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Stress in the Press or Stress in the Market: A New Measure of Perceived Financial Stress*

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Abstract

We develop a news-based measure of perceived financial stress for Canada using more than 900,000 business and economic news articles from 1977 to 2026. Using a data-driven keyword discovery algorithm, we construct an interpretable News-based Stress Index (NSI) that tracks major stress episodes and captures periods when concerns about financial risks intensify despite limited market disruption. Using linear and quantile-augmented VARs, we show that news shocks orthogonal to financial shocks primarily reduce unsecured consumer credit by shifting its entire distribution, whereas market-based financial shocks primarily worsen downside risks to both credit and real activity. This highlights perceived financial stress as a distinct transmission channel operating through household precautionary behavior.

Keywords: Financial stress, Perceived risk, Text analytics, Natural language processing
JEL Codes: G01; E44; C82; C55

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1 Introduction

Financial stress is usually measured through a wide range of market prices. However, households often experience financial risks through the narratives conveyed by the news rather than through direct observation of asset prices. As a result, perceptions of financial stress may diverge from market-based measures, with potentially important consequences for economic behavior.

This paper develops a news-based measure of perceived financial stress for Canada using more than 900,000 machine-readable business and economic news articles. News outlets act as information intermediaries, translating complex financial developments into narratives that describe events, assess implications, and shape expectations. Economic and business news therefore provide a high-dimensional record of what are perceived to be the most salient issues at each point in time. When financial stress intensifies, it should also be reflected in the content and intensity of news coverage.

Constructing a reliable text-based measure presents several methodological challenges. Topic models often generate diffuse and difficult-to-interpret themes, while purely researcher-curated dictionaries may omit relevant terminology in a setting where financial language evolves rapidly. In addition, stress-related terminology can vary across countries and events.

We address these limitations by adapting the keyword discovery algorithm of King et al. (2017) to construct data-driven financial stress dictionaries for Canadian business news. Building on the literature that studies the structure of business news (Bybee et al., 2024), we analyze the full text of The Globe and Mail, which comprises approximately 900,000 machine-readable English-language articles from November 1977 to July 2026. Beginning with an initial set of seed terms, we implement the algorithm on the news corpora. The procedure systematically expands and refines stress-related bigrams while preserving interpretability. Using the resulting dictionary, we construct a time-varying measure of financial stress based on the share of stress-related language in news articles, called the news-based stress index (NSI). We interpret this measure as capturing attention to financial stress at each point in time. The resulting index reflects soft information embedded in news environments and complements traditional market-based indicators based on hard data (Duprey, 2020).

Our main empirical findings are the following. First, we validate our measure by studying its association with periods of financial stress. We find that the NSI closely tracks major episodes of Canadian and global financial stress, and exhibits pronounced spikes during the early 1980s recession, 1987 stock market crash, early 1990s housing collapse, Global Financial Crisis (GFC), 2014-15 oil price shock, COVID-19 pandemic, 2022 monetary tightening cycle, and 2025 tariff episode. The NSI correlates closely with established macro-financial indicators that are related to financial stress. It co-moves with the market-based financial stress index (FSI) and the VIX during major crises, while exhibiting a negative relationship with consumer, business, and manufacturing confidence.

At the same time, there are periods of divergence. For example, the NSI rises sharply in early 2022 amid coverage of monetary policy tightening and again in 2025 due to tariff-related news, while actual financial stress captured by the FSI remains relatively subdued. These

patterns suggest that the NSI captures forward-looking and policy-driven stress narratives that may precede realized financial market strain, consistent with its role as a news-based measure of perceived financial stress.

Second, we examine the contemporaneous and lead–lag relationships between NSI and macro-financial indicators capturing financial risk, the banking and corporate sectors, and equity, government bond, money, commodity, foreign exchange and housing markets. NSI is strongly related to macro-financial conditions both contemporaneously and in lead-lag relations. It comoves with key indicators of financial stress, including market volatility, funding spreads, and asset price movements, and higher NSI is followed by higher financial stress, worsening banking conditions, and weaker macroeconomic conditions, including declines in GDP growth, credit growth, house prices, and consumer confidence in the next month.

Quantile lead–lag regressions show that the associations between NSI and macro-financial indicators are concentrated in the tails of their distributions. Higher NSI is followed by increases in financial and banking stress indicators, particularly at the upper quantiles, indicating that news-based stress attention is most closely related to extreme stress episodes. NSI is also associated with higher financial market uncertainty and volatile market conditions next period, as well as greater downside risk in house prices, GDP growth, and real credit growth.

Third, we document that news-based perceptions of financial stress have macroeconomic effects that are distinct from, and complementary to, market-based financial stress. Using a monthly Bayesian VAR for Canada, we separate stress shocks originating in financial markets from stress shocks that originate in the news and are not immediately reflected in asset prices. The two shocks propagate differently through the economy.

A financial stress shock derived from market data leads to a significant decline in industrial production, depresses equity prices on impact, and lowers interest rates, consistent with tightening financial conditions that directly constrain real activity. In contrast, a news-based stress shock has limited effects on industrial production, but generates a more persistent decline in real unsecured consumer credit (rather than mortgage credit), as well as a decline in manufacturing orders. This pattern is consistent with a precautionary response primarily by households, whereby heightened media attention to risks leads consumers to retrench even in the absence of immediate financial market stress. Overall, this confirms the literature on households' precautionary motives, whereby households reduce their consumption if they believe their income might fall (e.g. Wang, 2026) and more strongly reduce unsecured debt borrowing as they fear possible future financial constraints (e.g. Irwin, 2025; Du et al., 2025). This leads to a slower impact on the real economy, possibly ultimately taming growth (Ranciere et al., 2008) or reducing the vulnerability of the economy to a future downturn (Schularick and Taylor, 2012).

Finally, we complement our linear VAR analysis with a quantile-augmented VAR to assess the possible differences in the distributional effects of financial versus news stress shocks. Financial stress shocks worsen downside tail risks to both industrial production (consistent with Adrian et al., 2019) and consumer credit (consistent with Duprey and Ueberfeldt, 2020; Adrian et al., 2022), generating left-skewed outcomes. In contrast, news-based stress shocks

do not worsen downside risk to industrial production. Instead, they shift down the *entire* distribution of future consumer credit growth, indicating a pure location effect rather than heightened tail risk. This reinforces the interpretation of news-based stress as primarily operating through household expectations and precautionary behavior that impact the entire range of future credit outcome indiscriminately, rather than through binding financial constraints specific to the materialization of tail risks.

Section 2 highlights our contribution to the financial stress measurement literature and the growing literature on text analyses in economics. Section 3 discusses our rich dataset of Canadian news articles. Section 4 describes our methodology to construct the NSI. Section 5 validates our interpretation of the NSI as a measure of stress by comparing it to known episodes of stress or other indicators of stress. Section 6 assesses the mean and distributional impacts of news shocks on production and credit, contrasting it to the effect of traditional financial shocks derived from market prices. Section 7 studies the robustness of our results using alternative indexes. Finally, Section 8 concludes.

2 Literature review

Our paper contributes to at least two strands of literature. First, we contribute to the literature on measurement of financial market stress. A financial stress index (FSI, see Kliesen et al., 2012 for an early survey) is typically a composite indicator designed to quantify the level of stress in a financial system by aggregating information from multiple financial market variables (e.g. decline in asset prices, widening of spreads, increase in volatility) into a single summary measure. The key idea is that stress is more intense when it occurs simultaneously in multiple market segments (e.g. stocks, bonds, foreign exchange, housing) making it difficult to diversify away (Hollo et al., 2012; Chavleishvili and Kremer, 2025). Measures of financial stress typically balance the cross-sectional coverage (up to 100 input series for one country, Brave and Butters, 2012) with historical depth (e.g. starting in the 1960s for many countries, Duprey et al., 2017). Financial stress indices typically spike during known crisis events identified by experts via surveys (Illing and Liu, 2006), but the construction of financial stress indices can also be optimized to capture a set of pre-defined crisis episodes (Chatterjee et al., 2022). The current Canadian Financial Stress Index of Duprey (2020) builds on the precursor work of Illing and Liu (2006) just before the GFC.

These indices gained prominence after the GFC, as policymakers recognized that severe financial market disruptions can amplify macroeconomic downturns. High financial stress often correlates with tighter credit, reduced liquidity, and heightened uncertainty. Collectively, these factors can impair the functioning of the financial system and lead to weaker economic growth or even crises. Previous research carefully documented the regime-dependent effects of financial stress on the economy using various non-linear Vector Autoregression (VAR) models. Elevated financial stress can trigger changes in macro-financial elasticities and modify monetary policy effectiveness as well as the international transmission of shocks (Hubrich and Tetlow, 2015; Liu et al., 2019; Tuzcuoglu, 2024). Changes in financial conditions correlate with tail GDP risk (Adrian et al., 2019; Duprey and Ueberfeldt, 2020) and low industrial production growth (Duprey et al., 2017). Financial shocks decrease output (Gilchrist and

Zakrajšek, 2012) and generate skewness in GDP growth (Boire et al., 2025).

However, most of the literature focuses on extracting signals from market prices, while, at times, stress perceptions by households could deviate from market prices. For instance, the Canadian Survey of Consumer Expectations[1] describes a particularly pessimistic perception by households in 2025 with weak spending plans, uncertain income and worries about job security, despite historically low risk premiums and financial stress indices. Thus we complement this literature by building a measure of *perceived* financial stress, and we build on the VAR literature and Boire et al. (2025) to track the average and distributional effect of our new measure of perceived financial stress on credit aggregates.

Second, we contribute to the growing literature that uses text in economics (see Gentzkow et al. (2019) for an overview). The literature employs two primary natural language processing approaches to measure financial stress: topic models and dictionary-based methods. Topic models reduce the high-dimensional representation of a text corpus to a low-dimensional set of latent topics. Bybee et al. (2024) apply Latent Dirichlet Allocation (LDA) to full-text Wall Street Journal articles, construct business-cycle topics, and show that a recession topic predicts a broad set of macroeconomic variables. Ristolainen et al. (2024) use LDA on news headlines and show that the resulting topics predict financial crises. Ellingsen et al. (2022), Larsen and Thorsrud (2019), and Thorsrud (2020) apply LDA to news data to study macroeconomic forecasting. Istrefi et al. (2023) apply LDA to Federal Reserve communications and show that topic attention and negative tone forecast monetary policy changes. Fieberg et al. (2025) use TopicGPT on Federal Reserve communications and earnings call transcripts to predict financial stability.

