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Measuring News Sentiment*

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Abstract

This paper demonstrates state-of-the-art text sentiment analysis tools while developing a new time-series measure of economic sentiment derived from economic and financial newspaper articles from January 1980 to April 2015. We compare the predictive accuracy of a large set of sentiment analysis models using a sample of articles that have been rated by humans on a positivity/negativity scale. The results highlight the gains from combining existing lexicons and from accounting for negation. We also generate our own sentiment-scoring model, which includes a new lexicon built specifically to capture the sentiment in economic news articles. This model is shown to have better predictive accuracy than existing, "off-the-shelf", models. Lastly, we provide two applications to the economic research on sentiment. First, we show that daily news sentiment is predictive of movements of survey-based measures of consumer sentiment. Second, motivated by Barsky and Sims (2012), we estimate the impulse responses of macroeconomic variables to sentiment shocks, finding that positive sentiment shocks increase consumption, output, and interest rates and dampen inflation.

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1 Introduction

Policymakers and market participants care a great deal about current and future aggregate business conditions. The general nowcasting and forecasting toolkit relies on a broad array of models that incorporate both "hard" and "soft" information. The former includes objective and directly quantifiable variables such as production and employment, while the latter includes more subjective variables typically constructed from survey responses concerning attitudes about current and future economic conditions. There are a broad array of soft variables available, but the survey-based indexes of consumer sentiment by the University of Michigan and the Conference Board are the most widely followed. These measures have been shown to have important predictive power, helping to forecast macroeconomic outcomes even after controlling for a host of factors (for example, Souleles (2004), Carroll, Fuhrer, and Wilcox (1994), Bram and Ludvigson (1998)).

In this study, we consider an alternative approach to measuring sentiment, with a focus on the economic sentiment embodied in the news. Our news corpus consists of 238,685 economic and financial news articles from 16 major newspapers from January 1980 to April 2015. Unlike survey-based measures of economic sentiment, our index relies on extracting sentiment from these articles using computational text analysis. Text-based measures of economic activity are becoming increasing popular among researchers due to their apparent advantages over surveys in terms of cost, scope, and timeliness (see, for example, Fraiberger (2016), Nyman, Gregory, Kapadia, Ormerod, Tuckett, and Smith (2016), Thorsrud (2016a), Thorsrud (2016b), and Calomiris and Mamaysky (2017)). Surveys are inherently expensive to conduct, oftentimes based on relatively small samples of individuals, and therefore may be subject to sampling problems (Ludvigson (2004)). They also tend to be published at a monthly frequency and with a lag of two or more weeks, reducing their value at times of economic turning points.

Text sentiment analysis is a rapidly developing field of natural language processing (NLP) and is now widely used in an array of business applications, such as social media, algorithmic trading, customer experience, and human resource management. In recent years, such tools have begun to be used in economic and financial research. For example, Garcia (2013) measures financial-market sentiment from *New York Times* financial columns, Baker, Bloom, and Davis (2016) measure an index of economic policy uncertainty from 10 newspapers, and

Shapiro and Wilson (2019) apply text sentiment analysis to Federal Open Market Committee meeting transcripts to estimate the central bank's objective function.

In developing our time-series measure of news sentiment, we provide an overview of text-based sentiment-scoring models as well as a demonstration of their accuracy. Though we also consider recent machine learning approaches, our demonstration focuses primarily on "lexical" techniques, which measure the sentiment of a set of text based on the sentiment of the words contained therein. These techniques rely on lexicons, pre-defined lists of words with associated sentiment scores. Using a set of news articles whose positive/negative sentiment have been hand-labeled, we evaluate a variety of sentiment-scoring models. These models include "off-the-shelf" models that have been used previously in sentiment analysis. We find that, due to the limited overlap in their domains and dictionaries, combining existing lexicons can improve performance in terms of predicting the human ratings.

We then develop our own sentiment-scoring model, which combines existing lexicons with a new lexicon that we construct specifically to capture the sentiment in economic news articles. This new model, which is developed independently of the human ratings of the articles, is found to more accurately predict the human ratings than any of the other models we analyzed, highlighting the advantages of tailoring one's lexicon to the specific domain of interest. The model achieves a rank correlation with the human ratings of approximately 0.5. While we emphasize that these results are specific to economics news articles, and could therefore differ for other types of economics/finance text sources, part of our contribution is to demonstrate the techniques that economists can use to develop and evaluate models tailored to any particular source of text.

Using our best-performing sentiment-scoring model, we construct a national time-series measure of news sentiment. Specifically, we calculate sentiment scores for each of the large set of economic and financial articles dating back to 1980. We then aggregate the individual article scores into daily and monthly time-series indexes. The monthly index is found to comove with the business cycle and key economic news events and to correlate strongly with survey-based consumer sentiment indexes, indicating that the news sentiment index has a high signal-to-noise ratio.

Lastly, we provide two applications of our news sentiment measures to two economic research questions. First, we assess whether our daily news sentiment index can help predict the survey-based measures of consumer sentiment. We find that news sentiment in the days leading up releases of the Michigan Consumer Sentiment Index and the Conference Board's Consumer Confidence Index is strongly predictive of those releases. Second, we investigate how the macroeconomy responds, if at all, to sentiment shocks (for example, Barsky and Sims (2012), Angeletos and La'O (2013), Benhabib, Wang, and Wen (2015), and Benhabib and Spiegel (2017)). Specifically, we estimate impulse response functions of key macroeconomic variables to sentiment shocks, similar to Barsky and Sims (2012). Consistent with the theoretical predictions in that study, we find that positive innovations to sentiment increase consumption, output, and the real fed funds rate, but decrease inflation. Thus, we find that our text-based news sentiment measure acts in a similar fashion to the survey-based consumer sentiment measure in a standard macroeconomic framework.

The study is organized as follows. In section 2 we provide an overview of the general methodologies for performing sentiment analysis. We describe and evaluate various sentiment analysis models, including one that we develop for this paper, in section 3. In section 4, we describe the construction of the monthly news sentiment index and provide some descriptive analysis of the index. Section 5 presents our two applications. We conclude in section 6.

2 Computational Methods for Sentiment Analysis

The traditional approach to measuring economic sentiment is to construct indexes based on surveys. Two prominent examples are the Michigan Consumer Sentiment index and the Conference Board's Consumer Confidence index.[1] These indexes are based on monthly surveys that ask a sample of households about about their current situation and outlook regarding personal finances, economy-wide economic and financial conditions, and spending on consumer durables. (See Appendix for details.)

We propose using recently developed NLP text sentiment analysis techniques as an alternative method for measuring economic sentiment over time. Before discussing our specific application, here we provide an overview of the general approaches that have been developed for sentiment analysis and we discuss what we see as the key issues researchers must consider when applying these tools.

[1]Such survey-based indexes are not limited to consumer surveys. There are also sentiment/confidence surveys of business decision-makers such as the surveys underlying the Conference Board's "CEO Confidence Index" or the National Federation of Independent Businesses' "Small Business Optimism Index".

The sentiment of text (that is, a word, phrase, sentence, etc.) typically is framed as a ternary classification problem (positive, negative, neutral) or a rating problem (e.g., valence on a scale from 1-5). The sentiment of text is a measure of the speaker's tone, attitude, or evaluation of a topic, independent of the topic's own sentiment orientation (e.g., a horror movie can be "delightful.") Sentiment analysis is a well-studied subject in computational text analysis and has a correspondingly rich history of prior work.[2]

The literature on sentiment analysis emphasizes two key objectives in characterizing the sentiment of a given set of text: domain-specificity and complexity. Domain refers to the subject matter of the corpus of text that one wants to analyze. Words can have different meanings in different domains. In particular, as emphasized in Loughran and McDonald (2011), many words have a different sentiment when used in common parlance than they do when used in an economics or finance domain. For example, the word "liability" is generally neutral when used in a financial setting whereas it is typically negative in common parlance. Ideally, a sentiment analysis tool should be appropriate for the domain of the text to which the tool is applied.

Complexity relates to all of the multifaceted aspects of a set of text beyond just the prevalence of particular words. Sentiment expression is compositional and contextual. This complexity is evident in simple features such as negation, where a single word can directly affect the sentiment orientation of words that follow, e.g., from "good" to "not good", as well as in more compositional phrases, like "I wish I could have said I liked it," where the sentiment of an expression is clearly more than the sum of its words.

There are two general methodologies for quantifying sentiment in text. The first is known as the **Lexical** methodology. This approach relies on pre-defined lists of words, called lexicons or dictionaries, with each word assigned a score for the the emotion of interest.[3] For example, a valence lexicon consists of a list of words with each assigned a score indicating how positive or negative it is. Generally, these scores are simply 1, 0, and -1 for positive, neutral, and negative, but some lexicons (such as Vader, described below) have more than

[2]Note that sentiment analysis is just one type of computational text analysis. Another type that is increasingly being used in economics and finance is topic analysis (see, for example, Hansen and McMahon (2016), Hansen, McMahon, and Prat (2017), Thorsrud (2016a), and Thorsrud (2016b)). Topic analysis identifies the focal topics in a set of text.

[3]Technically, a lexicon can be a list of n-grams (multi-word phrases) rather than just unigrams (single words), though n-grams lexicons for n>1 are rare. Similarly, some lexicons use word stems to match all inflected variants of a given word.

three categories. Typical applications of this approach measure the emotional content of a given corpus of text based on the prevalence of negative vs positive words in the corpus. Such word-matching methods are referred to as bag-of-words (BOW) methods because each word's contextual characteristics, such as its order within the text, part-of-speech, co-occurrence with other words, and other contextual characteristics specific to the text in which the word appears, are ignored.

There are a number of examples of applications of the lexical approach in Economics and Finance. Loughran and McDonald (2011) construct their own dictionary of negativity, arguing that the Harvard General Inquirer (GI) dictionary considers as negative many words that are neutral in a financial/economic domain (like tax, costs, capital, expense, liability, risk, excess, depreciation). Shapiro and Wilson (2019) apply the Loughran and McDonald lexicon to meeting transcripts of the Federal Open Market Committee to study the committee's loss function. Heston and Sinha (2015) measure negativity in news articles about companies and estimate their impact on those companies' stock returns. They use the Harvard GI Dictionary along with Loughran and McDonald's dictionary. Fraiberger (2016) measures valence in international news articles using dictionaries from Loughran and McDonald (2011) and Young and Soroka (2012), and uses these measures to improve GDP forecasts.[4] Correa, Garud, Londono, and Mislang (2017) and Nyman, Kapadia, Tuckett, Gregory, Ormerod, and Smith (2018) develop lexicons designed to help assess financial stability risks.

Recent advances in lexical methods of sentiment analysis have focused on accounting for the contextual characteristics of words within the corpus of interest. A prominent example is the Vader open-source python tool, developed by Hutto and Gilbert (2014). Vader is a sentence-level sentiment classifier. It consists of both a lexicon—a list of several thousand words ("unigrams") labeled from -4 to 4 corresponding to most negative to most positive—and a set of heuristic rules that account for a word's context within the sentence. Vader assigns a (net) negativity score to a sentence by aggregating across negativity scores of words within the sentence. A word's score starts with its numerical negativity label (-4 to 4) in the lexicon, but it is then multiplicatively increased or decreased based on its context within the sentence. Context is captured by a set of simple rules related to negation, punctuation,

[4]Baker, Bloom, and Davis (2016) uses a methodology for measuring economic policy uncertainty consisting of several components, one of which is based on frequencies of pre-defined word combinations such as "uncertainty" & "economic policy."

capitalization, being preceded by versus following the word "but," and being preceded by a degree modifier such as "very," "extremely," "slightly," etc.

The second, more nascent, approach employs machine learning (ML) techniques to construct complex models for probabilistically predicting the sentiment of a given set of text.[5] Although Vader begins to account for word context and compositionality, it is still a rule-based scoring system. Natural language is too creative and complicated — and sentiment expression too nuanced — to be fully captured by a static lexicon and a fixed list of heuristic rules. Increasingly, sentiment analysis approaches leverage ML to build more expressive models. An ML predictive model is typically estimated/trained on a large training set of text containing a mapping between textual utterances and sentiment ratings assigned by humans. For instance, sentiment analysis models have been developed using social media data, such as Twitter or movie review data, that provide textual posts combined with user feedback identifying the positivity and/or negativity of the posts. Such data sets, containing *both* sentiment and text, allow for the application of structured machine learning techniques for building high-quality predictive models of sentiment.

The ability to train a predictive model using structured machine learning, rather than rely on a simple lexicon, is an important potential advantage of the ML approach over the lexical approach. ML approaches can leverage linear classifiers and, increasingly, deep learning architectures to automatically learn sentiment weights for words and entire phrases and to learn how to to combine these weights to measure the sentiment of an entire expression. However, the ML approach is only as good as its training set (that is, the data set pairing text with sentiment labels). ML methods, especially ones involving deep learning, typically require very large training sets in order to learn both lexical features of words as well as more complex features like sentence structure. Large labeled training datasets are time-consuming and expensive to construct. In addition, a trained ML model may only be appropriate for the domain associated with the training set; if the text in the training set is not representative of the text to which the predictive model is being applied, the predictions will be less accurate.

