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Abstract

Regulatory policy can create economic and social benefits, but poorly designed or excessive regulation may generate substantial adverse effects on the economy. In this paper, we present 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 493,418 news articles related to regulation from seven leading U.S. newspapers. As a result, we build monthly indexes of sentiment and uncertainty about regulation and categorical indexes for 14 regulatory policy areas from January 1985 to August 2020. Impulse response functions indicate that a negative shock to sentiment about regulation is associated with large, persistent drops in future output and employment, while increased regulatory uncertainty overall reduces output and employment temporarily. These results suggest that sentiment about regulation plays a more important economic role than uncertainty about regulation. Furthermore, economic outcomes are particularly sensitive to sentiment around transportation regulation and to uncertainty around labor regulation.

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.

While the existing research studying the economic effects of regulation has mostly focused on the quantity of regulation, subjective perceptions of regulation could also influence firms’ investment and hiring decisions and thus affect the aggregate economic activity. In this study, we construct news-based 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 computational text analysis of news data, which cover 493,418 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 over time, stressing the need to investigate the content of regulation-related news. We then use a lexicon-based sentiment analysis method 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, which capture the subjective attitudes toward the overall regulatory environment. As a result, we build monthly indexes of regulatory sentiment and uncertainty from 1985 to 2020. In addition to the aggregate indexes, we also categorize relevant news articles into 14 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 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 overall 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 regulatory sentiment shocks remain after controlling for news-based measures of general economic sentiment or economic policy uncertainty, implying that our regulatory sentiment measure contains some unique information that may be valuable for predicting future economic activity. Third, economic outcomes are particularly sensitive to sentiment and uncertainty around certain regulatory policy areas. Specifically, we find that negative sentiment shocks related to transportation regulation have negative, long-lasting effects on future output and employment, and sentiment shocks around finance and banking regulation have relatively transitory but measurable effects on employment. In addition, increased uncertainty about labor and workplace regulation leads to a persistent reduction in output.

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).
Survey-based measures of economic sentiment are most widely used in empirical studies, including 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 computational 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 methods can be applied to broader sentiment classifications to extract other subjective information in source material, such as emotional states (e.g., happiness, fear, and anger), subjectivity, confidence, and uncertainty.

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, 2019).
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 study 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. As detailed in the next section, this literature has mostly focused on the volume or restriction of regulation (Coffey et al., 2020; Dawson and Seater, 2013), so our study presents a new direction of considering 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 theoretical framework and empirical evidence in the existing literature for understanding the economic effects of regulation. In Section 3, we describe the data we use in this study, including text data of news articles and economic data used in the VAR analysis. In Section 4, we describe our approach to identifying the news content related to regulation and the evidence of increasing media attention to regulation.
over time. Section 5 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 regulatory sentiment and uncertainty shocks. In Section 6, we describe the categorical indexes that measure news sentiment and uncertainty in 14 regulatory policy areas and their varied roles in the impulse responses of macroeconomic outcomes. Section 7 concludes the study.

2 Economic Effects of Regulation

Regulations, also called rules, are the primary tools that the government uses to implement laws and achieve policy goals. Regulations often involve “specific standards or instructions concerning what individuals, businesses, and other organizations can or cannot do” (Dudley and Brito 2012 p.1). In this paper, we examine regulations in the U.S., with a focus on regulatory actions considered by the federal government. Federal agencies issue thousands of rules every year, covering a broad range of issues such as health, safety, transportation, and the environment. For example, the Food and Drug Administration (FDA) regulates the production, distribution, and packaging of certain foods and medical products to ensure consumer health and safety; the Environmental Protection Agency (EPA) issue regulations to control pollutants, manage waste and hazardous substances, restore wetlands, and ensure drinking water quality.

Given the broad scope of issues covered by regulatory policy, it can affect various industries and generate substantial impacts on the economy. These impacts are considered both incrementally and cumulatively. The incremental economic effects of regulations are partially reflected in agencies’ regulatory impact analyses. When issuing a new regulation that may have significant effects on the economy, executive branch agencies are required to estimate the costs and benefits of the intended regulation and adopt the regulation only if “the benefits...justify its costs” (Clinton 1993 p.51736). However, such regulatory im-
pact analysis is an ex-ante assessment of the effects of a regulation, based on unverifiable assumptions and models of the counterfactual (Dudley, 2017). Agencies rarely conduct retrospective analyses to assess the realized impacts of the regulation after it is implemented (Dudley, 2017). Scholarly research comparing available ex-post assessments of the costs and benefits of individual regulations and their ex-ante estimates suggests that the costs of regulations tend to be overestimated in ex-ante analyses (Harrington et al., 2000). In addition, many independent agencies (e.g., Federal Communications Commission) are not subject to the requirement of conducting regulatory impact analyses for issuing rules.

Even if individual regulations are estimated to generate net benefits, regulations can create indirect and cumulative economic impacts that are not considered in analyses of individual regulations. Eads (1980) discusses four channels through which regulation can affect innovation, which also have important implications for considering the aggregate economic effects of regulation. First, regulation imposes restrictions on firm behavior and thus diverts resources that otherwise might be used for production and innovation (Eads, 1980). While the direct costs for compliance with regulatory requirements are typically considered in regulatory impact analyses, the indirect effects on innovation and productivity are often overlooked.