Although topic models generate potentially informative topics, they often produce ambiguous and difficult-to-interpret word clusters and depend on the chosen number of topics, so a distinct financial stress topic may not emerge and stress-related terms may disperse across multiple topics. Dictionary-based methods offer an interpretable alternative by counting prespecified keywords. Baker et al. (2016) construct indices of economic policy uncertainty by counting researcher-curated keywords, and Correa et al. (2021) propose a financial stability dictionary to analyze central bank financial stability reports worldwide. Song and Stern (2025) construct a text-based measure of firm attention to macroeconomic news using SEC filings and document that firm attention is polarized, countercyclical, and leads to asymmetric responses to monetary policy.

However, financial stress arises from multiple sources and relies on specialized language that evolves over time, so researcher-curated lists may omit relevant terminology. King et al. (2017) highlight a central limitation of purely human-curated dictionaries: humans struggle to generate exhaustive term lists but perform well at screening candidate terms when presented with them. We adapt their keyword discovery algorithm to construct a comprehensive financial stress dictionary for Canadian news, and we use this dictionary to measure time-varying news attention to financial stress. Our approach builds on Sautner et al. (2023), who apply the King et al. (2017) framework to capture the technical language of climate change and construct measures of climate change exposure, and we extend it to

[1] https://www.bankofcanada.ca/publications/canadian-survey-of-consumer-expectations/

the measurement of financial stress.

3 Data

We construct a comprehensive text corpus from articles published in The Globe and Mail, one of Canada's largest and most widely read national newspapers. The machine-readable dataset spans November 1977 to July 2026 and contains 903,167 articles. These represent the subset of articles licensed from Dow Jones Factiva Analytics with subjects restricted to Commodity/Financial Market, Corporate/Industrial, and Economic News, excluding tables, awards, and corporate award announcements. The Globe and Mail provides broad coverage of political, business, and economic affairs and is generally regarded as a centrist and politically neutral publication, making it well-suited for constructing politically balanced news-based indicators. Each article includes its full text, publication date, and metadata such as section, title, and author information.

The other main data sources used in this paper include the Canadian Financial Stress Index (FSI) from Duprey (2020) and its constituent data mainly from Datastream or FRED. The FSI measures stress across seven market segments, namely the equity market, the Government of Canada bonds market, the foreign exchange market, the money market, the bank loans market, the corporate bonds market, and the housing market. The Consumer Confidence Index for Canada comes from OECD (2025). Monetary policy shocks come from Champagne and Sekkel (2018) and macro data from CAN-MD (Fortin-Gagnon et al., 2022). These series are used to evaluate the macro-financial relevance of the news-based index and to estimate impulse-response relationships in a VAR framework.

4 Methodology

4.1 Discovery of financial stress keywords

To quantify attention to financial stress, we build on Bybee et al. (2024), who use business news to identify and measure economically meaningful topics from textual data. Extracting stress-related language from news text is challenging. Financial stress is described using technical and evolving terminology that reflects shifts in regulation, market structure, geopolitical risk, and asset market conditions. Articles often discuss stress together with related topics such as monetary policy, trade, financial market activity, macroeconomic fundamentals, and corporate performance. This overlap creates ambiguity about whether a passage genuinely reflects financial stress or merely general economic discussion. Moreover, the vocabulary used to describe stress changes over time. King et al. (2017) highlight a key limitation in relying solely on human judgment for dictionary construction: while humans are generally poor at generating comprehensive lists of relevant terms, they excel at recognizing appropriate ones when presented to them.

To address these challenges, we adapt the keyword discovery algorithm of King et al. (2017) to identify bigrams (two-word phrases) related to financial stress. The algorithm does not require a comprehensive training library. Instead, it begins with a small set of initial keywords

that relate unambiguously to financial stress, such as "financial crisis," "systemic risk," "retaliatory tariff," and "mortgage default." These initial terms identify sentences that clearly pertain to stress. The algorithm then applies supervised learning methods to search the corpus for additional bigrams that predict stress-related sentences.

We apply the trained models to sentences that do not contain the initial keywords and classify whether they relate to financial stress. To expand the dictionary, we reverse-engineer the machine learning predictions and identify the bigrams that most strongly discriminate stress-related sentences from other content. Examples of algorithm-identified terms include "quantitative easing," "economic slump," "subprime mortgage," and "trade barrier". These terms reflect the broad and evolving contexts in which financial stress may arise. The final financial stress dictionaries consist of both the initial keywords and the newly identified bigrams.

This approach offers several advantages. First, it expands the relatively broad initial seed terms into more specialized and context-specific phrases. Second, it uncovers technical and region-specific terminology, such as references to particular financial institutions, housing market programs, or energy market shocks, that may signal stress but would be difficult to anticipate using pre-specified word lists. These features underscore the limitations of purely human-curated dictionaries and highlight the importance of a data-driven procedure for capturing the evolving language of financial stress in news environments.

4.2 Steps for dictionary construction

The construction of the financial stress dictionary follows a structured, semi-supervised process to extract financial stress bigrams from news articles. The final set of bigrams is created from the union of two separate sources: (i) an initial set of ex-ante specified stress keywords based on domain-specific knowledge, and (ii) a set of bigrams identified through machine learning algorithms that extract patterns directly from the news corpus.

4.2.1 Data preparation

The first step in the dictionary construction process involves preparing the textual data by breaking news documents into individual sentences.[2] Sentence-level tokenization enables more granular analysis by focusing on coherent textual units, which reduces noise and improves the precision of bigram identification.

Once tokenized, the text undergoes extensive preprocessing to ensure consistency and interpretability. All characters are converted to lowercase to maintain uniformity across the corpus. We remove common stop words such as "the," "he," and "of" using a standard English stopword list. Following Bybee et al. (2024), we extend their news-domain stopword framework to exclude publication-specific terms such as "bloomberg" and "globeandmail" thereby retaining only economically meaningful vocabulary. We strip punctuation and special characters to eliminate extraneous noise. Additionally, we apply lemmatization combined with

[2]This is achieved using the nltk.tokenize.sent_tokenize function, which allows for a more granular and precise analysis of textual content.

part-of-speech tagging to reduce words to their base forms, ensuring that variations such as "bankruptcies" and "bankruptcy" are treated equivalently. We exclude numeric values from the dataset to prevent mechanical bias in the subsequent bigram selection process.

To improve the signal-to-noise ratio, we restrict the training sample for the keyword algorithm to pre-specified periods listed in Table 1. These windows correspond to episodes of elevated economic and financial stress, including recession periods identified by the C.D. Howe Business Cycle Council.[3] We also include the 2014-15 oil price shock in our list of recessions. Although not included in the C.D. Howe dataset that uses multiple criteria including a decrease in employment, the oil shock led to two consecutive quarters of negative real GDP growth, a traditional way of calling a recession, and this macroeconomic impact justified monetary policy easing by the central bank to support the economy. These training windows are determined exogenously, corresponding to officially recognized Canadian recessions and major economic disruptions rather than being subjectively selected. Limiting the initial corpus to these time periods helps ensure that the algorithm is trained on well-documented periods of elevated economic stress, as recommended by King et al. (2017), thus reducing irrelevant noise and improving the precision of bigram extraction.

Table 1: Recession and Stress Periods in Canada between 1977 and 2026

Peak	**Trough**	**Description**
1981-June	1982-October	Monetary Policy Tightening
1990-March	1992-May	Housing Crisis
2008-October	2009-May	Global Financial Crisis
2014-December	2015-May	Oil Price Collapse
2020-February	2020-April	COVID-19 Pandemic

Notes: Recession dates follow the definition of the C.D. Howe Business Cycle Council, consistent with their most recent report (C.D. Howe Institute, 2021). The 2014–2015 oil price collapse is included as it meets the standard definition of two consecutive quarters of negative real GDP growth. Training windows used in the model correspond to the months between each peak and trough.

4.2.2 Defining the reference and search sets

The next step of the algorithm is to partition the news corpus into two key subsets: a reference set ($\mathbb{R}$) and a search set ($\mathbb{S}$).

The reference set comprises a curated collection of sentences from news articles that are ex-ante identified as relating to financial stress. The set is constructed using an initial set of 116 domain-expert keywords shown in Table 2, which capture core dimensions of financial stress, including financial risk, market volatility, mortgage distress, asset overvaluation, and trade tensions.[4] These keywords are informed by the definition and components of financial

[3] https://cdhowe.org/council/business-cycle-council/

[4] In the case of tariffs, the obvious keyword is a unigram, and the recent tariffs episode does not correspond

stress in Duprey (2020),[5] and include terms such as "financial crisis," "market turmoil," "housing bubble," and "pipeline disruption." The selection also reflects region-specific financial stressors relevant to the Canadian context, particularly housing market dynamics and oil price fluctuations. Sentences containing at least one of these keywords form the reference set and serve as positive examples for training the machine-learning classifiers, ensuring that the models learn from language that is strongly associated with established financial stress signals.

In contrast, the search set consists of a broader collection of news sentences that may or may not pertain to financial stress. A subset of $\mathbb{S}$ is used alongside $\mathbb{R}$ for training the classifiers, while the remaining (substantially larger) portion is reserved for out of sample classification. To maintain data quality, duplicate sentences are removed, and articles with missing text are excluded from further analysis.

4.2.3 Classifier-based filtering

To expand our dictionary and reduce classification noise, we employ a set of complementary machine-learning classifiers to identify sentences in the search set that are most strongly associated with financial stress. The classifiers are trained to distinguish sentences in the reference set (our positive examples identified through the initial keywords) from other sentences, and the objective is to calculate each sentence's predicted probability of belonging to this reference set. Specifically, we use Naive Bayes, Support Vector Machines, and Random Forests, each of which captures distinct and economically meaningful features of stress-related language in high-dimensional text data.

Naive Bayes provides a probabilistic baseline based on conditional independence across words and primarily captures frequency-driven signals. It is effective at identifying highly discriminative terms that appear consistently in stress-related contexts. Random Forests capture nonlinear interactions across words by aggregating multiple decision trees, allowing the model to detect combinations of terms that jointly signal stress. Support Vector Machines, which are well suited for high-dimensional sparse data, construct maximally separating decision boundaries and perform well when stress signals are subtle and distributed across multiple terms.