[5]See Liu (2010) for a detailed description of the ML approach to sentiment analysis. Seminal papers on developing ML techniques for sentiment analysis include Pang, Lee, and Vaithyanathan (2002) and Pang and Lee (2005).

3 Evaluating Alternative Sentiment Analysis Tools for Measuring News Sentiment

In this section, we discuss alternative sentiment analysis models for predicting the sentiment of economic news articles and we evaluate their predictive accuracy. First, we describe the raw textual data to which we will be applying these models.

3.1 A Corpus of Economic News Articles

Our ultimate objective in this paper is to apply a sentiment analysis model to a data set of economic news articles in order to construct a time series index of economic news sentiment. The raw data for this index is a large corpus of economic news articles from LexisNexis.

We purchased an archive of newspaper articles from the news aggregator service, LexisNexis (LN). We pulled all newspaper articles (including editorials) from 1980 to 2015 from 16 major U.S. newspapers[6] satisfying the following criteria:

1. LN classified "country subject" as "United States" (with an LN "relevance" threshold of at least 85%).
2. LN classified "topic subject" as "Economy" or "Economic" (with an LN "relevance" threshold of at least 85%).
3. LN did NOT classify the article as a "Brief" or "Summary" or "Digest."
4. Article had 200 words or longer.
5. Article contained at least one of the following words: said, says, told, stated, wrote, reported.

Restrictions 1 and 2 allow us to focus on articles that are related to U.S. economic news. Restriction 3 mitigates duplication of news in that those articles are typically summaries

[6]The newspapers are: Atlanta Journal-Constitution, Boston Globe, Chicago Tribune, Detroit Free Press, Houston Chronicle, Los Angeles Times, Memphis Commercial Appeal, Miami Herald, Minneapolis Star Tribune, New Orleans Times-Picayune, New York Times, Philadelphia Inquirer, San Francisco Chronicle, Seattle Times, St. Louis Post-Dispatch, and The Washington Post.

of articles appearing elsewhere. Restriction 4 is useful because computational sentiment measures for very short articles are likely to be more noisy. Restriction 5 is meant to focus our sample of articles on those likely to contain quotations or paraphrases of interviewees of the journalist writing the article. Arguably, such articles are likely to contain more emotive content than other articles. Articles containing those words typically express the sentiment (often, but not always, a quotation) of a person or group of people. After imposing these criteria, our data pull yielded approximately 238,685 articles.

3.2 Alternative Lexicons

We evaluated a variety of alternative lexical sentiment models.[7] We started by constructing several straightforward bag-of-words sentiment models that vary only in the lexicon used, where a "lexicon" is simply a list of words with assigned sentiment (here, valence) scores. For a given lexicon, we calculated the proportion of words in an article that are positive minus the proportion of words that are negative. We refer to this measure of valence as net positivity, or simply positivity.

We considered three lexicons popular in sentiment analysis applications: (1) Harvard General Inquirer (GI) Dictionary (as used, for example, in Heston and Sinha (2015) and as an input by Loughran and McDonald (2011)), (2) the 2014 updated version of the Loughran-McDonald (hereafter, LM) lexicon (originally developed in Loughran and McDonald (2011)), and (3) Hu and Liu (2004)'s lexicon (hereafter, HL). Table 1 provides information, for each lexicon individually as well as their union, about its size (number of words), feature space, and coverage in the news corpus. Each of these lexicons has certain advantages in terms of these metrics, which we discuss below.

The GI dictionary was one of the earliest valence lexicons, consisting of 3,626 words labeled positive or negative.[8] It is meant to be a general English language lexicon. The LM lexicon is somewhat smaller, at 2,707 positive or negative words, but has a key appeal

[7] We also experimented with building machine learning sentiment classifiers trained on a subset (training set) of the labeled news articles and validated on a separate subset. These models performed far worse than the lexical models, likely because the limited size of our training set.

[8] Each of these lexicons also includes a list of neutral words, which we ignore in these statistics. If one measures the sentiment of a text using the proportion of words that are positive less the proportion that are negative, these neutral words are treated no different than words that don't appear in the lexicon at all. However, for some other sentiment measures, such as term frequency - inverse document frequency (TF-IDF), the distinction between a word labeled neutral and a word not labeled at all can be important.

for our purposes which is that it is specific to the domain of economics and finance. In particular, the LM lexicon was constructed from a "feature space"—that is, a corpus of text—consisting of words that are prevalent in 10-K reports of publicly-traded companies. The positive and negative labels assigned to these words are thus specific to the meaning of these words in the finance domain. The Hu-Liu lexicon was developed from a feature space of online movie reviews. These movie reviews are assigned negativity/positivity scores by the reviewers themselves, affording a fairly large lexicon. Specifically, the HL lexicon consists of 6,786 words labeled positive or negative. However, a drawback of the HL lexicon for economics/finance applications is that it is not specific to the economics/finance domain.

The third and fourth columns of Table 1 show the number and fraction of words that are unique to each lexicon (relative to the other two lexicons). While LM is the smallest of the three lexicons, it has the largest fraction of its words being unique. Specifically, 58 percent of LM's words are in neither of the other two lexicons. By contrast, although GI's lexicon is larger than LM, it is well covered by the other two—69 percent of its lexicon is in either LM or HL, with most of them being in the HL lexicon.[9] HL has the advantage of being a large lexicon with a large fraction (57 percent) of its words being unique.

The fifth and sixth columns of Table 1 report statistics describing how well these lexicons are represented in the full news article corpus. It is striking to note how few of the words in the news articles corpus are scored as either positive or negative by any one of these three lexicons. The highest coverage rate is that of the GI lexicon, which scores only 6.4 percent of the unigrams in the news corpus; a little more than half of those (3.7 percent of all unigrams) are unique to the GI lexicon (i.e., not included in the other two lexicons). Fewer of the unigrams in the news corpus are uniquely scored by HL and LM (1.3 and 0.7 percent, respectively). Thus, even though HL and LM contain over 5,000 more unique words than GI, fewer of these words appear in the news articles. Collectively, the union of the three lexicons covers 9.1 percent of the words in the full news corpus.

Finally, in terms of agreement (not shown in Table 1), we find it is rare for these lexicons to disagree completely on the valence of a given word. Specifically, only 9 of the 1,040 (0.9%) words in common between HL and LM have opposite valence scores (scored positive in one lexicon and negative in the other). 1.4% of the HL-GI common words have opposite valences

[9]There is substantial overlap in lexicon coverage between the GI and HL, with about 2,400 words (66% of GI's lexicon) included in both.

and 2.7% of LM-GI common words have opposite valences.

Overall, no single lexicon appears to be a clear winner in terms of being the best suited to measure sentiment from the news corpus. The LM lexicon appears appropriate in terms of its economics/finance domain but is not as well covered in the news corpus as the other two lexicons. Conversely, the GI and HL lexicon have larger lexicons and each uniquely cover a larger number of words in the news articles, but it is not clear whether the valence of words used in these lexicons are strongly indicative of their valence in economic/finance news articles. Thus, each lexicon brings something to the table that may improve the accuracy of a sentiment-scoring model. This suggests there could be substantial improvements in performance of a model that combines these lexicons. Furthermore, the large number of words in the news corpus that are not scored by any of the models suggests there could also be improved performance by constructing a new lexicon that scores additional words.

3.3 Constructing a sentiment-labeled news article data set

To compare the performance of the alternative sentiment models, we need a set of text for which we know the "true" sentiment. To achieve this, we asked a team of 15 research assistants (RAs) at the Federal Reserve Bank of San Francisco to manually rate the negativity of each of 800 news articles. The 800 news articles were randomly drawn from our full corpus of 238,685 articles described above.

The RAs were instructed to read an article and assess its overall tone. The instructions were as follows (including underlining and bullet points):

> *What is the sentiment expressed in this article on a five point scale?*
> *Very Negative (1)   Negative (2)   Neutral (3)   Positive (4)   Very Positive (5)*
>
> *By sentiment, we mean the tone/feeling/emotion expressed* <u>*by the language*</u> *of the article rather than the economic substance of the article.*
>
> *For example,*
>
> - *If the writer is talking about a report of very high GDP growth but is expressing concern that this reflects overheating of the economy and monetary policy being behind the curve, then this could be the writer expressing negative sentiment even though he/she was talking about high growth.*

- *The writer could be talking about a sharp rise in inflation (which in some contexts would be considered a bad economic outcome), but the writer is expressing this with positive sentiment in the current environment because he/she considers inflation to be too low.*[10]

We refer to the resulting data set as our labeled news data set. The blue bars in Figure 1 show the distribution of human ratings. The distribution of human ratings appears reasonable with a unimodal distribution centered around articles deemed neutral. More articles were rated less than 3 (neutral), indicating a tendency for newspapers to report (what the raters ascertain as) negative news.

3.4 Evaluating Performance of Lexicon-Based Models

As noted above, the (net) positivity of each news article is constructed by calculating the proportion of words in the article that are positive minus the proportion of words that are negative. The advantage of this measure is that it is simple and transparent. We also explored more complicated measures, such as term frequency - inverse document frequency (TF-IDF), but found no improvement in performance. Note that this net proportion calculation is mathematically equivalent to averaging the word-specific valence scores across all words in the article, where positive words are assigned a score of 1 and negative words a score of -1. This averaging calculation is thus easily generalized to the use of lexicons that have more than simple binary classifications.

Using the 800 labeled news articles described above, we evaluate the performance of the net proportion "model" corresponding to each lexicon based on its goodness-of-fit in predicting the human ratings. The results are shown in Table 2. We report four measures of goodness-of-fit. The first is the Spearman rank correlation. We use the rank correlation given that the human ratings are on a discrete, ordinal scale from 1 to 5. The second is the R^2 from an OLS regression of the human ratings on the model scores. Given the ordinal nature of the dependent variable, we also report the pseudo-R^2 from an ordered logit regression. Lastly, we report the Macro-F1 statistic of classification accuracy, which is a common metric of model

[10] As the instructions emphasize, the task for the RAs was to extract an unbiased measure of the sentiment expressed by the *journalist*, not to impose their own sentiment based on the content of the article. The representativeness of human scorers is important only to the extent that this group of individuals can extract an unbiased score of the journalist's sentiment.

performance in the NLP sentiment analysis literature.[11] It measures the accuracy of a model in terms of its ability to correctly classify text into the discrete categories of interest. Here the task is classifying articles into one of three bins: positive, neutral, or negative. Since our models output continuous positivity scores rather than sentiment classes, we sort articles into classes based on their sentiment scores and the observed prior probability of each sentiment class. Given that news articles are not purely positive, neutral, or negative, but rather some degree of each, we prefer the first three performance metrics, but we report the classification accuracy as well for completeness.

The results in Table 2 show that the predictive accuracy of the LM and HL lexical models is very similar and both dominate that of the model based on the GI lexicon. Specifically, both LM and HL have rank correlations with the human ratings of approximately 0.44, while the GI lexicon model has a rank correlation of 0.27. A likely explanation is that HL model gains from having a much larger lexicon relative to the GI lexicon while the LM model gains, despite having a smaller lexicon, from being more domain-specific.

Next, we consider whether performance can be improved by combining lexicons and expanding the number of words covered. The row labeled "GI + LM + HL Lexicon" in Table 2 shows the goodness-of-fit statistics for a net proportions model based on the union of the three lexicons. For words included in multiple lexicons, we give preference to LM followed by HL. This model actually reduces the fit slightly. This is likely because the GI dictionary both substantially overlaps with HL (thus offering little value added) and is not domain specific (causing some deterioration in performance as reflected in its poor goodness-of-fit individually). Next, we combine solely LM and HL. As shown in the Table, this combined model outperforms the model combining all three lexicons. In sum, we see that combining lexicons can improve performance, especially if the individual lexicons are domain-specific and/or there is limited overlap in their separate lexical coverage.

In appendix B, we provide four examples of scored newspaper articles. Specifically, we show two examples where both the lexicons and the human raters agreed on the net positivity, and two examples where the human raters and lexicons disagreed. In the two cases where they disagreed, there are many instances where a word with a negative tone (for example,

[11] The ternary Macro-F1 statistic is the average of the Macro-F1 statistics of the three categories (positive, neutral, negative). A category's Macro-F1 statistic is the harmonic mean of its "precision" and "recall," where precision is the proportion of the category's predicted number that are correct and recall is the proportion of the category's true number that are correctly predicted.

"drop") is used to describe what the rater likely deciphered as something positive ("...drop in mortgage rates is one of the most welcome changes..."), and vice versa. More broadly, these are examples where the bag-of-words approach is not able to decipher the context of the words in the sentence.

3.5 Heuristic Rules

So far we have considered simple bag-of-words lexical models, based on averaging the valence scores of each word within an article. As discussed in the prior section, it is important to account for the contextual characteristics of words within the text—in other words, *how* a word is used within a sentence or larger section of text.