In academic research, theoretical models that incorporate the effects of regulation on innovation or productivity are also limited. Coffey et al. (2020) presents one way of considering the impact of regulatory constraints on productivity in an endogenous growth model. In their model, firm $i$ in industry $j$ produces goods with the following technology:

$$Y_{ij} = Z_{ij}^{\zeta_j(R_j)}[L_{Y_{ij}} - \phi_j(R_j)],$$

where $Z_{ij}^{\zeta_j(R_j)}$ is the total factor productivity, $Z_{ij}$ is the labor-enhancing knowledge specific to the firm, $\zeta_j$ is the elasticity of the firm’s output to knowledge, $L_{Y_{ij}}$ is the labor employed in producing $Y_{ij}$, $\phi_j$ is a fixed labor cost, and $R_j$ is regulatory constraints (Coffey et al., 2020).
The firm accumulates knowledge according to:

$$\dot{Z}_{ij} = \kappa(R_j)K_jLZ_{ij},$$

where $LZ_{ij}$ is the labor invested in knowledge accumulation, $K_j$ is the stock of public knowledge in the industry, and $\kappa(R_j)$ governs how much knowledge is generated by the firm’s investment given the regulatory restrictions $R_j$ (Coffey et al., 2020). Therefore, their model captures the direct effect of regulation on the firm’s fixed labor costs (i.e., labor used for compliance) and the indirect effect on the firm’s productivity growth.

Second, regulation may change the firm’s ability to calculate the payoffs to investments (Eads, 1980). This connects to the broad literature studying uncertainty. Uncertainty hampers firms’ ability to form a probability distribution of payoffs, making firms more cautious about their investment and hiring decisions. This is often referred to as the “real options” or “wait-and-see” effect (Bloom, 2014; Bachmann and Bayer, 2013). Regulatory uncertainty acts in a similar way. For example, a pharmaceutical company may have the option to invest in the development of a new drug; however, if the company is uncertain about whether the drug would be approved to enter the market by FDA, it may prefer to wait until some certainty is achieved. Less examined is other types of subjective attitude, such as sentiment about regulation, and how they affect firm behavior. The firm’s anticipation of payoffs may depend on whether business executives hold a positive or negative view about the current and future regulatory environment, which captures the idea of “animal spirits” that influence household and business behavior (Keynes, 1936; Shiller, 2017).

While the first two channels suggested by Eads (1980) point to the adverse effects regulation may impose on the economy, the other two channels imply indirect positive impacts of regulation. Eads (1980) argues that regulation may change the nature and the optional institutional patterns of research the firm undertakes. Examples include environmental regulations that stimulate innovation in pollution control techniques or new products or processes.
that bring less harm to the environment. This follows Michael Porter’s discussion on environmental regulation and industry competitiveness, also known as the “Porter hypothesis” (Porter and Van der Linde, 1995). Porter and Van der Linde (1995) argue that properly designed environmental regulations can stimulate innovation that may partially offset or even exceed their compliance costs.

While the theory suggests potential channels through which regulation may affect the economy, the aggregate effects of regulation need to be examined empirically. However, such efforts are often hindered by the difficulty of measuring regulation. Existing approaches to measuring regulation at an aggregate level primarily focus on the quantity of regulation, such as the number of rules published by federal agencies, and the number of pages, total words, and command words in the regulatory code (e.g., the Code of Federal Regulations) (Dawson and Seater, 2013; Mulligan and Shleifer, 2005; Coffey et al., 2020). Others use government spending and staffing devoted to regulatory activity as a proxy of regulation (Beard et al., 2011; Sinclair and Vesey, 2012). These studies generally find a negative or insignificant relationship between regulation and macroeconomic outcomes.

However, the existing empirical measures may not provide complete information about the aggregate effects of regulation. The quantity of regulation or regulators’ spending is far from a perfect measure of regulation itself. Moreover, these measures typically track one aspect of regulation on a relatively low frequency (mostly annually) due to the prolonged rulemaking or budget process. In contrast, sentiment and uncertainty about regulation are more likely fluctuate on a much higher frequency, since they are driven by most recent regulatory events, which might include the promulgation of a new regulation, a company’s regulatory compliance or violation, a regulatory investigation, or a lawsuit challenging agency regulatory actions. An aggregate measure of sentiment or uncertainty about regulation therefore reflects high-frequency information about subjective attitudes toward the overall regulatory environment. As discussed above, these subjective variables can influence firms’

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1 Many studies have discussed the limitations of the existing approaches of measuring regulation. See, for example, Calomiris et al. (2020) and Simkovic and Zhang (2019).
anticipation of payoffs and thus affect the aggregate economic activity.

While there is some existing research that examines different types of economic sentiment and policy uncertainty, little has been done specifically on regulation. The most closely related work to our regulatory uncertainty index is the categorical EPU index on regulation from Baker et al. (2016), which attempts to measure economic uncertainty around regulatory policy. Baker et al. (2016) use a pre-defined set of terms related to regulation, in addition to their economic, uncertainty, and policy terms, to identify news articles that reflect regulatory policy uncertainty and construct the index based on the volume of those articles. Our regulatory uncertainty index differs from theirs in at least three ways. First, we use a substantially broader set of regulatory terms to identify news content related to regulation. The set of terms is defined using computational text analysis of rule titles published by the federal government. Second, we assess regulatory uncertainty in articles using a lexicon-based sentiment analysis method, instead of based on whether the article contains any uncertainty terms. Third, we use regressions to construct the index following Shapiro et al. (2020) instead of using the volume of relevant articles. Neither Baker et al. (2016) nor other studies measure news sentiment about regulation.