We optimize each classifier using 5-fold cross-validation with grid search to select hyperparameters that maximize predictive performance on held-out data. Table A.1 provides the hyperparameters tuned for each model. The training sample includes all sentences in the reference set, approximately 6,200 observations, and a randomly selected subset of the search set of approximately 13,600 sentences. The remaining approximately 1.3 million sentences in the search set are reserved for out-of-sample classification.

to a recession period. So we instead considered a number of plausible tariffs related bigrams that add a stress qualifier.

[5] Duprey (2020) defines financial stress as "simultaneous financial market turmoil among the most important asset classes and is reflected by (a) the uncertainty in market prices, (b) sharp corrections in market prices, (c) a widening of spreads, and (d) the degree of commonality across asset classes. Asset classes are split along several dimensions: equities or bonds, long-term assets or short-term commercial papers, and financial or real assets (e.g., housing), denominated in Canadian dollars or foreign currencies."

Table 2: Initial financial stress dictionary by market segment

Panel A: Overall crisis, stress, and risk			
financial crisis	systemic crisis	financial risk	systemic risk
default risk	liquidity stress	financial stress	financial distress
risk aversion			
Panel B: Equity			
market turmoil	market crash	equity crash	stock crash
equity rout	equity selloff	market rout	stock correction
price collapse	price correction	price overvaluation	volatility spike
implied volatility	margin calls	forced selling	bearish sentiment
sharp selloff			
Panel C: Government			
sovereign default	sovereign stress	debt crisis	fiscal stress
bond selloff	widening spreads	yield spike	yield surge
Panel D: Foreign exchange			
currency crash	currency plunge	currency crisis	currency devaluation
sudden devaluation	depreciation pressure	speculative attack	reserve depletion
safe haven	dollar shortage		
Panel E: Money and credit			
funding freeze	liquidity shortage	liquidity freeze	liquidity strain
liquidity crunch	repo stress	repo spike	interbank stress
interbank freeze	cash hoarding		
Panel F: Banking and corporate finance			
credit crunch	bank run	deposit outflows	funding squeeze
funding stress	capital shortfall	capital erosion	solvency concerns
loan losses	credit losses	nonperforming loans	corporate default
credit deterioration	credit downgrade	rating downgrade	spread widening
junk bonds	credit spread	insolvency risk	earnings risk
Panel G: Housing and real estate			
mortgage default	mortgage arrears	housing bubble	housing correction
housing crash	housing downturn	rising delinquencies	loan delinquencies
negative equity	distressed sales	refinancing risk	refinancing stress
foreclosure surge	affordability crisis		
Panel H: Corporate and commodities			
production cuts	pipeline disruption	inventory glut	output disruption
trade war	trade conflict	trade tensions	trade retaliation
trade restrictions	tariff dispute	tariff hikes	retaliatory tariff
supply disruption	high tariff	impose tariff	tariff barrier
punitive tariff	tariff threat	slap tariff	face tariff
pay tariff	raise tariff	tariff war	tariff increase
reciprocal tariff	hit tariff	tariff impose	threat tariff

Note: The table presents the initial keywords used to identify financial stress in news. Each keyword is mapped to its primary financial market segment, following the segmentation of the Canadian Financial Stress Index (Duprey, 2020).

Selection into the target set is based on predicted probabilities: a sentence is assigned to the *target* set ($\mathbb{T}$) if and only if its predicted probability of belonging to the reference set exceeds 80% under at least one of the three classifiers. All remaining sentences are assigned to the *non-target* set ($\mathbb{S}\backslash\mathbb{T}$). The target set therefore consists exclusively of sentences that the models identify with high confidence as resembling the reference set, ensuring that it reflects a high-confidence signal of financial stress.

4.2.4 Dictionary compilation

The final stage of the process involves compiling the financial stress dictionary by selecting bigrams that best discriminate sentences in the target set ($\mathbb{T}$) from the non-target set ($\mathbb{S}\backslash\mathbb{T}$). First, we extract candidate bigrams from the preprocessed news sentences in the search set. We identify all two-word combinations and remove rare bigrams that appear fewer than 10 times to focus on terms that are economically meaningful and empirically reliable.[6] Bigrams such as "mortgage default" and "mortgage arrears" capture the technical specificity of financial concepts more effectively than single words. Using bigrams reduces ambiguity and improves the precision of the financial stress measure by distinguishing phrases such as "housing bubble" from "housing recovery," which may be conflated in a unigram-based framework.

Next, we mine all bigrams that appear in $\mathbb{T}$ but not in $\mathbb{S}\backslash\mathbb{T}$, which we call $\mathcal{C}^S$. For bigrams that appear in both $\mathbb{T}$ and $\mathbb{S}\backslash\mathbb{T}$, we compute their document frequencies in each set and retain those that occur much more frequently in the target set. For example, if a bigram appears in three out of 10 sentences in $\mathbb{T}$ and in 20 out of 100 sentences in $\mathbb{S}\backslash\mathbb{T}$, its frequency is 0.3 in $\mathbb{T}$ and 0.2 in $\mathbb{S}\backslash\mathbb{T}$, so it appears more frequently in $\mathbb{T}$.

We then rank the retained bigrams according to how well they discriminate between the two sets using a modified likelihood metric following King et al. (2017). Bigrams with the highest likelihood scores are sequentially added to the set $\mathcal{C}^S$. Following Sautner et al. (2023), we implement the likelihood calculation using a log-gamma function rather than a gamma function to accommodate the large size of the search set.

The final dictionary, denoted as $\mathcal{C}^{NSI}$, is constructed as the union of the 116 initial expert-curated keywords and 1,000 newly identified bigrams $\mathcal{C}^S$, yielding a total of 1,116 terms.

Figure 1 presents a word cloud of the 100 most prominent terms in the dictionary. These keywords reveal that the dictionary algorithm successfully captures intuitive and non-obvious stress terminology. For example, the algorithm identifies "oil price" and less obvious terms such as "middle east."

4.2.5 News-based stress index

Using the financial stress dictionary, we construct a measure of financial stress attention for each news article. This measure is based on how frequently the specified keywords in $\mathcal{C}^{NSI}$ appear in an article i in month t. To account for article length, we scale the count by the number of bigrams in the article:

[6] We implement this step using the `CountVectorizer` function from the `sklearn` library.

Figure 1: Word cloud of the financial stress dictionary



Note: This figure displays the 100 most common keywords in the corresponding corpus. Larger words indicate higher frequency. Internet Appendix Table A.2 reports the count of the top 100 most frequently occurring keywords.

$$\text{NSI}_{i,t} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} (\mathcal{I}[b \in \mathcal{C}^{NSI}]), \tag{1}$$

where $b = 1, ..., B_{i,t}$ are the bigrams in article i in month t and where $\mathcal{I}$ is the indicator function. Our baseline measure weights all dictionary bigrams equally, since it is difficult to assess ex-ante what the best weights are. The news-based stress index for each month is the equal-weighted average of $\text{NSI}_{i,t}$ across articles in each month:

$$\text{NSI}_t = \frac{1}{N_t} \sum_{i}^{N_t} NSI_{i,t}, \tag{2}$$

where N_t denotes the number of articles in month t.

We further adjust the NSI series to account for structural changes in article availability and seasonal variation in news production. Long historical newspaper archives often exhibit abrupt increases in the number of available articles due to changes in publication practices, archive digitization, or database coverage. To mitigate this issue, we adjust the NSI series by removing variation associated with periods characterized by abnormal spikes in article counts. Specifically, we estimate a regression of the NSI measure on a set of indicator variables corresponding to months with significant increases in article volume. We then construct an adjusted NSI series by subtracting the predicted values from the original index, thereby isolating the residual variation that reflects changes in the relative intensity of financial stress language rather than fluctuations in article availability. Finally, we remove remaining seasonal patterns in the adjusted series using the X-13 ARIMA-SEATS seasonal adjustment procedure, a standard method used by central banks. The resulting seasonally adjusted series isolates changes in financial stress language that are not attributable to predictable seasonal fluctuations.

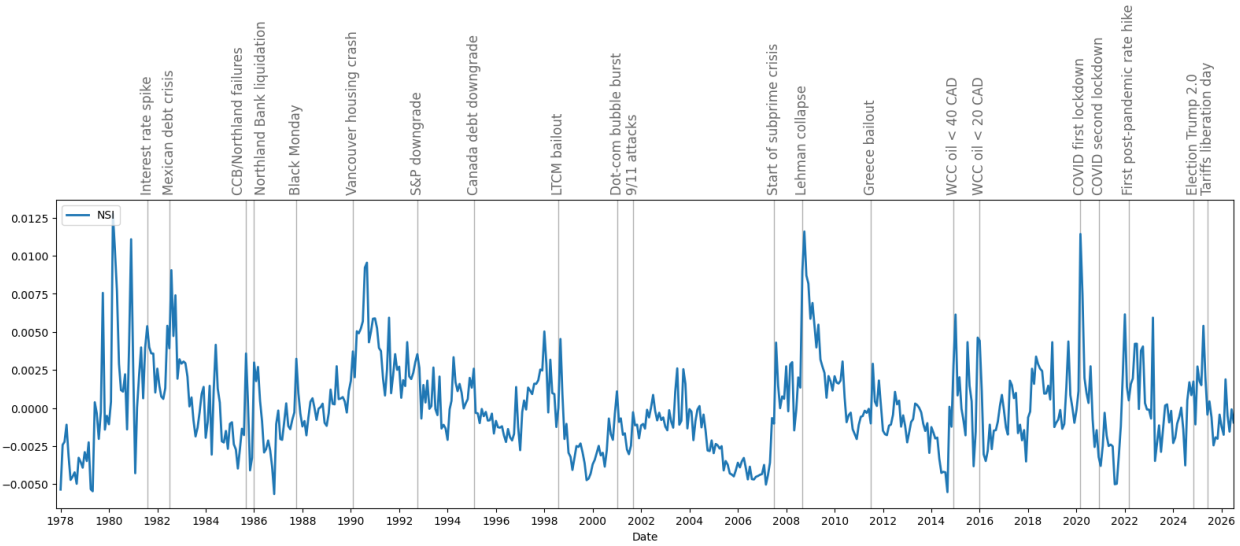
As robustness checks, Section 7 considers three alternative versions of the index. First, we construct an index built from the initial keywords alone, NSI^{IT}, to highlight the benefit of the machine learning algorithm in addition to human-curated dictionaries. Second, we construct a variant that weights each bigram by its distinctiveness in the corpus using term frequency-inverse document frequency weights, NSI^{TF-IDF}. It confirms our results are not driven by a handful of frequent but uninformative terms. Third, we construct a chronologically consistent variant, NSI^{CC}, in which the dictionary is re-estimated recursively using only the recession periods observed up to each point in time, so that the index reflects only information available in real time. This also identifies major stress episodes.