One simple approach is to define simple heuristic rules that modify the sentiment scores of words based on how those words appear within the text. The Vader model (Hutto and Gilbert (2014)) described in the previous section is one such model. Vader is a sentence-level model that scores the sentiment of a sentence based on summing the valence scores of the words within it. However, unlike the purely lexicon-based models we considered above, Vader modifies each word's score based on five rules related to negation (being preceded by a negation word like "not"), punctuation (e.g., exclamation points), capitalization (e.g., ALL CAPS), being preceded by versus following the word "but," and being preceded by a degree modifier such as "very," "extremely," "slightly," etc.. For example, if a word is preceded within three words by a negation term, the word's valence scores is multiplied by -0.74, indicating that negation reverses the valence of the word, though it reverses it by less than 100%. Both the initial unigram negativity labels (weights) and the scalar multiples associated with the rules are obtained from a large-scale human rating process (using Amazon's Mechanical Turk).

Unfortunately for our purposes, Vader is designed for the social-media domain, not the economics/finance domain. To get a sense of how much accounting for contextual characteristics, via heuristic rules, can improve performance, despite the lack of domain-specificity, we generated Vader scores for our 800 labeled news articles. To generate a Vader score, we obtained the Vader score for each sentence in an article, using the open-source Vader python package, and then averaged the scores across sentences weighting each by its word count. This weighted average across sentences is thus mathematically equivalent to averaging the word-specific scores (after rule modification) across all words in an article, as we did with the lexicon-based models. The predictive accuracy of this Vader model is shown in Table 2. Its performance is on par with that of the HL+LM combined lexicon model.

We also explored whether performance could be further improved by adding words from the earlier lexicons to the lexicon underlying the Vader package. The results of adding the LM and HL lexicons are shown in the subsequent row of the table. The performance improves slightly relative to the standard Vader package. As we found for the net proportions model, we also found (not shown in the Table) that additionally including the GI lexicon led to a deterioration in predictive ability.

One simple but potentially powerful rule that is easily added to any lexicon-based model is a negation rule (see Potts (2010)). Similar to Vader's negation rule, we modify the word-specific scores from each of the previously considered lexicon-based models by multiplying the score by -1 if the word is preceded (within three words) by a negation term (using Vader's list of negation terms). The goodness-of-fit metrics for the resulting models is shown in the "+ Negation Rule" rows in Table 2. In each case, there is a modest improvement in performance.

3.6 Constructing a New Lexicon for Economic News Articles

We found above that in addition to domain specificity, lexicon size is important for predicting sentiment. Here we attempt to infer the sentiment orientation for *all* unique words in our full corpus of 238,685 news articles. This process takes three steps. First, we assign a sentiment class, $c \in \{positive, neutral, negative\}$, to each sentence in the corpus based on the Vader sentence classifier, modified to include the LM and HL lexicons (i.e., the model labeled "Vader (plus LM + HL lexicons)" in Table 2). This provides us with a rough measure for the sentiment orientation of each sentence in the news corpus. Second, we create a word-by-class matrix,[12] counting the co-occurrence of each word with each of the three sentiment classes. Third, we calculate the degree to which each word in the article corpus is associated with positive, negative, and neutral sentences by re-weighting this count matrix using "pointwise mutual information"(PMI). Specifically, the PMI between a word w and a sentiment class c

[12]This matrix and the PMI re-weighting approach belong to a family of methods referred to as vector-space models (Turney and Pantel (2010)).

is defined as follows (Church and Hanks (1990)):

$$\text{PMI}(w, c) = log \left(\frac{p(w, c)}{p(w)p(c)} \right) \tag{1}$$

where, $p(w)$ is word w's share of total words in the news corpus, $p(c)$ is class c's share of total sentences in the corpus, and $p(w, c)$ is the probability that word w and sentiment class c co-occur. The PMI provides a measure of confidence that a given word is associated with a certain sentiment. Specifically, it allows us to quantify the degree to which a word and a sentiment class are related—given a sentence with word w, we want to know if the presence of that word makes it more, less, or just as likely for the sentence as a whole to be positive, negative, or neutral (see, for example, Turney (2002)). The overall sentiment score, S, for a word w is then defined as:

$$S(w) = \text{PMI}(w, positive) - \text{PMI}(w, negative), \tag{2}$$

where we normalize sentiment the score to range from -1 to 1 for each word.

We take this "news PMI lexicon"—taken from the domain of economics/finance news articles—and, as before, calculate the sentiment score for each article, a, as an average of the scores for the words contained therein, $S(a) = \overline{S(w)}$. The sentiment scores for words that are relatively infrequent will be noisy, but this lexicon will have the advantage of 100% coverage for our full domain-specific corpus.

The predictive accuracy of this news lexicon is shown in Table 2. Using this lexicon by itself yields slightly higher goodness-of-fit statistics than any of the other individual lexicons. Its performance also increases slightly with the addition of the negation rule. Moreover, we find that combining the news lexicon with the combined LM + HL lexicon – that is using the word scores from that combined lexicons (with preference given to LM in the case of overlaps) and then adding word scores for all other words from the news lexicon—and adding the negation rule yields the best performance.

This model yields a Spearman rank correlation of 0.491. The fit of this model is shown graphically in the panels of Figure 2, which shows a scatterplot of the human ratings, on the x-axis, versus the model ratings, on the y-axis. The solid red line is a linear regression fit line. The red circle for each rating category shows the mean model score across all articles assigned that rating by the team of research assistants. The shape of the distribution of model scores also looks similar to the human rating, as shown in Figure 1. The red line shows the kernel density model scores against the frequency distribution of human ratings. Both distributions are unimodal and show more negative than positive sentiment articles.[13]

To assess the statistical significance of the improvement in goodness-of-fit of this "winning" model, we use the pairwise Diebold-Mariano test (with zero bandwidth because the article ratings are not serially correlated) based on the mean squared error (MSE) of the predictions from the ordered logit model (estimated on the 800 labeled news article observations). We find that the mean squared error (MSE) of this winning model is not statistically significantly different from that of the 2nd-best model ("LM + HL Lexicon + Negation Rule"); it is significantly different than the 3rd-best ("LM + HL + News Lexicon" without negation rule) with a p-value of 0.08; it is significantly different than the 4th-best ("LM + HL Lexicon" without negation rule) with a p-value of 0.03; and significantly different than all the rest with p-values less than 0.01. So, for example, we can confidently say the best model has statistically significantly lower prediction errors than either the "off-the-shelf" Vader model or LM-lexicon model, which would seem to be the most natural benchmarks.

Overall, we find that our newly constructed news lexicon, combined with the LM and HL lexicons, and augmented with a negation rule yields the highest predictive accuracy for our set of labeled news articles. In the following section we use this model to measure sentiment for all 238,685 articles in our full corpus of business news articles and construct daily and monthly indexes of news sentiment. We then provide an application of this index, investigating the macroeconomic impact of news sentiment shocks.[14]

3.7 Machine Learning Techniques

Machine learning (ML) techniques can potentially identify the myriad of contextual characteristics that contribute to the sentiment of text beyond some simple rules. As discussed above, ML approaches can, in principle, learn sentiment weights for words and entire phrases, with the ability to measure the sentiment of an entire expression. The disadvantage of this technique is that it requires large labeled training datasets which are time-consuming and expensive to construct.

[13] Reported in Figure 1 is the kernel density of scores from the model. To aid in visual comparison, we re-scaled the distribution to have the same mean and standard deviation as the human ratings.

[14] In appendix B, we show four examples of scored text, which includes the score of this "winning model."

Here, we assess ML models which we train and test on the 800 human ratings. As is best practice, we split the labeled dataset into a training set, a development set, and a hold-out test set. The development and test sets have 100 observations each, leaving 600 observations for the training set. For each model presented, hyper-parameter optimization is done through grid search, using cross-validation on the training set to evaluate model performance for each possible set of hyper-parameters. The optimal model is then evaluated against the development set. Finally, after all models have been developed and tuned, we test them all against our hold-out test set for final results, which we report here.

We compare three different types of machine learning models, each a linear model but with different feature spaces. Our training set is not large enough to support training deep neural networks, but we are able to take advantage of recent advances in deep learning approaches by incorporating pre-trained models in our feature spaces.

The first model we consider is a simple unigrams, or "bag-of-words," model whereby the features are counts of each word (i.e., unigram). "Bag-of-words" models typically result in very high dimensional and sparse feature vectors, and pure word counts are often re-weighted using information theoretical measures such as tf-idf. "Bag-of-words" models have the advantage of being simple to implement, however they do not take into account word order, and the sparsity of feature vectors can pose modeling challenges, especially with small training sets.

The next two models we consider use embeddings — which encode words or entire documents into vectors — in order to bring in additional external knowledge about words and help compensate for the sparsity of the training data. The first of these models, GloVe (Global Vectors for Word Representation), is a type of transfer-learning model—a model pre-trained on a known task that has learned contextual relationships between words, developed at the Stanford NLP Group by Pennington, Socher, and Manning (2014). GloVe retrieves pre-trained word embeddings for each word, essentially modeling each word as a dense, fixed-length vector that encodes semantic information about the word (e.g., "horrible" and "terrible" are proximate in the GloVe vector space). Given GloVe vectors for each word in a document, we follow common practice and compute the document feature vector by taking the mean of the word vectors. The benefit of this approach is that it allows the model to take advantage of external knowledge (it doesn't need to see "horrible" in the training set in order to know it's a negative word if it's seen something similar such as "terrible") and results in a smaller and denser model. However, this model still does not take into account word order or context. Thus, we also consider a more recently developed transfer-learning model known as BERT, developed at Google by Devlin, Chang, Lee, and Toutanova (2018). Unlike GloVe, which provides fixed, pre-defined vectors for words, BERT (Bidirectional Encoder Representations from Transformers) generates context-aware word and document embeddings. Instead of processing text in one direction (left to right or right to left), BERT uses a bidirectional approach, and its performance on many common NLP tasks shows that this approach is a powerful way to incorporate context and sequential information in language modeling.

Results of the models' performances are shown in Table 3. To evaluate goodness-of-fit as in Table 2, we compare the original human-provided ratings to the predicted probabilities from the model in the test set, and to compute Macro-F1 scores, we compare the predicted sentiment classifications (positive, neutral, or negative) from the model human-provided ratings. For comparison, we also recalculate goodness-of-fit for the best-fitting lexical model from the prior subsection using the same test set of articles. An important caveat here is that, because we only have 800 human-rated articles and 700 are used in the training and develop steps of the machine learning process, there are just 100 articles remaining for testing performance. That concern notwithstanding, the results suggest that performance improves the more we are able to bring in external knowledge and incorporate additional information about word meaning and context. Compared to the best-fitting lexical model, we find that GloVe performs worse while BERT performs about as well.

While the BERT model seems promising, we rely on our preferred lexical model for the analyses in the remainder of the paper for a couple reasons. First, given these results are based on just 100 articles, we have less confidence in the robustness and generalizability of BERT's performance across the entire news corpus than we do in that of the lexical model, which was evaluated on 800 articles.[15] Second, and more importantly, given that an objective of this paper is to introduce text sentiment analysis tools to economists, we prefer to focus on more transparent and easier to implement methods. Common critiques of ML methods are that they are "black boxes" and difficult to implement and replicate.

[15]Investing in a larger training set would certainly improve model performance and confidence, but training sets are expensive to construct, especially when domain experts are required to provide the labels.

4 Constructing a News Sentiment Index

Economic policymakers and market participants rely on a broad array of models that incorporate what is called "soft" information. As opposed to "hard" information which includes objective and directly quantifiable variables such as production and employment, soft information includes subjective measures concerning attitudes about current and future economic conditions. There are a broad array of soft variables available, but arguably the most widely followed is the measures of consumer sentiment and confidence by the University of Michigan and the Conference Board. In this section, we aggregate the news article sentiment scores into a monthly index and assess its correlation with these survey measures. A strong correlation would help validate that our news sentiment measure is not pure noise and is capturing similar information to that of the surveys.

To construct a monthly index of news sentiment we estimate the month fixed effects ($\hat{f}_{t(a)}$) from the following regression over articles (indexed by a):

$$s_a = f_{t(a)} + f_{p(a),j(a)} + \varepsilon_a. \tag{3}$$

where s_a is the net positivity score for article a and $f_{t(a)}$ is a sample-month (t) fixed effect. Newspapers are indexed by j and article type – either editorial or regular article – is indexed by p. $f_{p(a),j(a)}$ is thus a newspaper*type fixed effect. Allowing for newspaper*type fixed effects ensures that the index is independent of changes over time in the composition of the sample across newspapers and editorials versus regular articles. This can be important because the tone of articles differ considerably across newspapers and between editorials and regular articles within a newspaper.