3 Data

Our initial news corpus includes 822,737 news articles that contain the keywords starting with “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. We access to the full texts and metadata of the news articles through ProQuest’s TDM Studio, which provides a comprehensive collection of historical and current newspapers in a machine readable format. We remove articles with

\[2\text{In a robustness check, we remove the articles containing the keywords “deregulat*”. The impulse response functions slightly change, but our main results remain unchanged. See Appendix L.}\]

\[3\text{Data for USA Today and the Washington Post are only available from January 1987.}\]
identical full text to a previous article, leaving 788,516 articles in the corpus.

Since the keyword “regulation” and its variants can be used in many contexts other than referring to government regulatory policy, we conduct further analysis to refine the corpus by defining a dictionary of regulatory noun chunks (i.e., certain noun phrases extracted from the text) 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 between 1995 and 2019, which are associated with 38,868 unique rules (as identified by Regulation Identifier Numbers (RINs)). Section 4 details our approach to define the dictionary and identify the news content related to regulatory policy. As a result, our final news corpus includes relevant regulatory sections from 493,418 news articles. Table 1 shows the number of articles from each newspaper.

In the VARs, we use the same economic variables as those in Baker et al. (2016). Those include monthly data on employment from the U.S. Bureau of Labor Statistics, effective federal funds rate and industrial production from the Board of Governors of the Federal Reserve System, and monthly averages of the S&P 500 index from the S&P Dow Jones Indices LLC. In the VAR model examining impulse responses of investment, we use quarterly data on real gross domestic product and real gross private domestic investment from the U.S. Bureau of Economic Analysis, and quarterly averages of effective federal funds rate and S&P 500. In addition, we add the Michigan Consumer Sentiment Index from the University of Michigan, VIX from the Cboe Global Markets, Inc., the EPU index of Baker et al. (2016), and the economic sentiment index of Shapiro et al. (2020) into the monthly VARs for robustness checks. The monthly data cover the period from January 1985 to August 2020, and the

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4For example, the term “regulation” and its variants 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.’”
quarterly data are from the first quarter of 1985 to the second quarter of 2020.

4 News Attention to Regulation

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

4.1 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 to identify news content 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 content related to regulation, we define a dictionary of regulatory noun chunks to assess the context in which the keyword “regulation” or its variants are mentioned in an article. Specifically, we examine the sentence that mentions “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 read through the noun chunks that occurred in all the news articles and manually filter out those general terms. After removing the general terms from the

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5For filtering out the general terms, two coders went through the list of noun chunks and marked general terms independently, compared their results, and discussed to solve the discrepancies.
results, there remains 10,645 unique noun chunks that occurred in 493,418 news articles, meaning that each of these articles contains 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 news articles.

Our sentiment analyses in the remainder of the paper are based on the corpus of the regulatory sections in the 493,418 news articles.

4.2 Increasing News Attention to Regulation

Tracking 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:

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

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

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

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 $t$, $\delta_{i,T}$ is the standard deviation of the scaled count $\frac{x_{it}}{N_{it}}$ over the time interval $\tilde{T}$ for standardization and normalization (i.e., January 1985 – December 2009).
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 since 1996. News attention to regulation raised during months of important regulatory developments and 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 the news content and their implications for the macroeconomy.

5 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 compute the monthly indexes of regulatory sentiment and uncertainty from 1985 to 2020. We then include the indexes in VAR models to examine how macroeconomic variables respond to regulatory sentiment and uncertainty shocks.

5.1 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
[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
[2011]. Because of its domain relevance, the LM dictionary has been frequently used in economic research (for example, [2016]; [2020]; [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 un-balanced, with substantially more negative words than positive words. One reason is that
[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” (2011, p.45). While an unbalanced dictionary
may not affect our interpretation of changes in sentiment over time, it will bias our senti-
ment assessment 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). The LSD comprises 2,857 negative words and 1,709 positive words.

Similar to our search of regulatory noun chunks, we use regular expression to count occurrences of each sentiment word in the preprocessed regulatory section of an article. We incorporate a negation rule to take into account negated positive and negative words. That is, if an English negation word, such as “not”, “don’t”, or “cannot”, occurs within three tokens before the opinionated word, then the opinionated word would be considered as the opposite orientation. For example, the following regulatory section contains two occurrences of negative words as defined by the LM dictionary: “hazard” and “violation”, and three occurrences of positive words: “boost”, “fear” (with the negation word “without”), and “boost”.

So, the department’s Occupational Safety and Health Administration in recent years has boosted spending on its consultation program, which allows little companies to ask for an OSHA visit to look for workplace hazards without fear of being cited for violations as a result of that visit. The idea is to boost voluntary compliance with safety regulations. The program’s funding rose 50% between fiscal 1996 and fiscal 2001, to $48.8 million, equal to about 11% of OSHA’s total budget.

We use a standard formula to calculate sentiment scores. The regulatory 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. Therefore, a positive sentiment score indicates an overall positive tone in the news about regulation, and a negative score means an overall negative tone.

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6The three pre-existing dictionaries combined in the LSD are the GI, the Regressive Imagery Dictionary (Martindale, 1975), and the Roget’s Thesaurus (Roget, 1911).

7The quote is from “GAO Criticizes OSHA’s Program for Small Businesses–Report Questions Effectiveness of Consultations as Visits and Hazards Decline” published by the Wall Street Journal on October 30, 2001.
We use a similar approach to assess uncertainty in regulation-related news content. The uncertainty category of the LM dictionary covers a broad range of terms in addition to “uncertainty” and “uncertain”, such as “ambiguity”, “confusion”, “doubt”, and “vague”. The regulatory uncertainty score of an article is the proportion of uncertainty words in the regulatory section of the article. A higher uncertainty score suggests a higher level of uncertainty expressed in the regulation-related news.