5 Validating the news-based stress index as a measure of perceived financial stress

5.1 The news-based stress index aligns with known stress episodes

Figure 2 presents the monthly NSI. The vertical lines mark major economic and financial events. The NSI exhibits pronounced spikes during well-known episodes of Canadian and global financial turmoil, including the early 1980s recession, the 1987 stock market crash, the early 1990s housing collapse, the GFC, the 2014-15 oil price shock, the COVID-19 pandemic, the 2022 monetary tightening cycle, and the 2025 tariff episode.

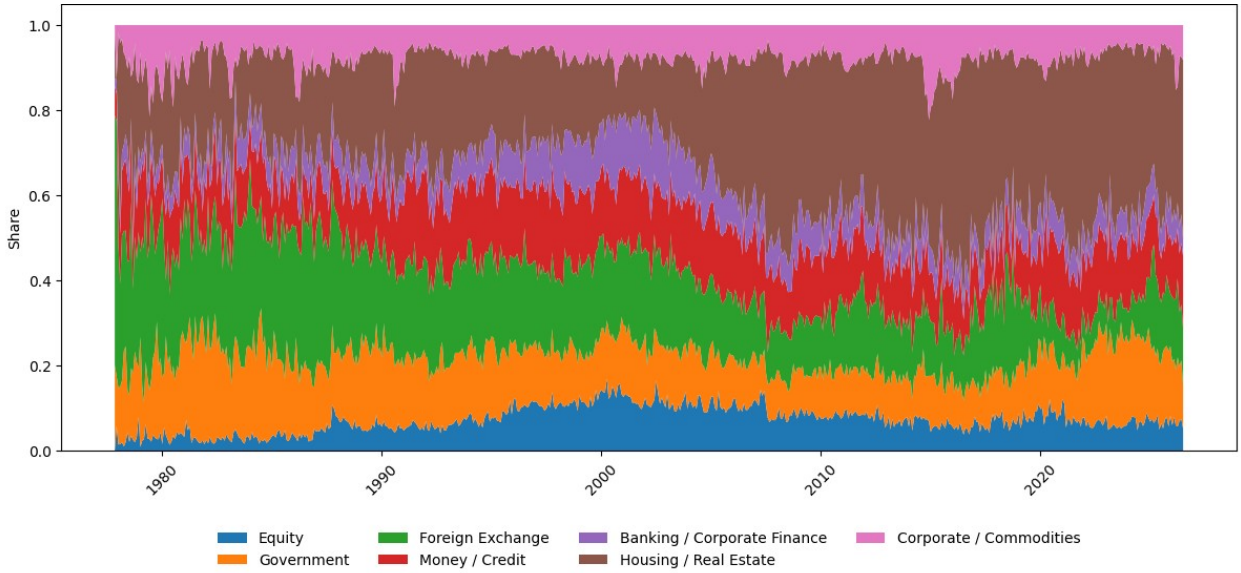
Figure 2: Monthly news attention to known stress events



Note: Vertical lines represent major Canadian and global stress events. The plotted series is the news-based stress index that is volume-and-seasonally-adjusted, hence possible negative values.

Figure 3 shows the monthly composition of financial stress attention across seven market segments. The relative shares vary substantially over time, indicating that the sources of perceived stress shift across economic regimes. In the 1980s, the foreign exchange segment is more prominent due to episodes like the Mexican debt crisis. It gains more prominence again in 2025, consistent with increased coverage of tariffs and trade tensions. In the 1990s with the housing market collapse and 2010s with a housing affordability crisis, the housing market stress perceptions gain more importance. Attention to equity stress increased during periods of boom or bust, e.g. in the lead up to the dot-com bubble and around COVID. Similarly, attention to the banking-related terms increased after the dot com, GFC or COVID period.

Figure 3: News attention across categories



Note: Shares represent the proportion of keywords by each of the seven market segments. Market segments are defined using the top-occurring keywords within each category (see Table A.3).

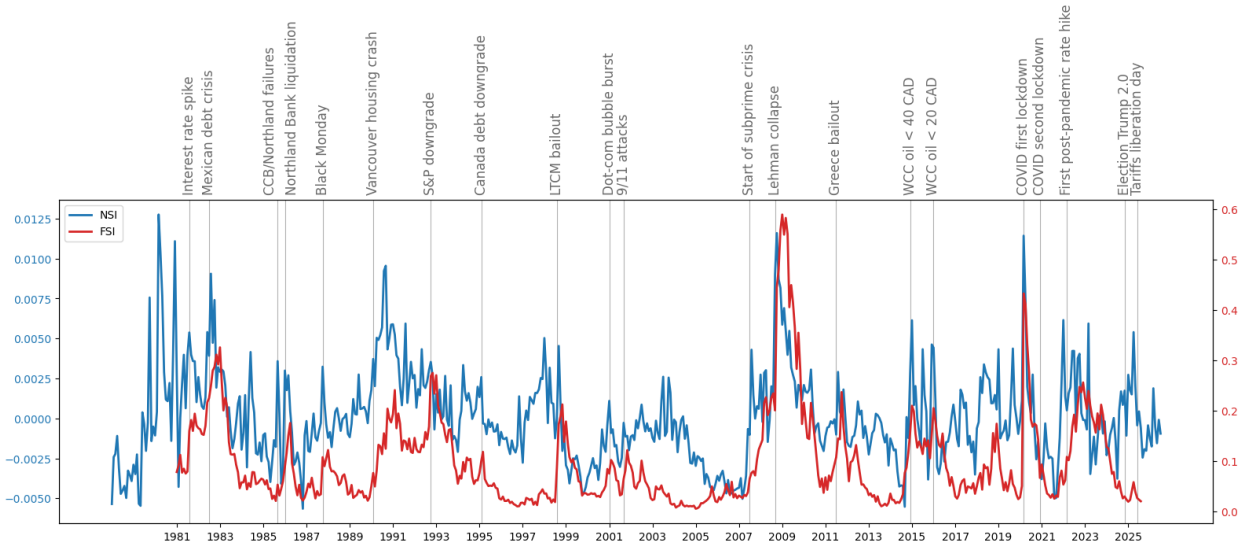
5.2 The news-based stress index correlates with other stress indices

Figure 4 plots the NSI with the market-based financial stress index (FSI) from Duprey (2020). The two stress measures are largely in agreement, particularly during major crises such as the GFC and COVID-19.[7]

However, there are notable periods where the two measures diverge. For example, in 2025 the NSI rises sharply in response to heightened tariff and trade-related coverage, while the market-based FSI remains relatively subdued. Similarly, NSI increases in early 2022 amid intensified reporting on higher inflation and possible monetary policy tightening, whereas the FSI does not rise until later in 2022. These divergences suggest that NSI may at times capture forward-looking worries or policy-driven risk narratives in the media that may or may not materialize as actual strain in financial market conditions.

[7]Internet Appendix Figure A.1 displays the receiver operating characteristic (ROC) curves evaluating the ability of NSI to contemporaneously signal periods of elevated financial stress under alternative intensity of financial stress. NSI is most effective at identifying severe stress episodes where the FSI is above 0.25.

Figure 4: News-based stress versus financial stress indices



Note: This figure plots the NSI (left axis) and the market-based financial stress index (FSI, right axis) from Duprey (2020), along with major stress events (vertical bars). The pairwise correlation between the NSI and FSI is 56.8%.

Figure 5 compares the NSI with several macro-financial indicators. The top panel shows that NSI co-moves closely with the VIX, with sharp increases during major crisis episodes. However, the intensity of the peaks differs at times, for instance during the oil shock of 2015 that was associated with a much larger NSI peak than in the VIX. The middle panel shows a strong negative relationship between NSI and consumer confidence: periods of elevated stress attention coincide with declines in consumer sentiment. The bottom panel displays similar patterns for business and manufacturing confidence, with stress spikes associated with deteriorating confidence indicators. Here again it suggests that the NSI may relate to variations in industrial production or manufacturing to the extent that those would reflect entrepreneurs deteriorating confidence in the economy.

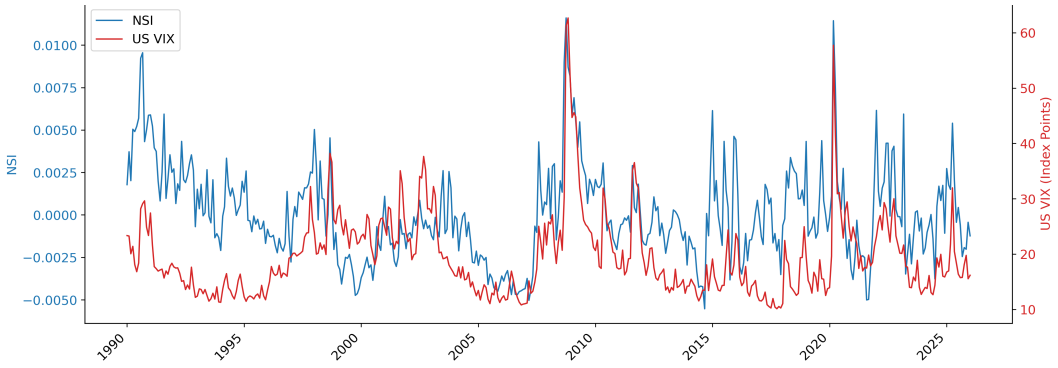
Overall, the strong correlation between measures of financial conditions as well as measures of confidence supports the interpretation of NSI as a measure of perceived financial stress. If so, one would expect the NSI to be associated with deteriorating macroeconomic conditions, possibly even more so during periods of acute stress. This is what we now turn to.