The monthly news sentiment index, NS_t, is the estimated monthly fixed effects from this regression. Figure 3 plots the measure over time (between 1980 and 2015), along with the University of Michigan Consumer Sentiment Index (MCSI), where both series are normalized by their mean and standard deviation. The news sentiment index is colored blue and the consumer sentiment series is colored orange. The two series are strongly correlated with a correlation of 58.3 percent over the full sample. The correlation improves over time increasing to 64.4 percent post-1990, 70.1 percent post-2000, and 73.7 percent post-2005. Although not depicted, the news sentiment measure has a slightly lower correlation (50.9 percent over the full sample) with the Conference Board's measure of consumer confidence.

As with the MCSI, the news sentiment index experiences large dips during recessions. The news sentiment measure, however, displays much larger dips during months of key historical events, such as the the Russian financial crisis (August 1998), the 9/11 terrorist attacks (September 2001), the Greek government debt crisis (July 2011), and the U.S. debt-ceiling crisis (October 2013). Although these are only simple correlations, the fact that news sentiment comoves with consumer survey responses and reflects key economic events suggests that the news sentiment index has a relatively high signal-to-noise ratio. We turn next to evaluating its predictive power for future economic activity.

5 Applications in Economics

5.1 Predicting Survey Measures of Economic Sentiment

As a first application, we explore whether news sentiment can help predict the Michigan Consumer Sentiment Index (MCSI) and/or the Conference Board's Consumer Confidence Index (CBCI). As discussed earlier, these two survey-based measures of sentiment have been shown to have strong predictive power for many macroeconomic variables and are closely followed by economic analysts. However, they are released at a relatively low frequency. One advantage of the news-based sentiment measure is that it can be constructed at a higher frequency, providing information about economic sentiment between releases of either of these survey measures. Accordingly, we perform a nowcasting experiment in which we test whether high-frequency news sentiment can help predict the current month's MCSI and/or CBCI.

Both surveys are conducted on a continuing basis throughout a given reference month and both release a preliminary estimate before the final number. Michigan's preliminary release is published approximately two weeks after the prior month's final release (and hence about two weeks before the current month's final release). The Conference Board publishes a preliminary number on the last Tuesday of the current month, along with the prior month's final number. A full history of (real-time) preliminary and final releases of the MCSI is publicly available; for the CBCI, a full history is publicly available only for the final release. Hence, for MCSI, we ask whether news sentiment over the days since the prior final release can help forecast the value of the current preliminary release. We focus here on forecasting the preliminary release, as opposed to forecasting the final release conditional on the preliminary release, because the preliminary and final releases (for the same reference month) tend to be very highly correlated. In other words, being able to predict the MCSI preliminary release given the prior month's final is much more valuable than being able to predict the final release given that month's preliminary release. For CBCI, we ask whether news sentiment over the days since the prior final release can help forecast the value of the current final release.

To answer these questions, we construct two alternative news sentiment indexes (one for each survey measure), as in equation (3), but including only those articles reported between between the release dates of the specific survey measure. For the MCSI, this is the two-week window of articles between the prior month's final release and the current month's preliminary release. For the CBCI, this is the one-month window of articles between final release dates.

For MCSI, we estimate the following:

$$Prelim_t = a + \sum_{\tau=1}^{3} \gamma_\tau Final_{t-\tau} + \beta_d NS_t^d + \sum_{\tau=1}^{3} \phi_\tau NS_{t-\tau} + \varepsilon_t, \tag{4}$$

where $Prelim_t$ is the preliminary MCSI release for reference month t, $Final_t$ is the final MCSI release for reference month t, NS_t^d is the news sentiment index including only articles published over the d days since the prior final MCSI release.[16] $NS_{t-\tau}$, for $\tau = 1$ to 3, represents three lags of the (full) monthly news sentiment index. For CBCI, because we do not have data on $Prelim_t$, we estimate the same regression specification but replace $Prelim_t$ with $Final_t$ and define NS_t^d as the news sentiment index including only articles published over the d days since the prior final CBCI release.

Table 4 shows the results of the nowcasting exercise for the preliminary release of the MCSI, for $d = 14$, between 1991 and 2015. Before adding NS_t^{14}, we start by estimating simple models including only the prior month's final release (Column 1) or that plus two additional lags (Column 2). Not surprisingly, the prior month's final release is highly predictive of the current month's preliminary release; earlier lags are economically and statistically

[16]That is, NS_t^d is constructed as described in the previous section – the monthly time fixed effects from estimating equation 3 – but using a subsample of articles published over the d days since a preliminary MCSI release.

insignificant. In Columns (3) and (4), we add NS_t^{14}, the measure of news sentiment between the prior month's final survey release and the current preliminary release. We find that in both cases, this news sentiment measure is highly statistically significant and results in an increase in the adjusted R-squared. To assess robustness, we estimate three additional specifications. Column (5) includes the full calendar-month news sentiment index for each of the three prior months and hence corresponds exactly to equation (4). NS_t^{14} remains highly statistically significant. Columns (6) and (7) are specifications where the dependent variable is the difference between the current preliminary release and last month's prior final release, which is equivalent to estimating equation (4) but restricting the coefficient on the prior month's final release to equal one. Comparing column (6), which excludes NS_t^{14}, to column (7), one can see that the inclusion of NS_t^{14} nearly doubles the adjusted R-squared.

Table 5 shows the analogous results for CBCI, where here the key regressor is NS_t^{28} which represents the news sentiment of articles published between the prior CBCI final release and the current CBCI final release. Similar to the results in Table 4, we find that NS_t^{28} is highly statistically significant and increases the adjusted R-squared of the forecasting model.

Lastly, to assess how additional days of news add to the predictive power of these nowcasting models, we estimate the model repeatedly, varying d from 1 to 14 for MCSI and from 1 to 28 for CBCI. We use the model corresponding to column (5) in Tables 4 and 5, so the coefficient on NS_t^d can be interpreted as the effect of news sentiment since the prior final release on the change in sentiment from that release to the new preliminary release. Figure 4 plots the point estimate and t-statistic for $\hat{\beta}_d$ over the range of d for each survey measure. The results show that the coefficient and statistical significance on the news sentiment measure generally increases as the number of days of news articles increases. The increase in the coefficient size highlights that each additional day of news articles provides important information in nowcasting the current month's MCSI or CBCI measure. It may also reflect the value of averaging over multiple days of news to reduce noise.

5.2 Estimating the Response of Economic Activity to News Sentiment

As a second exercise, we apply the news sentiment index to the literature regarding the relationship between sentiment and economic activity.[17] Specifically, we assess whether the news sentiment index impacts future economic activity. To do so, we use the local projection method of (Jorda (2005)) which is similar to the standard vector auto-regression (VAR) approach but less restrictive. Specifically, this method evaluates how a "shock" to the news sentiment index drives a given measure of economic activity. The news sentiment shock is constructed as the component of the news sentiment series that is orthogonal to current and 4 lags of economic activity as well as 4 lags of itself. This number of lags was chosen based on the AIC criterion. That is, for each forecast horizon h, a distinct regression is run of a given economic measure (y_i) on contemporaneous and lagged values the news sentiment index and four economic measures:

$$y_{i,t+h} = a_i^h + \beta_i^h NS_t + \sum_{\tau=1}^{4} \alpha_{i,\tau}^h NS_{t-l} + \mathbf{A}_i^h \sum_{\tau=0}^{4} \mathbf{Y}_{t-\tau} + \varepsilon_{i,t+h}. \tag{5}$$

where y_i is one of the four variables contained in the matrix $\mathbf{Y}$. These variables are consumption, output, the real fed funds target rate, and inflation. Consumption is measured by real personal consumption expenditures (PCE) produced by the Bureau of Economic Analysis (BEA), inflation is measured as the logarithm of the PCE price index (also produced by the BEA), and output is measured by the industrial production (IP) index produced by the Federal Reserve. We use IP because it is available monthly, whereas real GDP (the measured used by Barsky and Sims (2012)) is measured only at the quarterly frequency. These are the same macroeconomic variables considered in Barsky and Sims (2012) and are meant to cover broad aspects of the economy. The impulse response from a shock to news sentiment on economic measure y_i are traced out by the estimates of $\hat{\beta}_i^h$ from equation (5). We consider horizons up to 12 months after the shock.

The impulse responses to a sentiment shock are shown in Figure 5 along with 90 and 68 percent confidence bands, depicted in dark and light grey shaded areas, respectively. We

[17] For example, Barsky and Sims (2012), Angeletos and La'O (2013), Benhabib, Wang, and Wen (2015), and Benhabib and Spiegel (2017).

report the 68-percent bands for comparison to Barsky and Sims (2012) who report one-standard deviation bands only. The news sentiment shock is normalized to one standard deviation.

Figure 5 shows that a positive news sentiment shock increases consumption, output, and the real fed funds rate, but slightly reduces the price level. The effect on the price level is transitory, but the effects on consumption, output and the real fed funds rate are longer lasting, gradually rising up to 12 months past the shock. Extending the horizon out further (not depicted) indicates that the responses of consumption, output, and the real rate peak between 12 and 18 months after the shock before gradually waning.

These results are consistent with both the empirical and theoretical results in Barsky and Sims (2012), shown in their Figure 8. They found that a positive sentiment shock (measured using the University of Michigan's Consumer Sentiment Index) leads to persistent increases in consumption, output, and the real rate, but results in a transitory decline in inflation. In terms of magnitudes, the effects for output and the real rate that we obtain are similar to those in Barsky and Sims (2012) while their consumption and price responses are larger. The overall similarity of our results with theirs provides further evidence that the news sentiment measure has a similar macroeconomic impact as that of consumer sentiment. In additional analyses, we find that the qualitative results hold even after conditioning on current and 6 lags of either the Michigan consumer sentiment index or the Conference Board's consumer confidence index. See Appendix Figures A1 and A2. This suggests that the text-based sentiment measure contains some information orthogonal to survey-based consumer sentiment measures.

As a broader examination of assessing the predictive performance of the news-sentiment measure, we implement a variable-selection exercise using the LASSO (least absolute shrinkage and selection operation) estimator. Whereas OLS yields parameter estimates that minimize the sum of squared residuals (SSR), LASSO yields estimates that trade off minimizing the SSR with minimizing the absolute values of the parameters:

$$\hat{\beta} = arg\ min \sum_{i=1}^{n} \left(y_{i,t+12} - \sum_{j=1}^{p} x_{i,j} b_j \right)^2 + \lambda \sum_{j=1}^{p} |b_j| \tag{6}$$

where $y_{i,t+12}$ represents the forecasted economic outcome of interest i. The objective of minimizing the magnitudes of the parameters derives from the fact that large magnitudes increase out-of-sample variance. The LASSO algorithm forces parameters of a forecasting model toward zero based on a chosen penalty factor, λ, aimed at reducing in-sample overfitting (i.e., increasing out-of-sample prediction). λ is estimated using cross-validation techniques. Since the LASSO model does not need to be parsimonious, we include additional economic outcomes of interest in the model—specifically, employment and the S&P 500 index in addition to consumption, output, the real fed funds rate, and inflation (as in Barsky and Sims (2012)). The variables $x_{i,j}$ represent contemporaneous and 12 lags of these contemporaneous outcome variables as well as the two survey-based measures of sentiment (MCSI and CBCI) and the news sentiment index. If the LASSO model selects any news sentiment measure variable (any of the current and 12 lags), then it is an indication that news sentiment aids in the out-of-sample forecasting performance of the model.

We perform three versions of the LASSO model: (1) the general LASSO, (2) the adaptive LASSO, and (3) the group LASSO. The group LASSO[18], forces *groups* of parameters to zero simultaneously. We consider a "group" to be a specific economic outcome, survey, or sentiment measure (such as Employment, MCSI,) defined by its contemporaneous value and 12 lags. Details of the estimation methods are described in Appendix C.

The variables chosen as predictors by the LASSO estimator – that is, the variables for which at least one of the current or 12 lags of the variable (blocks in the case of the group LASSO) are estimated to have non-zero coefficients – are shown in Table 6. As expected, the LASSO estimators prefer rather parsimonious models. However, the results show that the LASSO estimators generally retain the news sentiment measure. Specifically, at least one of the LASSO versions prefers the news sentiment measure in forecasts of employment, output (IP), inflation, the real rate (FFR), and the S&P 500.

6 Conclusion

This study discussed currently available methodologies to perform sentiment text analysis and implemented these methodologies on a large corpus of economic and financial newspaper articles. We focused on lexicon-based methods, though we also considered nascent emerging machine learning techniques. We evaluated the performance of a wide array of sentiment models using a sample of news articles for which sentiment was hand-classified by humans.

[18]Calculations done in R through the *grplasso* package (Meier (2009)).

Our findings highlight that both the size of the lexicon as well as its domain specificity are important for maximizing classsification accuracy.

We then used our preferred sentiment model to develop a new time-series measure of economic sentiment based on text analysis of economic and financial newspaper articles from January 1980 to April 2015. This measure is based on a lexical sentiment analysis model that combines existing lexicons with a new lexicon that we construct specifically to capture the sentiment in economic news articles.