5.2 Regulatory Sentiment and Uncertainty Indexes

Table 2 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 opinionated words defined in the dictionary. Unsurprisingly, the sentiment measured using the LM dictionary is generally more negative compared with the GI and LSD. 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 2, 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 uncertainty words and estimated uncertainty scores for the examples.

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 regulatory sentiment indexes estimated using different dictionaries between January 1985 and August 2020. To focus on changes over time rather than relative polarity between indexes, we normalize the indexes by their means and standard deviations. The three time series demonstrate similar patterns 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 0.56; and the correlation between the LSD and GI indexes is 0.71. We also show the first principal component of the three standardized sentiment indexes in Figure 2, which explains 80 percent of the variance. All the three indexes and the principal component 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 negative tone when discussing regulation, while the sentiment largely improved around the mid-1990s and maintained at a stable and higher 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 and the principal component in Appendix C to show robustness.

Figure 3 plots the regulatory 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.

Appendix D compares our regulatory sentiment index with the economic sentiment index of Shapiro et al. (2020) and our regulatory uncertainty index with the EPU index of Baker et al. (2016). The correlation between the regulatory sentiment index and economic sentiment index is 0.38 and statistically significant. While the two time series comove in some time periods, they do not always coincide with each other. Similarly, the regulatory uncertainty index has a statistically significant correlation of 0.28 with the EPU index, but the two indexes demonstrate clear variations. These comparisons suggest that regulatory sentiment or uncertainty is distinct from aggregate economic sentiment or policy uncertainty, and possibly contains unique information about the economy. We further investigate this issue in the next section.

5.3 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 a regulatory sentiment or uncertainty shock. 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&P 500 index, the federal funds rate, log employment, and log industrial production.\footnote{We tested for stationarity of our regulatory sentiment and uncertainty indexes. The Phillips-Perron test rejects unit root for all the indexes, while the ADF and KPSS tests suggest more mixed results. See test statistics in Appendix E.} The VAR includes three lags of all variables. We show impulse responses up to 60 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 6 and 15 months after the shock and reach the maximum of a 0.35 percent 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 24 months after the shock, and the maximum estimated drop is 0.2 percent.

Figure 5 shows the impulse responses to a regulatory uncertainty shock. The effects of a one-standard-deviation shock that increases regulatory uncertainty are relatively short-lived, compared to the sentiment shock. Industrial production and employment drop by 0.13 percent and 0.16 percent, respectively, in the next month after the shock, but the effects start waning and are not statistically significant at the 10 percent level 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 regulatory sentiment and uncertainty indexes, respectively, suggesting that the estimates of impulse responses to regulatory sentiment shocks are robust to the modifications, while the estimates to regulatory 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 regulatory 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 news-based economic 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 economic sentiment or economic policy uncertainty. When the general economic sentiment index is placed after our regulatory sentiment index in the causal ordering, the estimated effects of a regulatory sentiment shock on output and employment are nearly unchanged. When economic sentiment is placed first in the ordering, the magnitude of the effects diminishes but still remains sizable.

In addition, we implement VARs using quarterly data to examine how gross investment responds to regulatory sentiment and uncertainty shocks. The identification of the quarterly VAR is based on three lags and Cholesky decomposition with the following order: our regulatory sentiment or uncertainty index, the log of S&P 500 index, the federal funds rate, log investment, and log gross domestic product. Appendix F plots the impulse response functions over 20 quarters after a shock. The estimates of investment responses to regulatory sentiment and uncertainty shocks are not statistically significant at the 10 percent level, regardless of which dictionary we use to measure sentiment.

It is possible that the effects of regulatory sentiment and uncertainty shocks are conditional on each other. Using the approach from Caggiano et al. (2017), we estimate an Interacted-VAR and compute state-dependent generalized impulse response functions (GIRFs) to see: (1) whether the impact of regulatory uncertainty shocks is different when regulatory sentiment is particularly low, and (2) whether the impact of regulatory sentiment shocks is different when regulatory uncertainty is particularly high. The results suggest no clear evidence that the impulse responses to regulatory sentiment shocks under high and low regulatory uncertainty are different: while the estimated negative effects of a regulatory sentiment shock are generally larger when regulatory uncertainty is high, the GIRFs under high and low uncertainty generally follow similar trajectories, and their differences are not statistically significant at the 10 percent level. Similar results are observed for GIRFs to regulatory uncertainty shocks under high and low regulatory sentiment. The details are discussed in Appendix G.

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 regulatory sentiment has a significant, persistent effect on future output and employment. The robustness of this effect after controlling for news-based measures of economic 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.

6 Sentiment and Uncertainty by Regulatory Policy Area

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 14 regulatory policy areas. We present the indexes and impulse response estimates in this section.

6.1 Categorizing News Articles

To categorize relevant news content by regulatory area, we rely on the dictionary of regulatory noun chunks described in Section 4.1. 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, EPA generally issues environmental regulations, FDA 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 14 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, and international relations. Appendix H 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 (8,919 out of 10,645) 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 (e.g., “final rule”, “administrative requirement”, and “technical amendment”). We use only the area-specific noun chunks (i.e., the regulatory noun chunks associated with only one area) for categorizing the news articles.

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 regulatory section:

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.9

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 common term used in rule titles and thus are associated with seven regulatory areas, whereas “seat belt” and “air bag” are noun chunks unique to the area of transportation in our dictionary. Therefore, we classify this article into the transportation category, based on the area associated with “seat belt” and “air bag”.