5.3 The news-based stress index correlates with macro-financial indicators

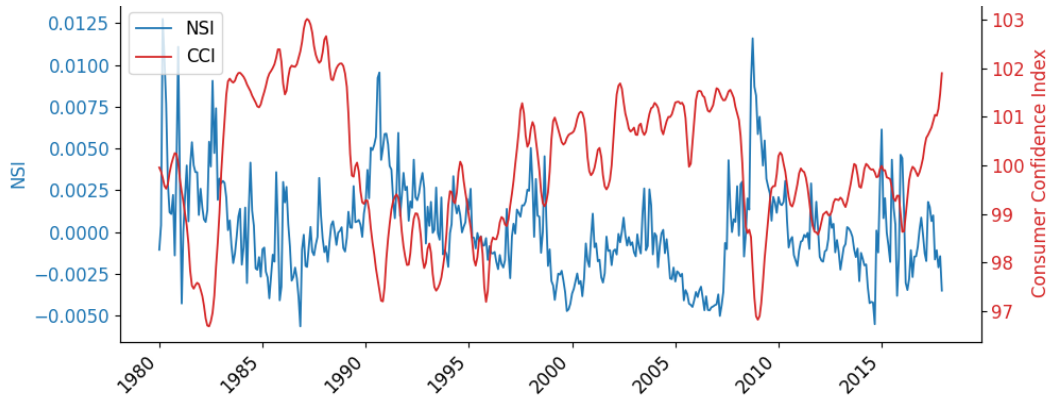
We now formally examine the contemporaneous and lead–lag relationships between the NSI and key macro-financial indicators using regression analysis. Internet Appendix Table A.4 provides detailed descriptions of the macro-financial indicators, which capture various sources of stress including financial risk; the banking and corporate sectors; and equity, government bond, money, commodity, foreign exchange and housing markets.

Figure 5: NSI and macro-financial indicators

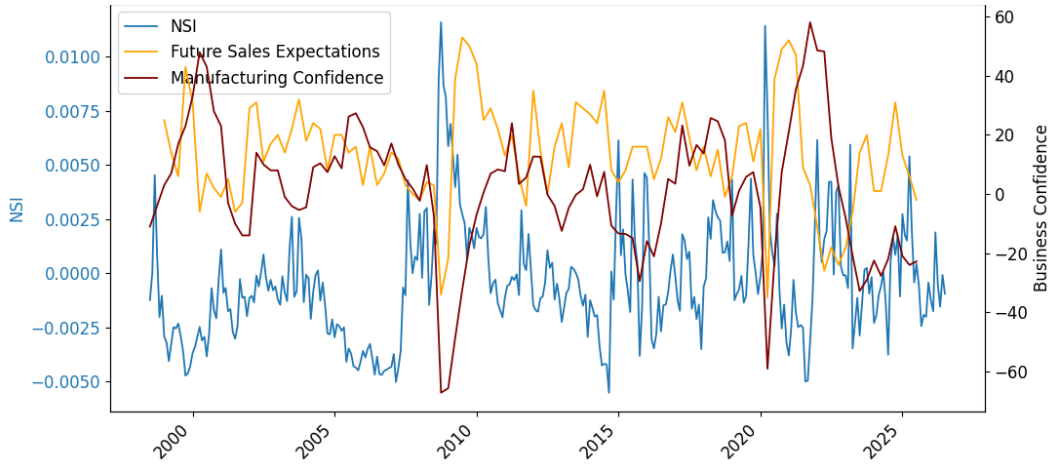
(a) NSI and US VIX



(b) NSI and consumer confidence index (CCI)



(c) Monthly NSI and quarterly business and manufacturing confidence indices



Note: The NSI pairwise correlation is 47.2% with the U.S. VIX (panel a), -45.6% with the consumer confidence index (CCI, panel b), -30.7% with future sales (a proxy for business confidence) and -46.7% with the manufacturing confidence index (both panel c). The monthly consumer confidence index from OECD (2025) is discontinued and ends in 2017.

5.3.1 Average lead-lag relationship

Following Correa et al. (2021), we test whether the NSI is associated with future movements in macro-financial indicators while controlling for the lagged dependent variable. Specifically, we estimate the following regression:

$$Y_t^{(j)} = \alpha^{(j)} + \beta_h^{(j)} \, \mathrm{NSI}_{t-h} + \rho^{(j)} Y_{t-h}^{(j)} + \varepsilon_t^{(j)}, \qquad h \in \{1, 3, 6, 9, 12\}. \tag{3}$$

In Equation (3), t is a monthly time index and $Y_t^{(j)}$ denotes macro-financial variable j, where $j = 1, \ldots, J$. We regress $Y_t^{(j)}$ on its own lag $Y_{t-h}^{(j)}$ and the NSI lagged h months, with $h \in \{1, 3, 6, 9, 12\}$. The coefficient $\beta_h^{(j)}$ captures the importance of NSI at horizon h, conditional on the information from $Y_{t-h}^{(j)}$. We also estimate a contemporaneous specification with $h = 0$, regressing $Y_t^{(j)}$ only on NSI_t. In parentheses are t-statistics computed using Newey–West standard errors.

We also consider the reverse to explore how information from macro-financial indicators is incorporated into the NSI:

$$\mathrm{NSI}_t = \alpha^{(j)} + \beta^{(j)} Y_{t-h}^{(j)} + \rho^{(j)} \, \mathrm{NSI}_{t-h} + \varepsilon_t^{(j)}, \qquad h \in \{1, 3, 6, 9, 12\}. \tag{4}$$

Table 3 reports the contemporaneous and lead–lag results. The $h = 0$ column shows the contemporaneous relationship between NSI and the macro-financial indicators. The left columns display the correlation between lagged NSI and macro-financial indicators (coefficient $\beta^{(j)}$ in Equation (3)). The right columns display the reverse relationship between lagged macro-financial indicators and the NSI (coefficient $\beta^{(j)}$ in Equation (4) scaled by 100).

Panels A and B of Table 3 show that lagged NSI is associated with deteriorating financial and banking stress: higher financial stress over a year, wider U.S. corporate spreads up to one month, higher systemic banking risk up to one month (marginal expected shortfall, MES) and worsening bank default risks up to 6 months (smaller distance-to-default). This suggests that news-based stress attention may sometimes precede deteriorating financial conditions. In the reverse regressions, higher FSI and corporate spreads are associated with higher NSI within one month for the FSI and up to one quarter for corporate spreads.

Panels A, B and C show that NSI is significantly related to contemporaneous stock market conditions: higher NSI coincides with higher VIX, lower TSX returns and lower bank stock returns, while lagged NSI shows no association with future TSX returns and a negative association with the VIX at longer horizons.

Monetary policy shocks are unrelated on average to past or future NSI (Panel D). This is reassuring that news-based stress does not, on its own trigger policy reactions on average. This also implies that any other effect of the NSI on yields would not be driven by the base rate, but instead may influence some measures of risks priced into a rate spread. For instance, the three-month treasury bill yield increases on impact, but the association turns negative from one month onward and stays negative up to one year, while other risk spreads (interbank, term premium, credit spread) are not contemporaneously impacted (Panels D, E, F). This is consistent with limited risk pricing after news events.

Panels G and H show that stress attention is also associated with a contemporaneous decrease in oil prices and a depreciation of the Canadian dollar. This is unsurprising since Canada is a major oil exporter and depends heavily on world markets as a small open economy.

The NSI is associated with stress on the housing market as households are likely to pay attention to housing-related stressors in the news (Panel I). Higher NSI correlates contemporaneously with lower house prices and higher mortgage spreads. Similarly, in the reverse regression, higher mortgage spreads are associated with future increases in NSI, making it more difficult for renting households to get a mortgage and for owning households to service their mortgage debt. This is likely the same reason why higher government term spreads increase future NSI (Panel D), since most mortgages are related to the five-year government bonds maturity.

Finally, Panel J indicates that lagged NSI is associated with weaker consumer confidence for up to 9 months as well as lower real credit growth over all horizons. After the contemporaneous decrease in consumer credit, new manufacturing orders also decrease one month later and other types of credit also tend to decrease after one month. The stronger and faster response of consumer credit is consistent with an interpretation of NSI as a perception of household stress. Lagged NSI is not strongly and persistently associated with future output.

5.3.2 Distributional lead-lag relationships

We next study the lead–lag relationships between the distribution of NSI and macro-financial indicators using quantile regressions. Similar to Equation (3), we estimate the following one-month ahead regression for the conditional distribution of macro-financial indicators:

$$Q_\tau\left(Y_t^{(j)} \mid \mathrm{NSI}_{t-1}, Y_{t-1}^{(j)}\right) = \alpha_\tau^{(j)} + \beta_\tau^{(j)}\,\mathrm{NSI}_{t-1} + \rho_\tau^{(j)} Y_{t-1}^{(j)}, \qquad \tau \in \{0.05, 0.25, 0.50, 0.75, 0.95\}, \tag{5}$$

where $Q_\tau(\cdot)$ denotes the conditional τ-quantile with $\tau \in \{0.05, 0.25, 0.50, 0.75, 0.95\}$. Similar to Equation (4), we also estimate reverse quantile regressions to examine whether lagged macro-financial indicators shape the future distribution of NSI:

$$Q_\tau\left(\mathrm{NSI}_t \mid Y_{t-1}^{(j)}, \mathrm{NSI}_{t-1}\right) = \alpha_\tau^{(j)} + \beta_\tau^{(j)} Y_{t-1}^{(j)} + \rho_\tau^{(j)}\,\mathrm{NSI}_{t-1}, \qquad \tau \in \{0.05, 0.25, 0.50, 0.75, 0.95\}. \tag{6}$$

Table 4 reports the quantile lead–lag regression results. The left columns evaluate the leading effect of NSI for the conditional distribution of macro-financial indicators (coefficient $\beta^{(j)}$ in Equation (5)), while the right columns examine the reverse relationship by estimating the leading effect of macro-financial indicators for the conditional distribution of NSI (coefficient $\beta^{(j)}$ in Equation (6), scaled by 100).

Elevated news-based stress attention appears to be especially informative about extreme financial stress episodes. Higher NSI is associated with higher odds of subsequent increases in the FSI, the U.S. VIX, and corporate spreads, reflected in the upper quantiles (Panel A), and with deteriorating systemic banking risk measures across most quantiles of the MES and of the distance to default (Panel B).