We considered two economic research applications using this news sentiment index. First, we investigated the extent to which daily news sentiment can help predict consumer sentiment releases, finding that news sentiment is highly predictive. Second, we estimated the impulse responses of key macroeconomic outcomes to sentiment shocks, at the monthly frequency. Positive sentiment shocks were found to increase consumption, output, and interest rates and to temporarily reduce inflation.

More broadly, our results show that text-based measures of sentiment extracted from news articles perform well in terms of capturing economically meaningful soft information. Importantly, they do so at a very low cost relative to survey-based measures. As computational methods in text analytics advance over time, we expect the accuracy of text-based sentiment measures to improve even further.

References

Angeletos, G.-M., and J. La'O (2013): "Sentiments," *Econometrica*, 81(2), 739–779.

Baker, S. R., N. Bloom, and S. J. Davis (2016): "Measuring economic policy uncertainty," *Quarterly Journal of Economics*, 131(4), 1593–1636.

Barsky, R. B., and E. R. Sims (2012): "Information, animal spirits, and the meaning of innovations in consumer confidence," *The American Economic Review*, 102(4), 1343–1377.

Benhabib, J., and M. M. Spiegel (2017): "Sentiments and Economic Activity: Evidence from U.S. States," Working Paper 23899, National Bureau of Economic Research.

Benhabib, J., P. Wang, and Y. Wen (2015): "Sentiments and aggregate demand fluctuations," *Econometrica*, 83(2), 549–585.

Bram, J., and S. C. Ludvigson (1998): "Does consumer confidence forecast household expenditure? A sentiment index horse race," *Economic Policy Review*, 4(2).

Calomiris, C. W., and H. Mamaysky (2017): "How News and Its Content Drive Risk and Returns Around the World," Unpublished paper, Columbia GSB.

Carroll, C. D., J. C. Fuhrer, and D. W. Wilcox (1994): "Does consumer sentiment forecast household spending? If so, why?," *The American Economic Review*, 84(5), 1397–1408.

Church, K. W., and P. Hanks (1990): "Word association norms, mutual information, and lexicography," *Computational linguistics*, 16(1), 22–29.

Correa, R., K. Garud, J. M. Londono, and N. Mislang (2017): "Sentiment in Central Banks' Financial Stability Reports," *Available at SSRN 3091943*.

Devlin, J., M.-W. Chang, K. Lee, and K. Toutanova (2018): "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*.

Fraiberger, S. P. (2016): "News Sentiment and Cross-Country Fluctuations," *Available at SSRN.*

Garcia, D. (2013): "Sentiment during recessions," *The Journal of Finance*, 68(3), 1267–1300.

Hansen, S., and M. McMahon (2016): "Shocking language: Understanding the macroeconomic effects of central bank communication," *Journal of International Economics*, 99, S114–S133.

Hansen, S., M. McMahon, and A. Prat (2017): "Transparency and Deliberation Within the Fomc: a Computational Linguistics Approach*," *The Quarterly Journal of Economics*, p. qjx045.

Heston, S. L., and N. R. Sinha (2015): "News versus sentiment: Predicting stock returns from news stories," *Robert H. Smith School Research Paper.*

Hu, M., and B. Liu (2004): "Mining and summarizing customer reviews," in *SIGKDD KDM-04.*

Hutto, C., and E. Gilbert (2014): "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text," in *Eighth International Conference on Weblogs and Social Media (ICWSM-14).*

Jorda, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161–182.

Liu, B. (2010): "Sentiment Analysis and Subjectivity.," *Handbook of natural language processing*, 2, 627–666.

Loughran, T., and B. McDonald (2011): "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *The Journal of Finance*, 66(1), 35–65.

Ludvigson, S. C. (2004): "Consumer confidence and consumer spending," *The Journal of Economic Perspectives*, 18(2), 29–50.

Meier, L. (2009): "grplasso: Fitting user specified models with Group Lasso penalty," *R package version 0.4-2.*

Nyman, R., D. Gregory, S. Kapadia, P. Ormerod, D. Tuckett, and R. Smith (2016): "News and narratives in financial systems: Exploiting big data for systemic risk assessment," Unpublished paper, Bank of England.

Nyman, R., S. Kapadia, D. Tuckett, D. Gregory, P. Ormerod, and R. Smith (2018): "News and narratives in financial systems: exploiting big data for systemic risk assessment," .

Pang, B., and L. Lee (2005): "Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales," in *Proceedings of the 43rd annual meeting on association for computational linguistics*, pp. 115–124. Association for Computational Linguistics.

Pang, B., L. Lee, and S. Vaithyanathan (2002): "Thumbs up?: sentiment classification using machine learning techniques," in *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*, pp. 79–86. Association for Computational Linguistics.

Pennington, J., R. Socher, and C. D. Manning (2014): "Glove: Global vectors for word representation," in *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pp. 1532–1543.

Potts, C. (2010): "On the negativity of negation," in *Semantics and Linguistic Theory*, vol. 20, pp. 636–659.

Shapiro, A. H., and D. J. Wilson (2019): "Taking the Fed at its Word: Direct Estimation of Central Bank Objectives using Text Analytics," Federal Reserve Bank of San Francisco, Working Paper No. 2019-02.

Souleles, N. S. (2004): "Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan consumer sentiment surveys," *Journal of Money, Credit, and Banking*, 36(1), 39–72.

Thorsrud, L. A. (2016a): "Nowcasting using news topics Big Data versus big bank," Unpublished paper, BI Norwegian Business School.

——— (2016b): "Words are the new numbers: A newsy coincident index of business cycles," Unpublished paper, BI Norwegian Business School.

Turney, P. D. (2002): "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," in *Proceedings of the 40th annual meeting on association for computational linguistics*, pp. 417–424. Association for Computational Linguistics.

Turney, P. D., and P. Pantel (2010): "From frequency to meaning: Vector space models of semantics," *Journal of artificial intelligence research*, 37, 141–188.

Young, L., and S. Soroka (2012): "Affective news: The automated coding of sentiment in political texts," *Political Communication*, 29(2), 205–231.

Table 1: Size and Coverage of Lexicons

Lexicon	Feature Space	Size	Unique Words		News Coverage Rate	
			Number	Fraction	Unique	Total
General Inquirer (GI)	General English	3626	1117	0.308	0.037	0.064
Loughran-McDonald (LM)	10-K Reports	2707	1569	0.580	0.007	0.028
Hu-Liu (HL)	Movie Reviews	6786	3832	0.565	0.013	0.044
Combined (GI+LM+HL)		9570				0.091

Notes: The total news coverage rate is the fraction of unigrams in the news corpus that are scored by the lexicon. The unique news coverage rate represents the fraction of unigrams in the news corpus that are scored only by the lexicon among the three.

Table 2: Goodness-of-Fit of Lexical Model Sentiment Scores for Predicting Human Ratings

Model	Feature Space	Lexicon Size	Ordered-Logit Pseudo R^2	OLS R^2	Rank Correlation	Macro-F1
GI Lexicon	General English	3626	0.023	0.064	0.264	0.406
+ Negation Rule			0.029	0.080	0.295	0.432
LM Lexicon	10-K Reports	2707	0.065	0.165	0.447	0.510
+ Negation Rule			0.066	0.169	0.449	0.500
HL Lexicon	Movie Reviews	6786	0.066	0.173	0.437	0.509
+ Negation Rule			0.072	0.186	0.453	0.503
GI + LM + HL Lexicon	Combined	9570	0.063	0.163	0.426	0.497
+ Negation Rule			0.070	0.180	0.444	0.500
LM + HL Lexicon	Combined	8453	0.077	0.195	0.476	0.516
+ Negation Rule			0.081	0.205	0.486	0.514
Vader	Social Media	7502	0.068	0.168	0.438	0.487
Vader (incl. LM + HL lexicons)	Combined	9057	0.075	0.189	0.452	0.480
News Lexicon	Econ/Finance	50754	0.071	0.180	0.459	0.525
+ Negation Rule	News Articles		0.075	0.188	0.469	0.525
News Lexicon + LM + HL	Combined	50754	0.078	0.197	0.480	0.524
+ Negation Rule			**0.082**	**0.206**	**0.491**	**0.525**

Notes: GI, LM, and HL refer, respectively, to the following lexicons: Harvard General Inquirer; Loughran and McDonald(2011), updated in 2014; and Hu and Liu (2004). The goodness-of-fit statistics are calculated using the full 800-article sample for which we have human ratings.

Table 3: Goodness-of-Fit of Machine Learning Model Sentiment Scores for Predicting Human Ratings

Model	Ordered-Logit Pseudo R^2	OLS R^2	Rank Correlation	Macro-F1
Unigrams	0.015	0.035	0.249	0.414
GloVe word embeddings	0.052	0.129	0.383	0.576
Bert document embeddings	0.155	0.336	0.599	0.590
News Lexicon + LM + HL + Negation Rule	0.105	0.250	0.602	0.645

Notes: LM and HL refer, respectively, to the following lexicons: Loughran and McDonald(2011), updated in 2014, and Hu and Liu (2004). The goodness-of-fit statistics are calculated using the 100-article test set, which was randomly drawn from the full 800-article sample for which we have human ratings. The other 700 articles were used for model-training (600 articles) and development (100 articles). See text for details.

Table 4: Nowcasting Preliminary Michigan Sentiment Release

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Prel.	Prel.	Prel.	Prel.	Prel.	Prel. - Prior Fin.	Prel. - Prior Fin.
News Sentiment (prior final release to preliminary release)			1.551***	1.611***	1.549***		1.375***
			(0.298)	(0.294)	(0.316)		(0.323)
Michigan Sentiment (Final, prior calendar month)	0.981***	0.972***	0.902***	0.835***	0.836***		
	(0.0154)	(0.0697)	(0.0232)	(0.0687)	(0.0674)		
Michigan Sentiment (Final, 2 months prior)		-0.0730		-0.0247	-0.00821	-0.152**	-0.147**
		(0.0960)		(0.0902)	(0.0893)	(0.0598)	(0.0611)
Michigan Sentiment (Final, 3 months prior)		0.0863		0.0965*	0.0920	0.104*	0.0859
		(0.0542)		(0.0543)	(0.0568)	(0.0563)	(0.0590)
News Sentiment (prior calendar month)					0.640	1.654***	0.519
					(0.477)	(0.412)	(0.476)
News Sentiment (2 months prior)					-0.880*	-0.965*	-0.983**
					(0.480)	(0.519)	(0.499)
News Sentiment (3 months prior)					0.0645	0.199	0.210
					(0.368)	(0.396)	(0.371)
Constant	1.392	0.999	7.762***	7.337***	6.222***	3.610*	4.721**
	(1.370)	(1.490)	(1.917)	(1.979)	(2.189)	(1.951)	(1.885)
N	284	284	284	284	284	284	284
Adjusted R-squared	.909	.909	.919	.92	.92	.059	.106

Dependent variable is the preliminary release of the Michigan survey (columns 1 through 5) and the preliminary release minus the prior final release (columns 6-7)

News Sentiment (prior final release to preliminary release) includes articles from the day of the prior final release to one day prior to the preliminary release.