In longer regulatory sections, it is common that there are many regulatory noun chunks that are linked to multiple unique areas. In that case, we define the dominant area of an article as the most common area across all the regulatory noun chunks with unique areas in the regulatory section. This approach intends to capture the primary regulatory areas discussed in the relevant text of a news article. Mathematically, suppose there are $n$ noun chunks with unique areas in the regulatory section (duplicated noun chunks are counted multiple times), $a_{p}^{m \times 1}$ denotes a $m \times 1$ vector for the $p$th noun chunk, where the $q$th element of the vector $a_{p}^{q} = 1$ if the $p$th noun chunk is associated with the $q$th area ($q = \{1, 2, \ldots, m\}$), and otherwise $a_{p}^{q} = 0$. We add the vectors for all noun chunks:

$$\sum_{p=1}^{n} a_{p}^{m \times 1} = b_{m \times 1}.$$ 

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

Appendix J shows the top 30 area-specific regulatory noun chunks with most occurrences in the regulatory sections of news articles in each area. For example, “food and drug administration”, “public health”, and “child care” occur frequently in the articles classified into the consumer safety and health category. For robustness checks, we conduct human checking of the most common area-specific noun chunks in each area. Specifically, we manually filter
out certain general or irrelevant terms from the top 100 regulatory noun chunks in each area
and then reclassify news articles. When filtering out general or irrelevant terms, we take two
alternative approaches: one is a relatively conservative approach that removes a small set
of terms that are unlikely associated with the corresponding area or very likely associated
with multiple areas, and the other is a relatively aggressive approach that keeps only the
terms that are more likely associated with the corresponding area than any other areas (see
Appendix K). These alternative approaches result in slightly different classifications of news
articles, and we discuss how they change the impulse response functions in Section 6.3.

6.2 Categorical Indexes

We use the same approach to construct the categorical indexes as we did for the aggregate
sentiment and uncertainty indexes. Namely, 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. The specification is:

\[ s_{j,q} = u_{t(j,q)} + v_{i(j,q)} + \epsilon_{j,q}, \]

where \( s_{j,q} \) is the estimated sentiment or uncertainty score for article \( j \) in area \( q \), \( u_{t(j,q)} \) is a
year-month fixed effect, and \( v_{i(j,q)} \) is a newspaper fixed effect. The estimated coefficients on
the year-month fixed effects \( u_{t(j,q)} \) from the regression compose the monthly sentiment or
uncertainty index for regulatory area \( q \).

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.

6.3 Impulse Responses

We conduct VAR analyses using the categorical indexes and the same economic variables as described in Section 5.3 and compute impulse response functions. Our baseline analysis suggests particularly strong linkage between our sentiment and uncertainty measures in some regulatory areas and future economic outcomes. Some of the impulse response patterns change in terms of significance or magnitude when we use filtered regulatory noun chunks to reclassify news articles into regulatory areas (see Appendices K.1-K.8). Therefore, we put more weight on the regulatory areas that are robust to the alternative classifications when interpreting the results.

Figure 12 shows the impulse responses of industrial production to a negative sentiment shock for each regulatory area. Sentiment shocks about regulation concerning transportation, general business and trade, or agriculture and rural development are associated with statistically significant drops in future output. The point estimates of the reductions in industrial production are generally between 0.2 percent and 0.4 percent. However, the effects of sentiment shocks about general business and trade regulation or agriculture and rural development regulation are not statistically significant at the 10 percent level in at least one robustness check in which we filter the regulatory noun chunks in each area. The impulse response functions related to transportation regulation are robust to the alternative classifications, regardless of whether we use a conservative or aggressive approach for filtering the regulatory noun chunks, and the effects are relatively large and persistent.

Figure 13 shows that a regulatory sentiment shock related to consumer safety and health, transportation, finance and banking, general business and trade, or agriculture and rural development reduces future employment. The point estimates range from 0.1 percent to 0.2 percent. The impulse responses for transportation regulation and finance and banking
regulation remain statistically significant in both robustness checks, and a sentiment shock around transportation regulation has more persistent employment effects.

While we do not observe statistically significant effects of an aggregate regulatory uncertainty shock (as discussed in Section 5.3), there are variations in the responses of economic activity to uncertainty shocks in different regulatory areas. Our baseline analysis indicates that a one-standard-deviation shock that increases uncertainty around transportation regulation or labor and workplace regulation leads to relatively large and persistent drops in future output (Figure 14). However, only the effects of uncertainty shocks around labor and workplace regulation remain statistically significant in the robustness checks.

An uncertainty shock to transportation regulation is also associated with statistically significant reductions in future employment in our baseline analysis (Figure 15), but it is still not robust to alternative approaches for article classification. Although the responses of employment to uncertainty shocks around labor and workplace regulation and energy regulation are not significant at the 10 percent level in the baseline analysis, both robustness checks indicate statistically significant impulse responses, implying possible negative effects of regulatory uncertainty shocks in those areas on employment.

In sum, our analyses suggest that economic outcomes are particularly sensitive to sentiment and uncertainty around certain regulatory policy areas. Negative sentiment shocks related to transportation regulation have persistent, large negative effects on future output and employment. Sentiment shocks to finance and banking regulation are associated with relatively transitory but measurable drops in future employment. Increased uncertainty about labor and workplace regulation leads to persistent reductions in future output. These impulse response patterns are also robust to alternative approaches for article classification.
7 Conclusion

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 overall only has transitory effects. Notably, the responses to sentiment shocks largely remain after controlling for existing news-based measures of general economic sentiment and policy uncertainty, which suggests that our measure of regulatory sentiment captures 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 14 regulatory policy areas. Our estimates of impulse responses using the categorical indexes suggest that sentiment shocks related to transportation regulation have persistent, large negative effects on future output and employment, and negative sentiment around finance and banking regulation has a transitory effect on employment. Regardless of the lack of findings on persistent effects of aggregate regulatory uncertainty shocks in our analysis, we find that increased uncertainty around labor and workplace regulation has long-lasting adverse effects on output.