Table 3: Lead-lag specification results

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Panel A: Financial Stress & Risk											
FSI	19.05***	3.10***	5.17***	8.18***	7.62***	7.31***	0.23**	0.10	-0.12	-0.06	-0.02
	(5.73)	(3.42)	(3.23)	(3.72)	(3.72)	(3.47)	(2.29)	(0.56)	(-0.54)	(-0.27)	(-0.08)
VIX (US)	1261.36***	69.08	-4.82	32.05	-279.02*	-533.43***	0.00	-0.00	-0.01**	-0.00	-0.00
	(3.83)	(0.60)	(-0.03)	(0.17)	(-1.77)	(-3.52)	(0.37)	(-1.02)	(-2.28)	(-1.29)	(-0.56)
Corp Spread (US)	159.64***	12.95*	5.89	5.42	-14.41	-27.31	0.03**	0.04*	0.03	0.04	0.06**
	(2.89)	(1.77)	(0.48)	(0.30)	(-0.86)	(-1.45)	(2.25)	(1.65)	(0.90)	(1.56)	(2.43)
Panel B: Banking Sector											
MES (Banks, CA)	142.73***	31.16**	27.62	27.73	7.06	-5.21	0.01	0.01	-0.02	-0.02	-0.02
	(3.46)	(2.31)	(1.56)	(1.33)	(0.40)	(-0.27)	(0.52)	(0.73)	(-1.21)	(-1.14)	(-0.79)
Distance-to-Default (Banks, CA)	-85.43*	-11.25***	-22.59***	-39.82**	-34.89	3.87	0.00	0.01	0.01	0.01	0.01
	(-1.94)	(-3.83)	(-2.77)	(-2.57)	(-1.60)	(0.15)	(0.11)	(0.54)	(0.88)	(0.68)	(0.81)
Δ log Bank Equity Index (CA)	-3.22***	0.07	0.33	0.17	0.46	0.35	-0.17	-0.11	0.18	0.24	-0.19
	(-2.99)	(0.08)	(0.34)	(0.18)	(0.65)	(0.53)	(-0.85)	(-0.36)	(0.58)	(0.75)	(-0.62)
Panel C: Equity Markets											
Δ log TSX (SA)	-3.91***	-0.49	0.46	-0.84	-0.34	0.45	-0.05	-0.02	0.77**	0.21	-0.01
	(-3.97)	(-0.67)	(0.72)	(-1.17)	(-0.53)	(0.78)	(-0.20)	(-0.04)	(2.21)	(0.59)	(-0.03)
Panel D: Government Bond Markets											
Monetary Policy Shock	-4.33	-9.13	-2.33	-2.55	11.59	2.35	0.03	0.02	0.01	-0.00	-0.01
	(-0.39)	(-1.18)	(-0.38)	(-0.34)	(1.15)	(0.32)	(1.19)	(0.85)	(0.41)	(-0.04)	(-0.43)
T-bill 3M (CA)	316.79**	-18.49*	-82.06***	-106.93***	-103.32**	-140.07***	0.00**	0.01**	0.01**	0.01***	0.02***
	(2.36)	(-1.94)	(-3.28)	(-3.31)	(-2.18)	(-2.61)	(2.11)	(2.16)	(2.31)	(2.87)	(3.41)
Term Spread 5Y–3M (CA)	-6.45	-5.90	-0.76	-11.56	-13.12*	-16.26*	0.02	0.07**	0.08**	0.07*	0.09**
	(-0.52)	(-1.04)	(-0.09)	(-1.39)	(-1.65)	(-1.94)	(1.07)	(2.29)	(2.13)	(1.90)	(2.31)
Panel E: Money Markets											
Interbank Spread (CA)	6.19	-5.33	-4.55	-6.33	-6.00	-13.60*	-0.00	-0.01	-0.02	-0.02	0.01
	(0.47)	(-1.64)	(-0.76)	(-0.74)	(-0.70)	(-1.74)	(-0.02)	(-0.42)	(-0.40)	(-0.58)	(0.17)
Panel F: Corporate Sector											
Credit Spread BBB-A (CA)	9.88	4.19*	3.79	10.15*	10.42	15.00*	-0.01	-0.02	-0.03	-0.02	-0.03
	(1.23)	(1.78)	(0.85)	(1.67)	(1.39)	(1.70)	(-0.43)	(-0.81)	(-0.75)	(-0.80)	(-0.89)
Corp Paper–Tbill Spread 3M (CA)	-3.69	-21.66***	-32.21***	-13.83	-3.43	-13.93*	0.00	-0.02	-0.01	-0.02	-0.03
	(-0.26)	(-2.67)	(-3.80)	(-1.30)	(-0.27)	(-1.71)	(0.20)	(-0.61)	(-0.31)	(-0.37)	(-0.98)
Panel G: Commodity Markets											

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h=0$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Δ log Oil (WCS/WCC)	-7.98*	-3.46	1.07	-2.54	1.84	-0.85	-0.01	0.11*	0.08	0.18**	0.10
	(-1.96)	(-1.07)	(0.51)	(-1.26)	(0.93)	(-0.65)	(-0.23)	(1.81)	(1.10)	(2.01)	(1.23)
Panel H: Foreign Exchange Markets											
Δ log REER (CA)	-0.83***	-0.06	0.33	-0.05	0.13	0.38*	-0.44	0.82	0.89	1.36	0.49
	(-2.64)	(-0.21)	(1.34)	(-0.17)	(0.58)	(1.72)	(-0.84)	(1.13)	(1.15)	(1.42)	(0.48)
Panel I: Housing Markets											
Δ log House Prices (CA)	-0.64**	-0.57*	-0.02	-0.13	-0.07	-0.25	-0.47	-0.88	-1.42**	-0.75	-0.60
	(-2.35)	(-1.77)	(-0.05)	(-0.37)	(-0.21)	(-0.99)	(-0.98)	(-1.52)	(-1.97)	(-1.23)	(-1.01)
Mortgage Spread (CA)	98.84***	5.03	-13.97*	-26.13**	-25.39*	-44.08***	0.04***	0.06***	0.08***	0.10***	0.11***
	(5.26)	(1.00)	(-1.73)	(-2.05)	(-1.71)	(-2.80)	(3.42)	(3.21)	(3.22)	(4.28)	(4.52)
Panel J: Real Economy											
Consumer Confidence (CA)	-2544.88***	-436.76***	-574.69***	-779.60**	-840.86*	-617.09	-0.00**	-0.00**	-0.00	-0.00	-0.00
	(-6.05)	(-3.26)	(-2.79)	(-2.43)	(-1.96)	(-1.32)	(-2.08)	(-2.10)	(-0.54)	(-0.64)	(-0.67)
Δ log Real Credit (Cons, SA)	-0.43***	-0.46***	-0.35***	-0.31***	-0.33***	-0.26***	-1.68	-3.13	-5.67**	-4.06	-5.37**
	(-3.25)	(-3.98)	(-3.71)	(-2.70)	(-3.41)	(-2.88)	(-1.26)	(-1.49)	(-2.39)	(-1.30)	(-2.12)
Δ log Real Credit (Bus, SA)	-0.09	-0.23**	-0.33***	-0.34***	-0.33***	-0.22*	-1.18	-2.60	-2.16	-1.19	1.85
	(-0.64)	(-2.40)	(-2.81)	(-2.84)	(-2.84)	(-1.71)	(-0.95)	(-1.51)	(-1.31)	(-0.65)	(0.92)
Δ log Real Credit (Mortgage, SA)	-0.16	-0.23***	-0.29***	-0.16**	-0.21**	-0.21**	-3.11*	-4.11	-4.09	-2.03	-3.10
	(-1.25)	(-3.21)	(-3.71)	(-2.18)	(-2.35)	(-2.24)	(-1.75)	(-1.43)	(-1.28)	(-0.45)	(-0.81)
Δ log CPI (SA, CA)	-0.01	0.06	0.12**	0.05	0.05	-0.00	3.66	8.38**	15.96***	14.69***	20.03***
	(-0.15)	(1.05)	(2.04)	(0.75)	(0.73)	(-0.03)	(1.36)	(2.09)	(3.26)	(3.48)	(4.43)
Δ log New Orders (Mfg, SA)	-0.61	-2.65**	-0.84	0.03	-0.26	0.46	-0.17	-0.20	-0.15	-0.34	-0.14
	(-0.99)	(-2.48)	(-0.87)	(0.06)	(-0.52)	(0.91)	(-1.05)	(-1.07)	(-0.72)	(-1.37)	(-0.68)
Δ log IPI (SA, CA)	-0.36**	-0.19	-0.06	-0.12	-0.01	-0.20	-0.34	2.02	4.77**	3.96*	5.90***
	(-2.32)	(-1.62)	(-0.37)	(-0.81)	(-0.04)	(-1.47)	(-0.31)	(0.93)	(2.01)	(1.80)	(2.92)
Δ log GDP (SA, CA)	-0.93	-0.53**	-0.07	-0.32	0.15	0.14*	1.77***	1.87	2.41	2.52	-0.67
	(-1.61)	(-2.19)	(-0.31)	(-1.44)	(0.72)	(1.88)	(3.15)	(1.26)	(1.34)	(1.61)	(-0.46)

Notes: Coefficient estimates are multiplied by 100 for the right-most set of columns with t-statistics in parentheses below each coefficient. * p<0.10, ** p<0.05, *** p<0.01. Variables definition and sources are listed in Appendix C Table A.4.

Panels B to G show that higher NSI is associated with higher financial market uncertainty and volatile funding conditions next period. It is characterized by a widening of both the left and right tails of the distribution of stock returns[8] and funding spreads for banks, firms and the Government of Canada. This indicates that news-based perceptions of stress reflect amplified overall uncertainty priced into the market, which may, in turn, incentivize households and firms to remain more prudent.

Panel I suggests that increases in the NSI are associated with worsening housing risks, with risks of higher mortgage spreads and lower house price growth. Consumer confidence is more likely to be lower.

Finally, Panel J shows that elevated NSI is associated with downside risks to the real economy. Higher NSI shifts the entire distribution of real consumer credit growth down and worsens the downside risk to real business credit growth, which is consistent with high NSI increasing the odds of precautionary behaviors. Higher NSI is also associated with risks of a somewhat lower industrial production, risks of fewer manufacturing orders, and downside risks to GDP.[9]

The reverse regressions show more limited effects, suggesting that news-based stress attention primarily precedes rather than reacts to changes in macro-financial conditions.