Newey-west (3 lags) standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Nowcasting Consumer Confidence Release

	(1) CC	(2) CC	(3) CC	(4) CC	(5) CC	(6) CC - Prior CC	(7) CC - Prior CC
News Sentiment (prior release to current release)			2.818***	3.049***	3.673***		3.545***
			(0.395)	(0.419)	(0.581)		(0.587)
Consumer Confidence (prior calendar month)	0.975***	1.015***	0.926***	0.866***	0.871***		
	(0.0127)	(0.0550)	(0.0156)	(0.0525)	(0.0547)		
Consumer Confidence (2 months prior)		-0.0947		-0.0654	-0.0540	-0.152**	-0.171***
		(0.0881)		(0.0842)	(0.0868)	(0.0627)	(0.0611)
Consumer Confidence (3 months prior)		0.0551		0.126**	0.126**	0.105*	0.122**
		(0.0573)		(0.0522)	(0.0517)	(0.0567)	(0.0555)
News Sentiment (prior calendar month)					-0.477	1.916***	-0.717
					(0.801)	(0.646)	(0.779)
News Sentiment (2 months prior)					0.447	0.549	0.417
					(0.768)	(0.838)	(0.823)
News Sentiment (3 months prior)					-1.278**	-0.982	-1.204*
					(0.649)	(0.687)	(0.662)
Constant	2.348*	2.309*	5.940***	5.826***	4.555***	3.910***	3.896***
	(1.277)	(1.287)	(1.344)	(1.430)	(1.462)	(1.425)	(1.312)
N	284	284	284	284	284	284	284
Adjusted R-squared	.951	.951	.959	.960	.960	.070	.189

Dependent variable is the current release of the Consumer Confidence survey (columns 1 through 5) and the current release minus the prior release (columns 6-7)
News Sentiment (prior release to current release) includes articles from the day of the prior release to one day prior to the current release.
Newey-west (3 lags) standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: LASSO Models

	Employment			**IP**			**Inflation**		
	General	*Adaptive*	*Group*	*General*	*Adaptive*	*Group*	*General*	*Adaptive*	*Group*
I. Hard Data Measures									
Employment	✓	✓	✓	✓	✓	✓	–	–	✓
IP	–	–	✓	✓	✓	✓	✓	✓	✓
Inflation	–	–	✓	–	–	✓	✓	✓	✓
FFR	✓	–	✓	✓	✓	✓	✓	✓	✓
Consumption	–	–	✓	–	–	✓	✓	✓	✓
S&P 500	✓	✓	✓	✓	✓	✓	–	–	✓
II. Survey Data Measures									
MCSI	✓	–	–	✓	✓	–	✓	✓	✓
CBCI	✓	–	✓	✓	✓	–	✓	✓	✓
III. News Sentiment Measure									
Sentiment	✓	–	–	✓	✓	–	✓	✓	✓

	FFR			**Consumption**			**S&P 500**		
	General	*Adaptive*	*Group*	*General*	*Adaptive*	*Group*	*General*	*Adaptive*	*Group*
1. Hard Data Measures									
Employment	–	–	✓	–	–	–	–	–	✓
IP	✓	✓	✓	✓	✓	✓	–	–	✓
Inflation	–	–	✓	–	–	✓	✓	✓	✓
FFR	✓	✓	✓	✓	✓	✓	✓	✓	✓
Consumption	–	–	✓	✓	✓	✓	–	–	✓
S&P 500	✓	✓	✓	✓	✓	✓	✓	✓	✓
II. Survey Data Measures									
MCSI	–	–	–	✓	✓	–	✓	✓	–
CBCI	✓	✓	✓	–	–	–	✓	✓	–
III. News Sentiment Measure									
Sentiment	✓	✓	✓	–	–	–	✓	✓	✓

Notes: Checkmarks signify that at least one potential regressor indicated in the row heading was estimated to have non-zero coefficients by the LASSO estimator indicated by the column heading. The three types of LASSO estimators are the standard ("general") LASSO, Adaptive LASSO, and Group LASSO. For the group lasso, a checkmark signifies that the distributed-lag group (contemporaneous value and 12 lags) associated with a given variable was estimated to have a non-zero coefficient. The economic measure being forecasted is listed above the column headings.

Figure 1: Model Scores Versus Human Rating: Distributions

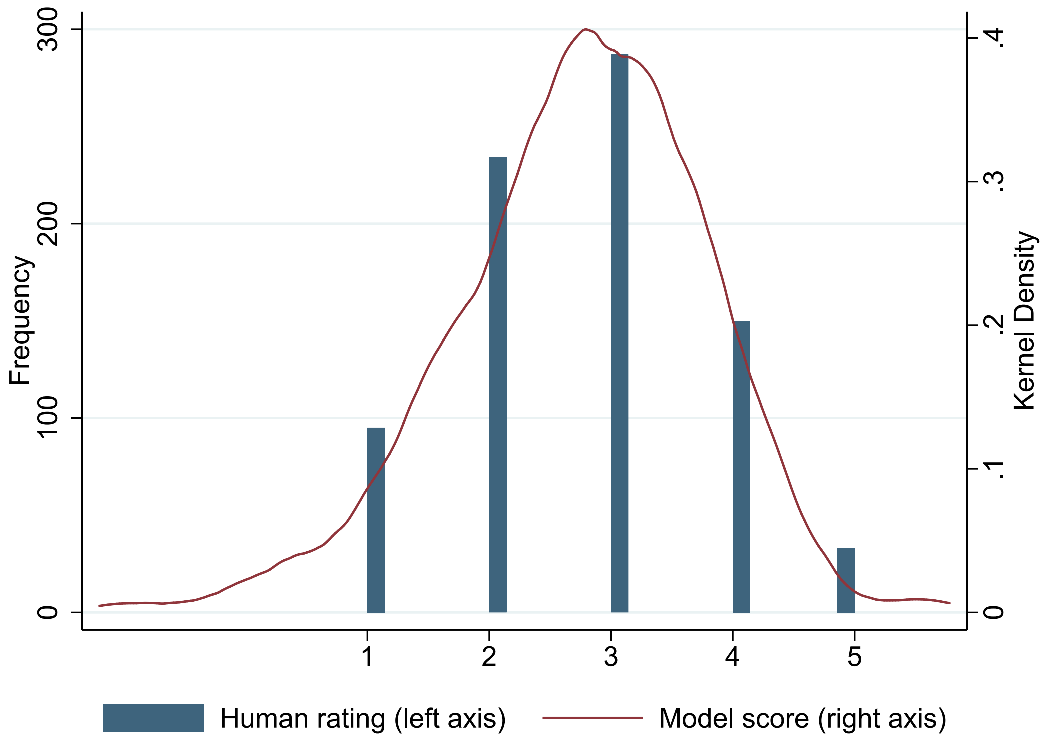
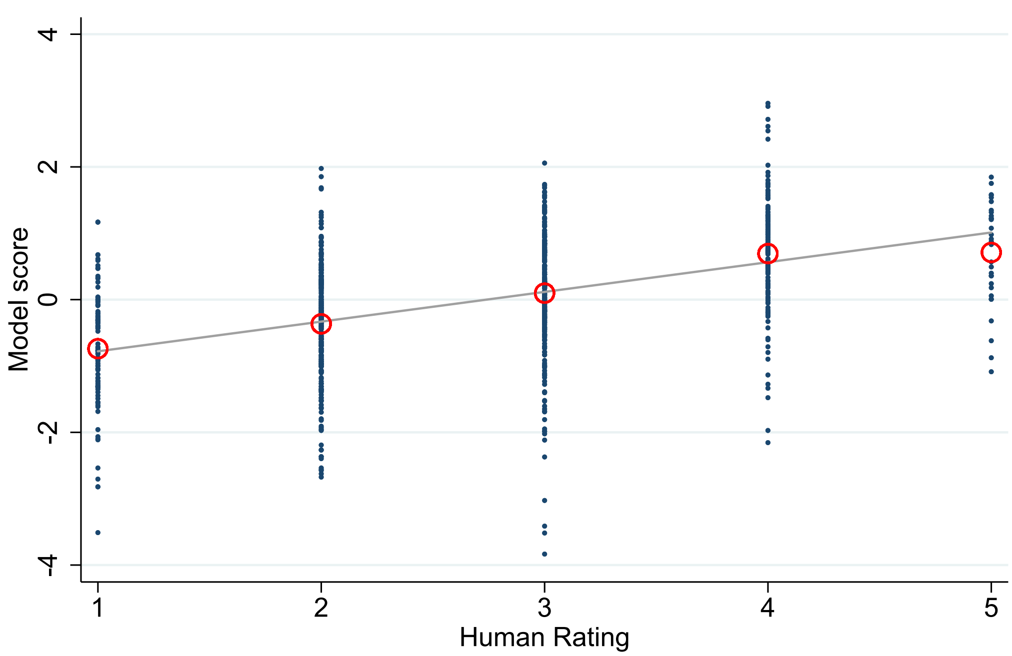
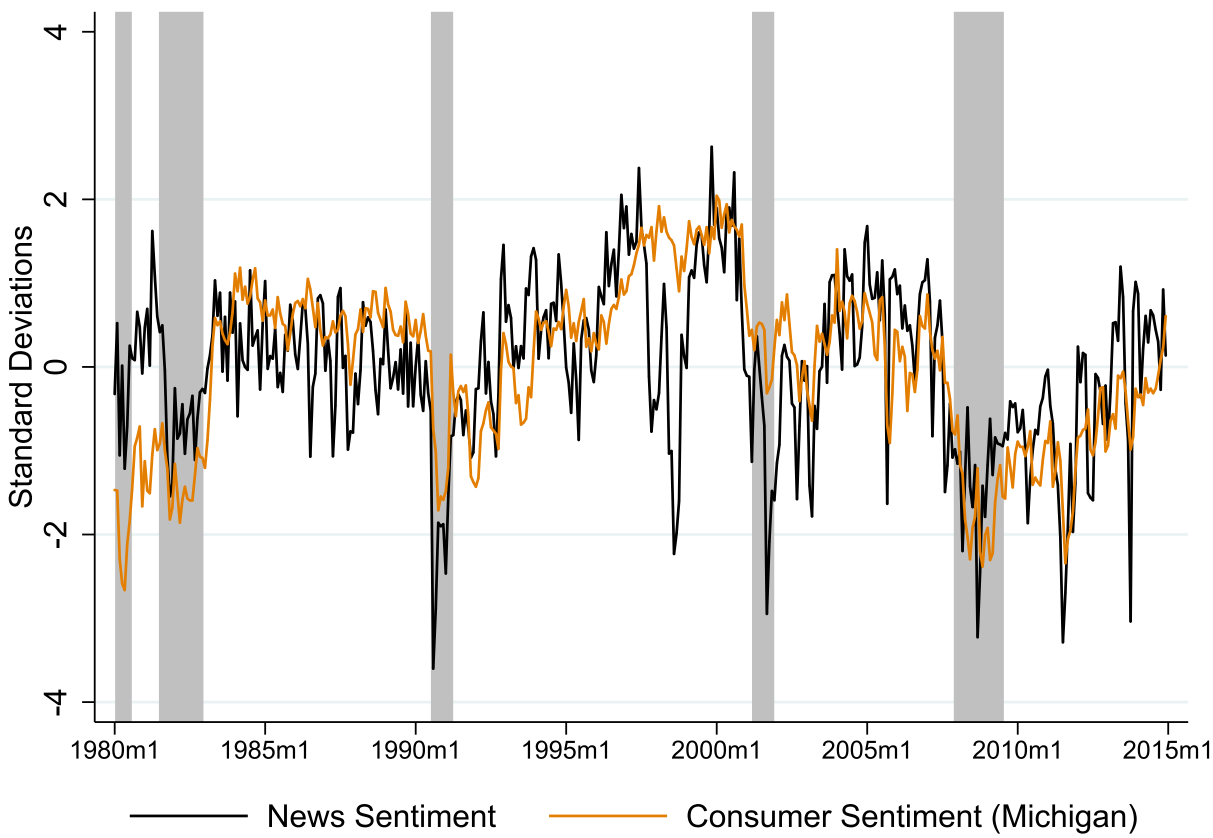


Figure 2: Model Scores Versus Human Rating: Correlation



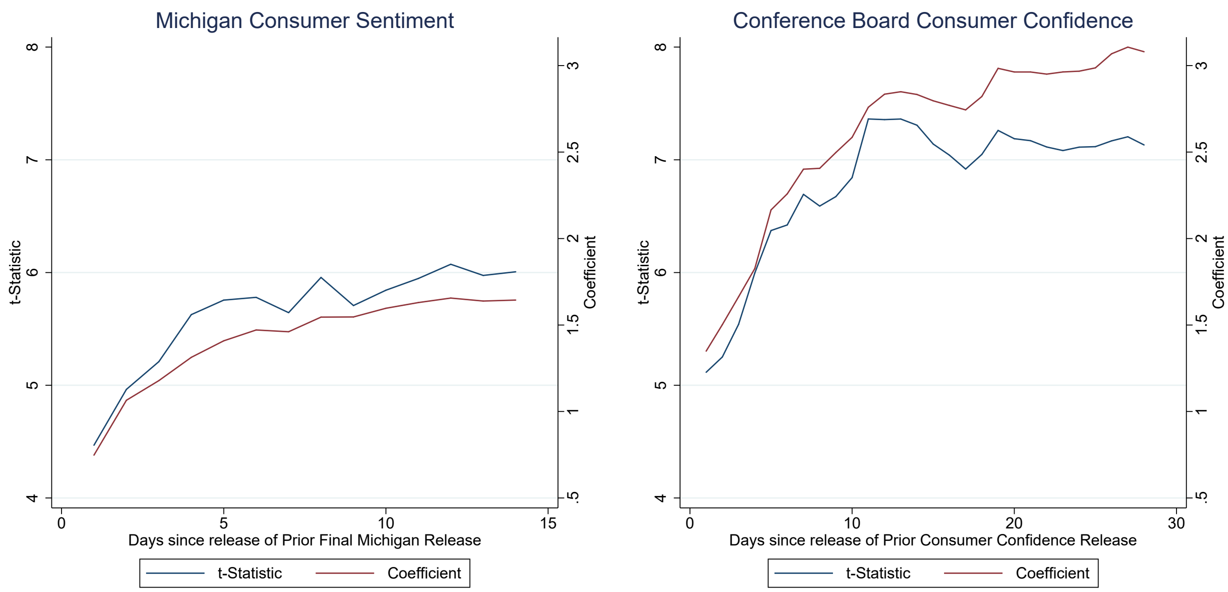
Spearman Rank Correlation = 0.49 ; N = 799
Notes: Blue dots are raw data points, solid line is linear regression fit line, and red circles are within-rating means of raw data points.