As our analysis suggests, sentiment about regulation plays a more important role in the aggregate economy than uncertainty about regulation. Future research could further explore the mechanisms through which regulatory sentiment affects macroeconomic outcomes. The text-based approaches used in our study could also be applied to constructing industry-
specific or topic-specific regulatory sentiment and uncertainty measures to examine their economic effects.
Tables

Table 1: Article Counts by Newspaper

<table>
<thead>
<tr>
<th>Newspaper</th>
<th>All articles</th>
<th>Unique articles</th>
<th>Regulatory articles</th>
<th>First regulatory article</th>
<th>Last regulatory article</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall Street Journal</td>
<td>251,983</td>
<td>242,084</td>
<td>163,788</td>
<td>1985-01-02</td>
<td>2020-08-31</td>
</tr>
<tr>
<td>New York Times</td>
<td>125,270</td>
<td>117,441</td>
<td>72,852</td>
<td>1985-01-01</td>
<td>2020-08-31</td>
</tr>
<tr>
<td>Los Angeles Times</td>
<td>121,406</td>
<td>120,802</td>
<td>73,568</td>
<td>1985-01-01</td>
<td>2020-08-31</td>
</tr>
<tr>
<td>Chicago Tribune</td>
<td>90,023</td>
<td>89,600</td>
<td>51,740</td>
<td>1985-01-01</td>
<td>2020-08-31</td>
</tr>
<tr>
<td>Boston Globe</td>
<td>78,922</td>
<td>72,456</td>
<td>43,445</td>
<td>1985-01-01</td>
<td>2020-08-30</td>
</tr>
<tr>
<td>USA Today</td>
<td>38,361</td>
<td>36,917</td>
<td>20,577</td>
<td>1987-04-01</td>
<td>2020-08-31</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>822,737</strong></td>
<td><strong>788,516</strong></td>
<td><strong>493,418</strong></td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2: Descriptive Statistics of Estimated Sentiment and Uncertainty Scores

<table>
<thead>
<tr>
<th></th>
<th>Sentiment Score</th>
<th>Uncertainty Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LM</td>
<td>GI</td>
</tr>
<tr>
<td>Mean</td>
<td>-2.07</td>
<td>1.04</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.58</td>
<td>4.00</td>
</tr>
<tr>
<td>Minimum</td>
<td>-37.50</td>
<td>-30.77</td>
</tr>
<tr>
<td>Maximum</td>
<td>13.33</td>
<td>30.77</td>
</tr>
<tr>
<td>Articles with negative scores</td>
<td>359,302</td>
<td>168,220</td>
</tr>
<tr>
<td>Articles with positive scores</td>
<td>58,973</td>
<td>277,573</td>
</tr>
<tr>
<td>N</td>
<td>493,418</td>
<td>493,418</td>
</tr>
</tbody>
</table>
Notes: The index is constructed by standardizing the monthly counts of regulation-related news articles scaled by the monthly counts of all news articles in each newspaper and normalizing the time series to a mean of 100 from January 1985 to December 2009. The index is calculated 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 regulatory sentiment indexes estimated using the Loughran and McDonald (LM) dictionary, the General Inquirer (GI) dictionary, and the Lexicoder Sentiment Dictionary (LSD), respectively, and the first principal component of the three indexes. 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 uncertainty category of the Loughran and McDonald (LM) dictionary.
Figure 4: Impulse Responses to a Negative Sentiment Shock about Regulation  
(Monthly VAR)

**Industrial Production**

**Employment**

*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 sentiment index is estimated using the Loughran and McDonald (LM) dictionary. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P 500 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&P 500 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 Negative 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 sentiment index is estimated using the Loughran and McDonald (LM) dictionary. The modifications include 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.
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 S&P index, including the VIX, including time trends, and including the Michigan Consumer Sentiment Index.
Figure 8: Impulse Responses to a Negative 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). The sentiment index is estimated using the Loughran and McDonald (LM) dictionary.
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 Negative 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 sentiment indexes are estimated using the Loughran and McDonald (LM) dictionary. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P 500 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 Negative 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 sentiment indexes are estimated using the Loughran and McDonald (LM) dictionary. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment index, the log of S&P 500 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&P 500 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&P 500 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.
References


Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as data. *Journal of Economic Litera-


Appendices

A The Most Common Regulatory Noun Chunks in News Articles


Notes: The above shows 100 most common regulatory noun chunks that occurred in all the non-duplicated news articles in our initial corpus (N=788,516). The number indicates the number of occurrences of the noun chunk across all news articles. The noun chunks are lemmatized, so, for example, “hold company” is a lemmatized version of “holding company.”
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, 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]
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 Alternative Regulatory Sentiment Indexes (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, using the sentiment indexes estimated from the General Inquirer (GI) dictionary and the Lexicoder Sentiment Dictionary (LSD) as well as the first principal component of the GI, LSD, and Loughran and McDonald (LM) sentiment indexes. Gray areas show 90 percent confidence bands.
D Compare Sentiment and Uncertainty Indexes