Overall, the results validate that NSI serves as a useful quantitative summary of financial stress perceptions. However, they do not establish whether NSI conveys information distinct from the financial markets or other macroeconomic indicators. In addition, the lead–lag patterns reported in Table 3 do not prove causality and suggest that NSI and macro-financial indicators may be endogenously determined. The next section addresses those issues with additional structural restrictions within a linear or non-linear VAR framework.

[8]Since measures of systemic banking stress are composite indices that are already conditional on a bad realization of stock returns, and this is becoming more likely, it is not too surprising that higher NSI worsens systemic banking stress measures across most quantiles.

[9]Note that monthly GDP is only available over half of our sample, so we instead focus on industrial production in the remaining part of the paper.

Table 4: Quantile lead-lag regression results (h=1)

	Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$q = 0.05$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.95$	$q = 0.05$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.95$
Panel A: Financial Stress & Risk										
FSI	0.50	0.64	1.16***	1.65***	3.62**	0.05	0.32***	0.14	0.26**	0.34
	(1.15)	(1.58)	(2.60)	(2.73)	(2.22)	(0.52)	(3.28)	(1.42)	(2.11)	(1.40)
VIX (US)	-84.09	-90.00	-46.29	35.74	523.84*	0.00	0.00	-0.00	0.00	-0.00
	(-1.51)	(-1.61)	(-0.89)	(0.54)	(1.83)	(0.48)	(0.75)	(-0.71)	(0.71)	(-1.58)
Corp Spread (US)	-7.97***	-1.81	1.46	8.83***	17.24***	0.07***	0.05***	0.02	0.01	-0.03
	(-3.91)	(-0.85)	(0.62)	(2.77)	(3.43)	(6.83)	(3.23)	(1.24)	(0.53)	(-0.69)
Panel B: Banking Sector										
MES (Banks, CA)	5.52	20.40***	25.70***	25.20**	44.51**	0.01	0.02*	-0.01	-0.00	0.03
	(1.19)	(3.40)	(3.77)	(2.57)	(1.99)	(0.32)	(1.79)	(-0.67)	(-0.17)	(0.58)
Distance-to-Default (Banks, CA)	-13.80**	-9.36***	-9.86***	-11.81***	-7.26	-0.00	0.01	-0.00	-0.00	-0.02
	(-2.02)	(-3.01)	(-4.35)	(-3.79)	(-1.50)	(-0.00)	(0.95)	(-0.36)	(-0.28)	(-1.25)
Δlog Bank Equity Index (CA)	-4.81***	-0.90	-0.26	1.96**	2.64*	0.48**	-0.11	-0.18	-0.13	-0.40
	(-4.02)	(-1.12)	(-0.40)	(2.52)	(1.91)	(2.45)	(-0.59)	(-1.06)	(-0.58)	(-0.77)
Panel C: Equity Markets										
Δlog TSX (SA)	-2.46*	-1.43**	-1.08**	1.13*	1.63	0.04	-0.13	0.07	0.17	-0.38
	(-1.87)	(-2.36)	(-2.19)	(1.82)	(1.30)	(0.20)	(-0.52)	(0.31)	(0.66)	(-0.46)
Panel D: Government Bond Markets										
Monetary Policy Shock	-55.19***	-26.89***	-0.00	-5.12	79.12***	-0.01	0.03	0.05***	0.07***	0.11
	(-3.18)	(-4.60)	(-0.00)	(-1.03)	(4.72)	(-0.20)	(1.50)	(2.70)	(3.34)	(1.25)
T-bill 3M (CA)	-37.86***	-25.72***	-5.22**	2.36	35.28***	-0.00	0.00	0.00**	0.01***	0.01
	(-5.13)	(-7.20)	(-2.05)	(0.79)	(6.30)	(-1.46)	(0.42)	(2.05)	(2.98)	(1.11)
Term Spread 5Y–3M (CA)	-46.29***	-25.78***	-8.23	4.48	35.64**	-0.00	-0.01	0.01	0.04	0.06
	(-3.97)	(-4.59)	(-1.45)	(0.70)	(2.30)	(-0.23)	(-0.53)	(0.55)	(1.60)	(1.05)
Panel E: Money Markets										
Interbank Spread (CA)	-12.00***	-4.48***	-1.77	2.27*	24.79***	-0.02	-0.01	-0.01	0.02	0.04
	(-5.31)	(-3.19)	(-1.57)	(1.78)	(4.07)	(-1.20)	(-0.56)	(-0.41)	(0.86)	(1.32)
Panel F: Corporate Sector										
Credit Spread BBB–A (CA)	-11.78**	-0.60	1.35	6.70***	31.37***	0.05*	0.04**	0.00	-0.01	-0.07
	(-2.11)	(-0.48)	(1.22)	(3.54)	(4.91)	(1.72)	(2.11)	(0.10)	(-0.34)	(-1.21)
Corp Paper Tbill Spread 3M (CA)	-102.21***	-28.19***	-4.45**	-1.40	60.04***	-0.02	0.01	0.00	0.01	0.17***
	(-6.65)	(-6.62)	(-2.30)	(-0.41)	(3.07)	(-0.51)	(0.42)	(0.12)	(0.83)	(3.15)
Panel G: Commodity Markets										

	Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$q = 0.05$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.95$	$q = 0.05$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.95$
Δlog Oil (WCS/WCC)	-8.30*	-2.75	-1.34	-0.66	9.84**	-0.03	0.05	-0.02	0.04	-0.09
	(-1.82)	(-1.48)	(-1.06)	(-0.40)	(2.50)	(-0.24)	(0.60)	(-0.37)	(0.76)	(-0.52)
Panel H: Foreign Exchange Markets										
Δlog REER (CA)	-0.35	0.17	0.25	0.08	-0.27	0.58	0.12	-0.22	-0.81	-2.79*
	(-0.81)	(0.67)	(1.04)	(0.31)	(-0.68)	(0.68)	(0.20)	(-0.42)	(-1.27)	(-1.69)
Panel I: Housing Markets										
Δlog House Prices (CA)	-4.21***	-0.94***	-0.34	0.37	0.64	-0.49	-0.56	-0.35	0.04	-0.54
	(-5.31)	(-3.65)	(-1.42)	(1.19)	(1.06)	(-0.81)	(-1.45)	(-0.88)	(0.08)	(-0.57)
Mortgage Spread (CA)	-1.88	-4.49	-1.57	5.12	43.88***	-0.04***	0.01	0.03***	0.05***	0.10***
	(-0.29)	(-1.21)	(-0.45)	(1.29)	(3.15)	(-2.85)	(0.81)	(2.67)	(3.82)	(2.59)
Panel J: Real Economy										
Consumer Confidence (CA)	-849.56**	-376.43***	-0.00	-227.00	-781.69***	-0.00**	-0.00**	-0.00	-0.00***	-0.00
	(-2.50)	(-4.46)	(-0.00)	(-1.54)	(-4.08)	(-2.14)	(-1.97)	(-1.63)	(-2.59)	(-0.95)
Δlog Real Credit (Cons, SA)	-0.44***	-0.35***	-0.35***	-0.45***	-0.40*	-1.12	0.49	-1.06	-2.56	-2.73
	(-2.68)	(-4.25)	(-4.68)	(-4.91)	(-1.86)	(-0.85)	(0.36)	(-0.83)	(-1.45)	(-0.61)
Δlog Real Credit (Bus, SA)	-0.57***	-0.24**	-0.26***	-0.11	-0.15	0.06	-1.16	-1.84*	-3.30***	-1.96
	(-2.78)	(-2.46)	(-2.80)	(-0.95)	(-0.68)	(0.04)	(-1.02)	(-1.69)	(-2.59)	(-0.64)
Δlog Real Credit (Mortgage, SA)	-0.42***	-0.18***	-0.26***	-0.14**	-0.11	-0.19	-1.45	-2.47	-2.32	-4.19
	(-2.73)	(-3.01)	(-4.60)	(-2.01)	(-0.44)	(-0.11)	(-0.92)	(-1.63)	(-1.11)	(-0.79)
Δlog CPI (SA, CA)	-0.13	-0.06	0.08*	0.10	0.13	-7.63**	-1.60	1.91	5.78**	19.48**
	(-1.28)	(-1.08)	(1.81)	(1.60)	(0.89)	(-2.08)	(-0.67)	(0.87)	(2.10)	(1.99)
Δlog New Orders (Mfg, SA)	-5.57***	-1.53**	-1.34**	-0.24	0.03	-0.11	-0.21	-0.09	0.12	-0.75*
	(-3.91)	(-2.21)	(-2.31)	(-0.38)	(0.02)	(-0.38)	(-1.21)	(-0.55)	(0.67)	(-1.87)
Δlog IPI (SA, CA)	-0.30	-0.24**	-0.08	-0.07	-0.23	-0.94	-0.81	0.45	1.88	-1.96
	(-0.82)	(-2.06)	(-0.79)	(-0.58)	(-0.94)	(-0.57)	(-0.64)	(0.42)	(1.44)	(-0.56)
Δlog GDP (SA, CA)	-0.48***	-0.40***	-0.30***	-0.31***	0.18	-0.41	1.65	1.54	3.50***	7.25
	(-3.70)	(-4.35)	(-3.95)	(-3.48)	(0.79)	(-0.12)	(1.09)	(1.54)	(3.17)	(0.70)

Notes: Quantile regression estimates for $h = 1$. Coefficient estimates are multiplied by 100 for the right panel columns with t-statistics in parentheses below each estimate. * p<0.10, ** p<0.05, *** p<0.01.

6 Macroeconomic effect of the news-based stress index

6.1 Linear VAR

Linear specification. We estimate a monthly Bayesian VAR over 1981m1-2025m7 to assess the impact of news-related innovations and contrast it with financial shocks.[10],[11] As a benchmark, we include the log difference of industrial production, the log difference of unsecured credit, the log difference of the consumer price index, the difference in the short-term rate,[12] the financial stress index of Duprey (2020) and the news-based stress index. Variables are seasonally adjusted and expressed in real terms as needed. The choice of variables is limited by the monthly frequency and the start date of 1981.[13] We use three lags throughout.[14]

Stress shocks are decomposed into two sources, either purely news perceptions, or stress simultaneously reflected both in the news and in financial markets. This identification strategy relies on the recursive ordering of the variables with a Cholesky decomposition of the residuals. The news-based stress index is ordered last in the VAR such that news perception shocks are not reflected in financial prices or macroeconomic variables within a month. The financial stress index is ranked second to last, such that financial shocks are immediately reflected in the news index but do not impact macroeconomic variables within a month. For the financial shock identification, we follow the seminal work by Gilchrist and Zakrajšek (2012) who use a Cholesky ordering such that real economic shocks affect financial conditions contemporaneously while financial shocks affect the real economy only with a lag.