Figure 3: Sentiment Indexes Over Time



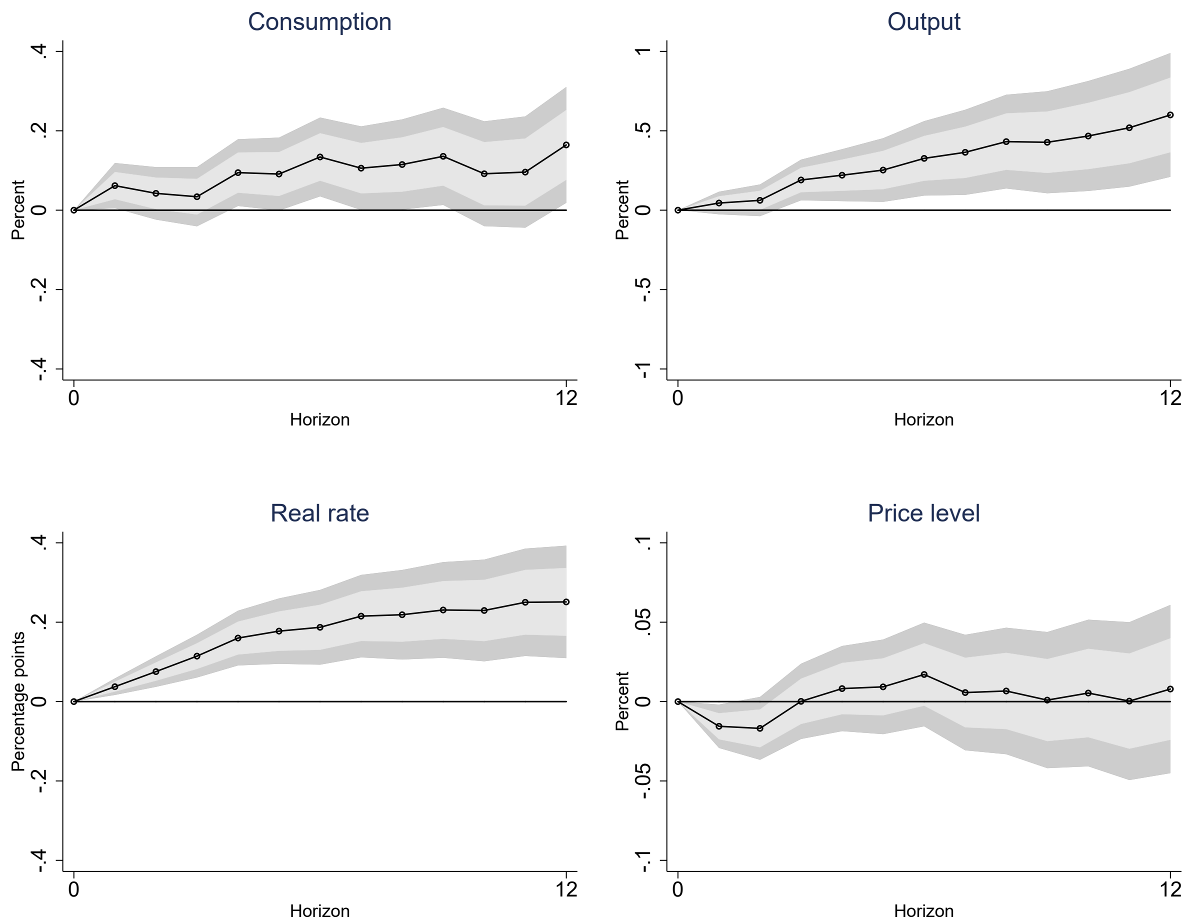
Notes: Shown are the point estimates of the time dummies (in months) for the news sentiment measure (black line) and the University of Michigan Consumer Sentiment Index (orange line). Both measures are normalized to have mean equal to zero and standard deviation equal to one.

Figure 4: Effect of Cumulating Daily News Sentiment Since Prior Survey Release



Notes: Plotted are the coefficients and t-statistics of β_d from estimating equation (4), with γ_1 restricted to one, for alternative values of d.

Figure 5: Impulse Response of a Positive News Sentiment Shock on Economic Activity



Notes: Plotted are impulse responses from a news sentiment shock. The real rate is measured by the federal funds rate, consumption is measured by real personal consumption expenditures (PCE) produced by the Bureau of Economic Analysis (BEA), inflation is measured as the logarithm of the PCE price index (also produced by the BEA), and output is measured by the industrial production (IP) index produced by the Federal Reserve. The news sentiment shock is constructed as the component of the news sentiment series that is orthogonal to current and 6 lags of economic activity as well as 6 lags of itself (in months). Plotted are the point estimates, 68 (light grey), and 90 (dark grey) percent confidence bands.

Appendix

A Details on Survey-Based Sentiment Indexes

A.0.1 Michigan Consumer Sentiment

The University of Michigan's Consumer Sentiment Index (MCSI) dates back to the late 1940s.[19] It is based on a monthly telephone survey of at least 500 respondents across the U.S. The index is constructed as a normalized sum of the relative scores (percent of responses that are favorable minus percent of responses that are unfavorable) from the following five questions:

(1) "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

(2) "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

(3) "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

(4) "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

(5) "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

A.0.2 Conference Board Consumer Confidence

The Conference Board's Consumer Confidence index (CBCI) dates back to 1967 and is based on their Consumer Confidence Survey. Since 1977, this survey has been conducted monthly. The Conference Board aims to get responses from roughly 3,000 households. Similar to the Michigan index, the CBCI is based on the responses to five survey questions. The first

[19]Further details about the Michigan Consumer Sentiment index and the underlying survey can be found at: `https://data.sca.isr.umich.edu`.

two questions relate to current business conditions and current employment conditions. The other three questions relate to expectations of business conditions, employment conditions, and family income six months ahead.

B Examples of Scored Newspaper Articles

B.1 Article 1: Positive Human Rating, Positive Model Score

"Stocks Surge to Records" (*The Washington Post*, July 10, 1999)

Stocks sailed to record highs today as continued optimism about corporate profits and strong consumer spending offset the effects of a rocky bond market.

The Dow Jones industrial average rose 66.81, to 11,193.70, topping its previous record close of 11,187.36, set Wednesday. The Dow was up 54.46, or 0.49 percent, for the week.

The Standard & Poor's 500-stock index and the Nasdaq composite index also set records. For the Nasdaq, rich with technology stocks, today was the sixth record-setting day in seven sessions as it rose 21.21 to close at 2793.07. The S&P 500 rose 8.86, to 1403.28.

Stocks have been flourishing as the first few companies to report second-quarter earnings meet Wall Street's high expectations. With the robust economy continuing its expansion, analysts are predicting the strongest profit growth since the third quarter of 1997.

Dell Computer led technology issues, rising 2 7/8, to 42-13/16, after Goldman Sachs raised its rating on the company. Analysts said the positive evaluation from Goldman sparked interest in the whole technology sector, helping the Nasdaq extend its winning streak.

The Dow's gain would have been much more modest without McDonald's, which rose 3-15/16, to 44-9/16. Wall Street investment firm Schroder & Co. upgraded the company's stock, citing strong expectations for the fast-food chain's second-quarter sales.

DuPont rose 3-3/16, to 71-11/16, after the company unveiled some details of the spinoff of its Conoco unit.

Despite the solid gains, stocks were somewhat unsettled by continuing fluctuations in the bond market.

Early in today's session, stocks fell along with bond prices as the credit markets absorbed an $8.6 billion offering by Ford Motor and its Ford Motor Credit unit. The offering is the largest corporate bond deal ever, topping AT&T's $8 billion sale earlier this year.

Prices evened out as the market digested the offering. The yield on the Treasury's 30-year bond, which had risen as high as 6.03 percent at noon, edged back to 6 percent, which was up slightly from the 5.99 percent level it was at late Thursday. The long bond's price fell $1.56 per each $1,000 invested.

Stocks recovered, although it was a quiet summer Friday with little news to stimulate trading. Advancing issues outnumbered decliners by 18 to 11 on the New York Stock Exchange, where volume came to 701 million shares, down from 830.6 million on Thursday.

The NYSE composite index rose 3.63, to 657.68; the American Stock Exchange composite index rose 4.04, to 812.73; and the Russell 2000 index of smaller companies rose 3.23, to 457.98.

Human Rating: 5 (Very Positive), **GI: 0.02**, **HL: 0.03**, **LM: 0.01**, **Winning Model: 0.06**

B.2 Article 2: Positive Human Rating, Negative Model Score

"Big Savings On Mortgages" (*The San Francisco Chronicle*, December 24, 1991)

The drop in mortgage rates is one of the most welcome changes resulting from the Federal Reserve Bank's cuts in the discount rate. Many families with a $150,000 mortgage can expect to save $100 a month or more in house payments – far more than they could get from the tax programs presently being discussed by Congress and the administration.

Such unencumbered savings should have far fewer negative side effects than some of the current proposals for tinkering with federal tax laws. Both parties agree that some revision of the nation's tax code is advisable, but it would be risky to increase the deficit unnecessarily.

When homeowners' disposable income rises, there is no such problem.

Frank Schultz, an executive vice president of Bank of America told Chronicle staff writer Laura Evenson that it is still too early for the savings consumers have realized from lower interest rates to be translated into purchases. But the extra money will inevitably be available, both for increasing the sales of automobiles, furniture, appliances and other major items and for reducing consumer debt.

In fact, consumer debt has already declined by 5.7 percent from last year's figure of $388 billion.

What the change will mean for pension funds and other investors in the secondary mortgage market is more difficult to calculate. Their income will drop, but so will the cost of money they need to operate.

It is too early to tell when the recession will end. But getting mortgage rates under control is a sound first step.

Human Rating: 5 (Very Positive), **GI: -0.03**, **HL: -0.01**, **LM: -0.02**, **Winning Model: -0.08**

B.3 Article 3: Negative Human Rating, Negative Model Score

"U.S. Trade Gap Hits Record $19.4 Billion" (*The Los Angeles Times*, April 21, 1999)

Americans' insatiable appetite for imported goods, along with weak overseas demand for U.S. products, combined to produce a record $19.4-billion trade deficit in February, the Commerce Department said Tuesday.

The deficit has soared as the U.S. economy increasingly has become an island of prosperity amid a global slowdown. Economic growth here has meant a strong domestic market for imports, while the slowdown abroad has cut into offshore sales of U.S. producers.

"It's a simple story. You have the U.S. economic train going fast and no one can stop it. On the other hand, economies in Latin America and Asia are slowing down or mired in recession," said Fernando Losada, senior economist at ING Barings in New York.

But the size of February's deficit, up from January's revised deficit of $16.8 billion, also a record, exceeded expectations, mainly because the spending binge by U.S. consumers has exceeded anyone's expectations. Imports rose to $96 billion in February from $93.9 billion in January. Imported consumer goods, especially autos, led the way.

Much of the added imports came from Japan, Mexico and Europe, causing U.S. deficits with those regions to widen further. But exports declined slightly to $76.6 billion from $77.1 billion in January, with most of the slippage due to a decline in airplane shipments from Boeing Co. Aircraft shipments alone fell by nearly $1 billion, adding to declines in food, automotive and industrial supplies.

"This is the flip side of a domestic economy that's flying," Salomon Smith Barney economist Brian Jones said.

The U.S. economy seems to be defying gravity and the problems of its trading partners. Observers have repeatedly had to upgrade their forecasts of U.S. economic activity.

Driving that growth is the estimated 6% surge in consumer spending so far this year, a reflection of high consumer confidence, low unemployment and $1 trillion in stock market profits over the quarter, said Bruce Steinberg, chief economist at Merrill Lynch in New York.

"As the U.S. economy continues to chug merrily along, others are hurting, so it shouldn't come as a surprise there is a trade deficit," said Brink Lindsey of the Cato Institute.

But there is a downside to continued deficits if they persist, which is likely. Some economists warn that the deficit is impeding U.S. domestic economic growth by pushing sales and jobs offshore.

"The trade sector is mitigating the strength of the U.S. economy," Goldman Sachs economist John Youngdahl said. Moreover, the growing imbalance has already rekindled protectionist sentiment in Congress. The House earlier this year passed a measure to restrict foreign steel imports.

Federal Reserve Chairman Alan Greenspan this month warned that growing protectionism threatens the country's economic well-being.

But the near-record-low unemployment levels enjoyed by American workers has so far tended to defuse the anti-import lobby.

And the widening trade deficit has not yet weakened the U.S. dollar, which is a risk of widening trade gaps, said William Stevenson, senior portfolio manager at Montgomery Asset Management in San Francisco.

The global economic malaise has only made U.S. dollars more desirable to hold, he said.

For now, most economists are resigned to the deficit as an inevitable outgrowth of a global economy in which the U.S. is clearly lapping its trade partners. What's needed to rekindle demand for U.S. goods is a global recovery.

The deficit with Japan, the second-biggest U.S. commercial partner behind Canada, widened to $5.3 billion in February from $4.7 billion in January and $5.3 billion in February 1998.