D.1 Compare Regulatory Sentiment Index and Economic Sentiment Index

Notes: The figure plots the regulatory sentiment indexes estimated using the Loughran and McDonald (LM) dictionary and the economic sentiment index of Shapiro et al. (2020). Both indexes are normalized to have mean equal to zero and standard deviation equal to one.
D.2 Compare Regulatory Uncertainty Index and Economic Policy Uncertainty Index

Notes: The figure plots the regulatory uncertainty indexes estimated using the Loughran and McDonald (LM) dictionary and the economic policy uncertainty index of Baker et al. (2016). Both indexes are normalized to have mean equal to zero and standard deviation equal to one.
### E Stationarity Tests for the Regulatory Sentiment and Uncertainty Indexes

<table>
<thead>
<tr>
<th>Index</th>
<th>ADF test statistic</th>
<th>Phillips-Perron test statistic</th>
<th>KPSS test statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM sentiment index</td>
<td>-3.4107 (p=0.0106)</td>
<td>-15.2300 (p&lt;0.0001)</td>
<td>0.2542 (p=0.1833)</td>
</tr>
<tr>
<td>GI sentiment index</td>
<td>-2.0719 (p=0.2560)</td>
<td>-16.6369 (p&lt;0.0001)</td>
<td>0.6249 (p=0.0195)</td>
</tr>
<tr>
<td>LSD sentiment index</td>
<td>-4.1658 (p=0.0008)</td>
<td>-14.5903 (p&lt;0.0001)</td>
<td>0.8013 (p=0.0072)</td>
</tr>
<tr>
<td>Sentiment PC</td>
<td>-2.3863 (p=0.1456)</td>
<td>-15.1323 (p&lt;0.0001)</td>
<td>0.6713 (p=0.0149)</td>
</tr>
<tr>
<td>Uncertainty index</td>
<td>-3.7472 (p=0.0035)</td>
<td>-17.0986 (p&lt;0.0001)</td>
<td>0.8722 (p=0.0049)</td>
</tr>
</tbody>
</table>

*Notes:* The sentiment PC represents the first principal component of the LM, GI, and LSD sentiment indexes.
F Investment Responses to Regulatory Sentiment and Uncertainty Shocks (Quarterly VAR)

Notes: The figures plot VAR-estimated investment responses to a one-standard-deviation negative shock to sentiment about regulation or a one-standard-deviation upward shock to regulatory uncertainty. Sentiment measures are indexes estimated from the Loughran and McDonald (LM) dictionary, the General Inquirer (GI) dictionary, the Lexicoder Sentiment Dictionary (LSD), and the first principal component (PC) of the three sentiment indexes. Gray areas show 90 percent confidence bands.
G Interaction between Regulatory Sentiment and Uncertainty

Following the approach of Caggiano et al. (2017), we estimate an Interacted-VAR with an interaction term of regulatory sentiment and uncertainty. The Interacted-VAR is as follows:

$$y_t = \alpha + \sum_{j=1}^{k} A_j y_{t-j} + \left[ \sum_{j=1}^{k} c_j (sent_{t-j} \times unc_{t-j}) \right] + u_t$$

where $y_t = [sent_t, lsp_t, ffr_t, lemp_t, lip_t, unc_t]'$ is the $(n \times 1)$ vector of endogenous variables including the regulatory sentiment index, log S&P 500, federal funds rate, log employment, log industrial production, and the regulatory uncertainty index, $(sent_{t-j} \times unc_{t-j})$ is an interaction term of regulatory sentiment and uncertainty, $A_j$ are $(n \times n)$ matrices of coefficients, $c_j$ are $n \times 1$ vectors of coefficients, and $u_t$ is the $(n \times 1)$ vector of error terms. Same as our baseline VAR, we include three lags of all variables.

We then compute generalized impulse response functions to examine: (1) whether the effects of regulatory sentiment shocks are different under the state of particularly high regulatory uncertainty, and (2) whether the effects of regulatory uncertainty shocks are different under the state of particularly low regulatory sentiment. The settings and results are shown in Appendices G.1 and G.2.
G.1 Generalized Impulse Response Functions to Regulatory Sentiment Shocks under High and Low Regulatory Uncertainty

The high regulatory uncertainty state is defined as the months above the 75th percentile of the regulatory uncertainty index, and the low regulatory uncertainty state is the months below that. To identify regulatory sentiment shocks, we use the Cholesky decomposition with the following ordering: regulatory sentiment (the LM-based index), log S&P 500, federal funds rate, log employment, log industrial production, and regulatory uncertainty. The following figure plots the generalized impulse response functions for industrial production and employment to a one-standard-deviation negative regulatory sentiment shock.

Notes: Dashed-red line: low regulatory uncertainty state. Solid-blue line: high regulatory uncertainty state. Solid-red lines and gray areas: 90 percent confidence bands.
G.2 Generalized Impulse Response Functions to Regulatory Uncertainty Shocks under High and Low Regulatory Sentiment

The low regulatory sentiment state is defined as the months below the 25th percentile of the regulatory sentiment index, and the high regulatory sentiment state is the months above that. To identify regulatory uncertainty shocks, we use the Cholesky decomposition with the following ordering: regulatory uncertainty, log S&P 500, federal funds rate, log employment, log industrial production, and regulatory sentiment (the LM-based index). The following figure plots the generalized impulse response functions for industrial production and employment to a one-standard-deviation upward regulatory uncertainty shock.

Notes: Dashed-red line: low regulatory sentiment state. Solid-blue line: high regulatory sentiment state. Solid-red lines and gray areas: 90 percent confidence bands.
### H Examples of Agencies, Regulatory Areas, and Rule Titles

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

Notes: The figure plots the number of news articles classified into each regulatory policy area in our sample.
J  The Most Common Regulatory Noun Chunks by Regulatory Area

Area Name: consumer safety and health
Unique Regulatory Noun Chunks: 1397
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: national and homeland security
Unique Regulatory Noun Chunks: 802
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: transportation
Unique Regulatory Noun Chunks: 784
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: labor and workplace
Unique Regulatory Noun Chunks: 244
Top 30 Regulatory Noun Chunks and Occurrences:

**Area Name:** environment and natural resources

**Unique Regulatory Noun Chunks:** 1656

**Top 30 Regulatory Noun Chunks and Occurrences:**


**Area Name:** energy

**Unique Regulatory Noun Chunks:** 383

**Top 30 Regulatory Noun Chunks and Occurrences:**


**Area Name:** finance and banking

**Unique Regulatory Noun Chunks:** 1218

**Top 30 Regulatory Noun Chunks and Occurrences:**


**Area Name:** general business and trade

**Unique Regulatory Noun Chunks:** 621

**Top 30 Regulatory Noun Chunks and Occurrences:**
Area Name: agriculture and rural development
Unique Regulatory Noun Chunks: 254
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: education and culture
Unique Regulatory Noun Chunks: 161
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: communications
Unique Regulatory Noun Chunks: 227
Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: criminal justice
Unique Regulatory Noun Chunks: 101

Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: society

Unique Regulatory Noun Chunks: 660

Top 30 Regulatory Noun Chunks and Occurrences:

Area Name: international relations

Unique Regulatory Noun Chunks: 84

Top 30 Regulatory Noun Chunks and Occurrences:
K Filtering Regulatory Noun Chunks for Article Classification

We conduct human checking of the most common regulatory noun chunks that occur in the news articles classified into each area. Specifically, we manually filter out certain general or irrelevant terms from the top 100 regulatory noun chunks in each area and then reclassify news articles. When filtering out general or irrelevant terms, we take two alternative approaches: one is a relatively conservative approach that removes a small set of terms that are unlikely associated with the corresponding area or very likely associated with multiple areas, and the other is a relatively aggressive approach that keeps only the terms that are more likely associated with the corresponding area than any other areas.

As a result, 258 terms were removed using the conservative approach, and 449 terms were removed using the aggressive approach. See the top 15 regulatory noun chunks for the labor and workplace category as an example (the strikethrough terms are the regulatory noun chunks filtered out through each approach):

<table>
<thead>
<tr>
<th>Conservative Approach</th>
<th>Aggressive Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>stock option, minimum wage, airline regulation, labor regulation, fire safety, other drug, drug testing, voting right, union official, investment advice, large employer, legal requirement, foreign worker, civil action, construction industry</td>
<td>stock option, minimum wage, airline deregulation, labor regulation, fire safety, other drug, drug testing, voting right, union official, investment advice, large employer, legal requirement, foreign worker, civil action, construction industry</td>
</tr>
</tbody>
</table>

Appendices K.1-K.4 plot VAR-estimated impulse responses to regulatory sentiment or uncertainty shocks by regulatory area using the conservative approach to reclassify news articles and create categorical indexes. Appendices K.5-K.8 plot impulse responses to regulatory sentiment or uncertainty shocks by regulatory area using the aggressive approach to reclassify news articles and create categorical indexes. The VAR specification is the same as the baseline VAR discussed in the paper.
K.1 Industrial Production Responses to a Negative Sentiment Shock By Regulatory Area (Conservative Approach)
K.2 Employment Responses to a Negative Sentiment Shock By Regulatory Area (Conservative Approach)
K.3 Industrial Production Responses to an Uncertainty Shock By Regulatory Area (Conservative Approach)
K.4 Employment Responses to an Uncertainty Shock By Regulatory Area (Conservative Approach)
K.5 Industrial Production Responses to a Negative Sentiment Shock By Regulatory Area (Aggressive Approach)
K.6 Employment Responses to a Negative Sentiment Shock By Regulatory Area (Aggressive Approach)
K.7 Industrial Production Responses to an Uncertainty Shock By Regulatory Area (Aggressive Approach)
K.8 Employment Responses to an Uncertainty Shock By Regulatory Area (Aggressive Approach)
Sentiment and Uncertainty about Regulation and Deregulation

L.1 Regulatory Sentiment Index Removing Articles about Deregulation

Notes: The figure plots the regulatory sentiment index estimated using the Loughran and McDonald (LM) dictionary. The baseline index is used in the main analysis in the paper. The revised index is estimated after removing news articles that contain words starting with “deregulat”.
L.2 Regulatory Uncertainty Index Removing Articles about Deregulation

Notes: The figure plots the regulatory uncertainty index estimated using the uncertainty category of the Loughran and McDonald (LM) dictionary. The baseline index is used in the main analysis in the paper. The revised index is estimated after removing news articles that contain words starting with “deregulat”.

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L.3 Impulse Responses to a Regulatory Sentiment or Uncertainty Shock

Notes: The figures plot VAR-estimated impulse response functions for industrial production and employment to a one-standard-deviation negative regulatory sentiment shock or a one-standard-deviation upward regulatory uncertainty shock. The sentiment and uncertainty indexes are estimated using the Loughran and McDonald (LM) dictionary, after removing news articles that contain words starting with “deregulat”. The shock is orthogonalized by using the Cholesky decomposition with the following ordering of variables: the regulatory sentiment or uncertainty index, the log of S&P 500 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.