The deficit with Asia's newly industrialized countries rose to $1.8 billion in February from $1.6 billion in January and $885 million in February 1998.

A narrowing of the deficit with China in February was good news for the Clinton administration's efforts to strike a trade deal that would enable the Chinese to join the World Trade Organization.

But so far this year, the gap with China totals $9.5 billion, up sharply from $7.7 billion in the year-earlier period. The deficit with Canada decreased to $2.4 billion in February. The deficit with Mexico widened to a record $1.8 billion. The deficit with Western Europe increased to $2.2 billion.

Human Rating: 1 (Very Negative), **GI: -0.02**, **HL: -0.004**, **LM: -0.04**, **Winning Model: -0.10**

B.4 Article 4: Negative Human Rating, Positive Model Score

"State is Losing Edge in Median Incomes" (*Minneapolis Star Tribune*, September 9, 2012)

Workers need more education to fill high-wage jobs.

If you've lived in this state for more than a few years, the Minnesota you know is a place where educational attainment and median household income are well above the national average. It's a place where the quality of life gets a boost from those higher incomes as they are donated and taxed in ways that keep schools good, crime low, nature unspoiled, and arts and amenities flourishing.

Evidence is mounting that in the wake of the Great Recession, Minnesota's income advantage over the rest of the nation is shrinking. The latest: A Star Tribune analysis of state labor data shows that the portion of jobs paying $10 to $25 an hour has dropped sharply in the past decade, from nearly two-thirds of all job postings in 2002 to 43 percent today. Meanwhile, more than a third of today's openings are for jobs paying less than $10 an hour.

That's in keeping with the latest U.S. Census Bureau analyses putting Minnesota's median household income at $57.820 in 2011. While that's still 15.5 percent above the national median, and represents a gain from Minnesota's 6.3 percent advantage in 2010, the state stood 29.2 percent above the national level on the same measure in 2000.

Does that mean that Minnesota's quality of life is at risk? Yes, said recently retired state demographer Tom Gillaspy, if Minnesota doesn't move aggressively to take advantage of the flip side of the postrecession employment trend. That side is also evident in the Star Tribune analysis: Jobs paying at least $25 an hour have grown from 4 percent of Minnesota vacancies in 2002 to 19 percent in 2012. (These figures are adjusted for inflation.)

The recession has accelerated a workforce trend that Gillaspy and his research partner, state economist Tom Stinson, have long forecast. Generic, middle-income, middle-management jobs are disappearing as enterprises learn to function with fewer of them. Low-skill, low-wage jobs are again in demand now, but many remain in jeopardy of replacement by technology. If robots can do a job, they will, and soon.

But workers with specialized skills and the capacity to be both analytic and creative "can name their price" in many fields, Gillaspy said.

Securing more of those high-wage jobs and the benefits their incomes provide means improving Minnesota's educational attainment. Other states and nations are catching up to the educational advantage Minnesota built for itself in the last half of the 20th century.

To stay above average in income and the rest, Minnesota needs another major leap forward in educational attainment in the next decade. The 20th-century K-12 educational norm should give way to an expectation that every youngster will experience formal learning from prekindergarten through "grade 14" – that is, at least two years of postsecondary study.

This state's leading higher educators have been busy in the last year devising strategies for increasing post-high-school educational attainment. But they can't do the job alone. Enrolling more 4- and 5-year-olds in quality preschools must also be part of a grand plan. So must a better, more individualized melding of high school with college study and communitywide efforts to keep youngsters in school.

All this effort needs an orchestrator to coordinate and harmonize it – and there's no one better positioned for the task than Gov. Mark Dayton. Minnesota needs a new grand plan for success in the new economy. As Dayton stumps the state for his party's candidates this fall, we hope he is also gathering ideas and steam for the strategic planning exercise that the 2013 legislative session should include.
Human Rating: 2 (Negative), **GI: 0.04**, **HL: 0.02**, **LM: 0.02**, **Winning Model: 0.05**

Figure A1: IRF with Michigan Consumer Sentiment Index Control

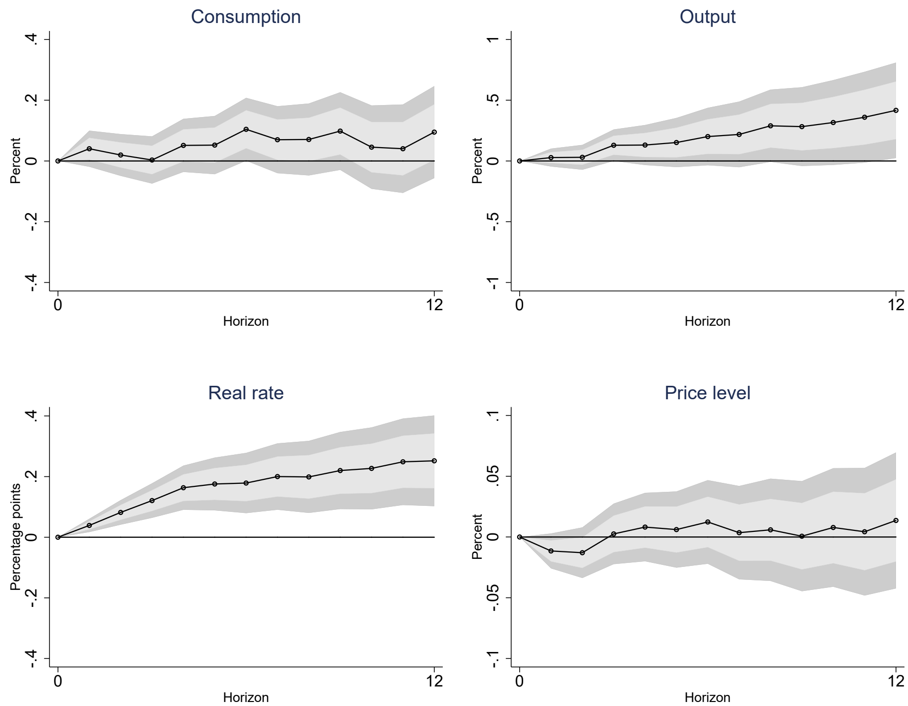
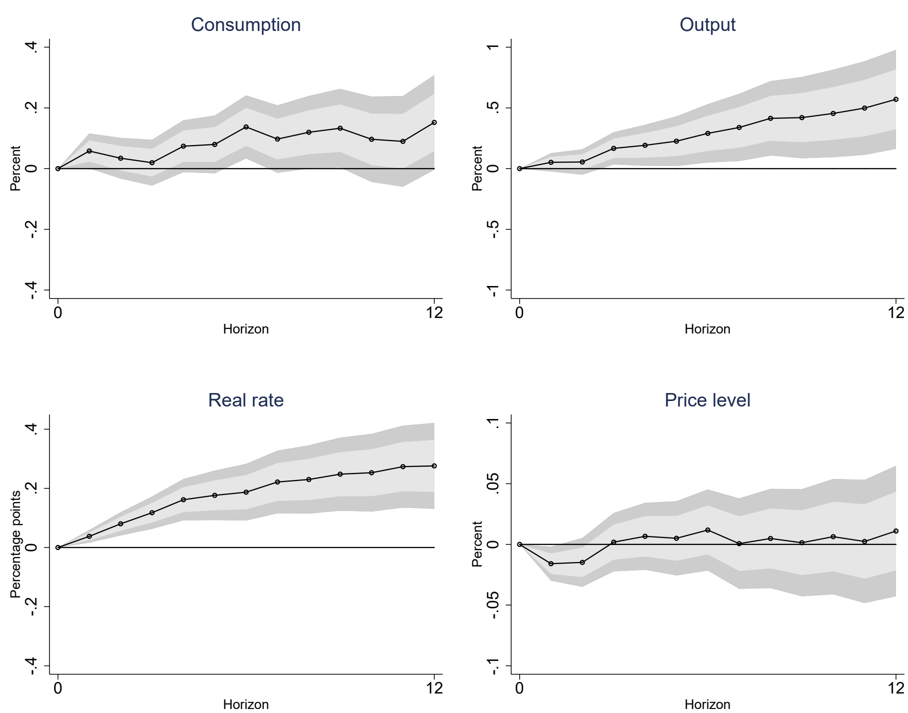


Figure A2: IRF with Conference Board Consumer Confidence Control



Notes: Plotted are impulse responses from a news sentiment shock with additional controls. Panel A reports the news sentiment shock constructed as the component of the news sentiment series that is orthogonal to 6 lags of itself, current and 6 lags of economic activity, current and 6 lags of the Michigan consumer sentiment index. Panel B reports the news sentiment shock constructed as the component of the news sentiment series that is orthogonal to 6 lags of itself, current and 6 lags of economic activity, current and 6 lags of the Conference Board's consumer confidence index. Plotted are the point estimates, 68 (light grey), and 90 (dark grey) percent confidence bands.

C Details of LASSO Estimation

We first use a general LASSO model, which selects parameters without additional restrictions. The general LASSO is defined as:

$$\hat{\beta} = arg\ min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{i,j} b_j \right)^2 + \lambda \sum_{j=1}^{p} |b_j| \tag{7}$$

where y_i represents the forecasted economic outcome of interest i, and x represents variables of interest.

The optimal penalty parameter λ^* for each y_i is chosen based on a cross-validation procedure. We choose λ^* such that it yields the minimum out-of-sample RMSE across a series of rolling 20-year-sample regressions. That is, we do a grid search over possible values of λ, and for each possible λ we estimate the general LASSO model for each 240-month sample (rolling from initial month of October 1986 to initial month of December 1996) and collect the 12-month ahead forecast error. We then calculate, for each possible λ, the RMSE across the 123 rolling samples. λ^* is the λ yielding the minimum RMSE.

Last, we estimate the general LASSO model using the penalty parameter λ^* and the full sample to see which parameters are selected as useful predictors. If any of the parameters (contemporaneous or lag) for each economic, survey, or news sentiment measure are chosen as predictors in the general LASSO model, it is shown in Table 1.

We next use an adaptive LASSO model, which is a weighted variation of the general LASSO model. The adaptive LASSO is defined as:

$$\hat{\beta} = arg\ min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{i,j} b_j \right)^2 + \lambda \sum_{j=1}^{p} w_j |b_j| \tag{8}$$

where w_j is a known weights vector such that $\hat{w} = 1/|\hat{\beta}|$. This variation of the general LASSO model has oracle properties when λ is properly chosen.

Like in the general LASSO model, λ^* is chosen such that it yields the minimum out-of-sample RMSE across a series of rolling 20-year-sample regressions. For each 240-month sample we calculate a separate weights vector, which requires a second cross-validation procedure. On each 240-month sample we estimate a series of rolling 8-year-sample regressions for $\tilde{\lambda}$ corresponding to the 240-month sample and collect the 12-month ahead forecast error.

We then calculate for each possible $\tilde{\lambda}$ the RMSE across the 133 rolling samples. $\tilde{\lambda}^*$ is the $\tilde{\lambda}$ yielding the RMSE. The coefficients corresponding to $\tilde{\lambda}$ are $\hat{\beta}$ and are used to calculate $\hat{w}$. We re-scale each 240-month sample and for each possible λ estimate the general LASSO model on each sample (rolling from initial month of October 1986 to initial month of December 1996) and collect the 12-month ahead forecast error. We then calculate, for each possible λ, the RMSE across the 123 rolling samples. λ^* is the λ yielding the minimum RMSE.

With λ^*, we estimate the general LASSO model on the full sample to see which parameters are useful predictors. If any of the parameters (contemporaneous or lag) for each economic, survey, or news sentiment measure are chosen as predictors in the general LASSO model, it is shown in Table 1.

For the last exercise, we estimate the group LASSO model which forces *groups* of parameters to zero simultaneously. The group LASSO is defined as:

$$\hat{\beta}_{j,\lambda} = arg\ min(||Y_j - X_j\beta_j||_2^2 + \lambda \sum_{g=1}^{G} ||\beta_j I_g||_2) \tag{9}$$

where Y_j represents the forecasted economic outcome of interest j. X is the design matrix and I_g is the index for the gth group of variables. We consider a "group" to be a the block of the contemporaneous value and 12 lags of each variable.

The optimal penalty parameter λ^* is chosen, separately for each forecasted outcome (Y_j), based on a cross-validation procedure. We choose λ^* such that it yields the minimum out-of-sample RMSE across a series of rolling 20-year-sample regressions. That is, we do a grid search over possible values of λ, whereby for each possible λ we estimate the group LASSO model for each 240-month sample (rolling from initial month October 1986 to initial month December 1996) and collect the 12-month ahead forecast error. We then calculate, for each possible λ, the RMSE across the 123 rolling samples. λ^* is the λ yielding the minimum RMSE.

Lastly, we estimate the group LASSO model using the penalty parameter λ^* and using the full sample to see which "groups" (economic outcome, survey, and news sentiment measures) are selected as being useful predictors. The groups chosen as predictors in the group LASSO model are shown in Table 1.