News shock versus financial shocks. Figure 6 contrasts the response to a financial versus news-based stress shock in a Bayesian VAR. Although a financial stress shock decreases industrial production growth, a news-based stress shock persistently decreases consumer credit growth. If we omit the financial variable and associated shock (Figure B.2), then the shock associated with the NSI no longer isolates the news component, but also captures NSI spikes related to financial stress. And as expected, such a shock decreases both industrial production and consumer credit.

Our results suggest that overall stress shocks can have two components. First, a financial stress shock derived from market data worsens future industrial production. Second, a news shock that reflects diffused perceptions of stress unrelated to financial markets data

[10] The shorter time-span compared to our NSI is due to the availability of the financial stress index.

[11] Results are not driven by the COVID-19 pandemic. Internet Appendix Figure B.5 displays similar impulse responses when all variables are pre-filtered using the change in the COVID-19 policies stringency index from Hale et al. (2021) and the number of excess deaths due to COVID-19 from Mathieu et al. (2020).

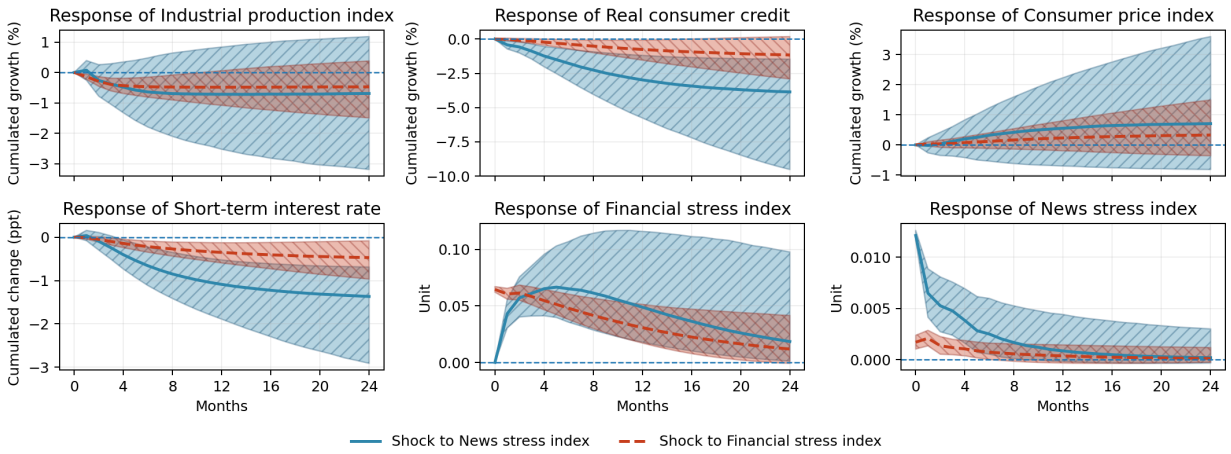
[12] Figure B.4 shows that the results are robust to using the short-term rate in level instead of a first difference. And unreported results are also similar when instead using the five-year mortgage rate or the cumulative Canadian monetary policy shocks of Champagne and Sekkel (2018).

[13] For instance, Canadian gross domestic product or consumption are not available at a monthly frequency before the end of the 1990s.

[14] Internet Appendix Figure B.1 shows the information criterion for the choice of the lag order in our benchmark VAR. It suggests at most three lags. But unreported specifications with four lags for instance would display the same pattern.

worsens future unsecured credit growth, consistent with precautionary motives by concerned households.

Figure 6: Impulse response after a financial or news shock



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

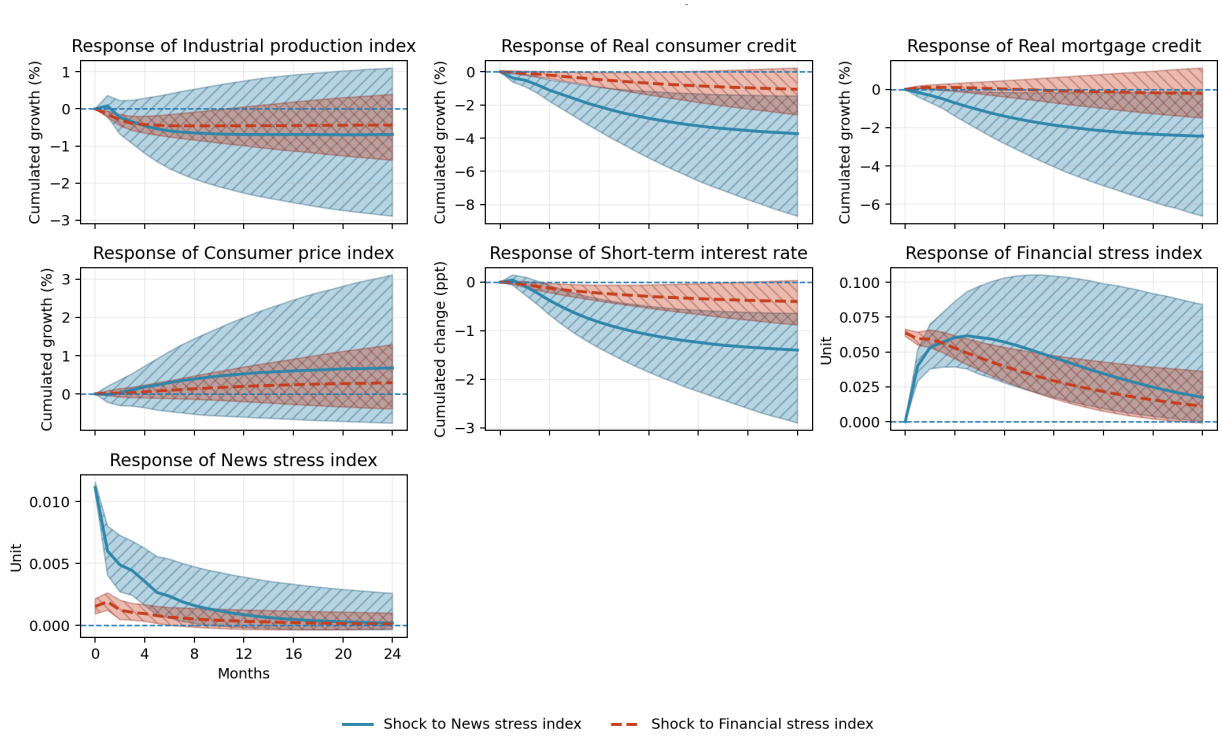
Consumer versus mortgage credit after a news shock. If news shocks are primarily increasing precautionary motive by households, we would expect that they would primarily reduce consumer credit more than mortgage credit. This is what Figure 7 confirms. Consumer credit decreases more than mortgage credit that is not significant at conventional levels.[15],[16]

Impact on future orders rather than current production. Figure 8 replaces the industrial production index by the value of new orders estimated in a given month for the manufacturing sector. As previously, consumer credit decreases more with the news shocks. However, orders now also decrease after a news shock. This is consistent with consumers reducing their use of credit and thus reducing their consumption temporarily, thereby reducing orders. But the effect is not as severe to also decreases manufacturing production. Thus with sustained industrial production but reduced orders for future production, news shocks are more likely to be absorbed temporarily by firms, possibly via inventories. This may

[15]The two types of credit do not have the same maturity and rate, but unreported simulations show that using the five-year mortgage rate instead of the short-term rate does not change the results.

[16]Internet Appendix Figure B.3 adds additional financial variables with the US VIX or the Toronto stock exchange. As expected, a financial shock depresses stock prices immediately and increases the VIX persistently. After a news shock, the response of stock prices and the VIX is more muted and less significant. Still, consumer credit decreases more in the presence of news shocks.

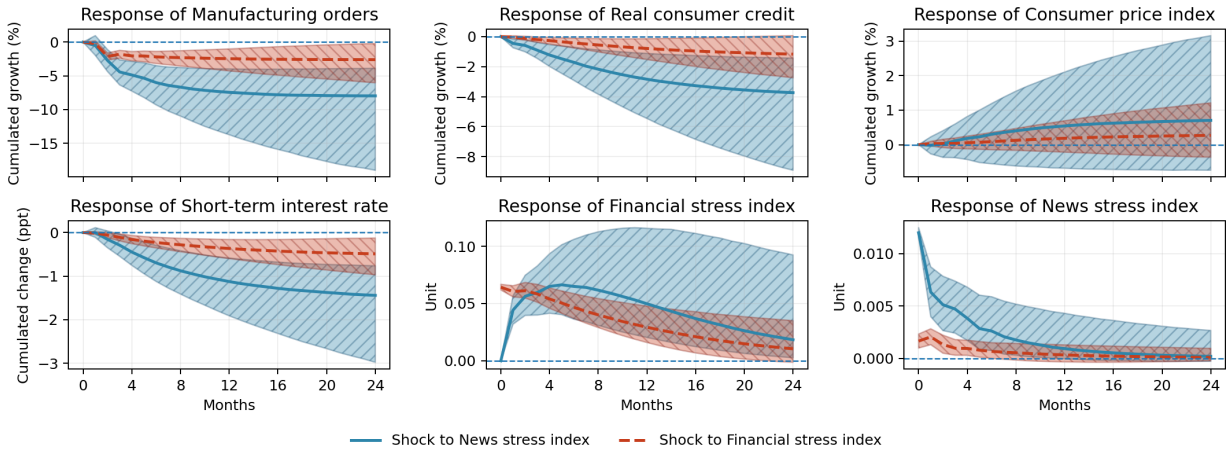
Figure 7: Impulse response after a financial or news shock: effect on consumer rather than mortgage credit



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

reflect the perception around stress and the expectations that households may reduce their consumer credit only temporarily unless accompanied by a larger financial stress episode.

Figure 8: Impulse response after a financial or news shock: robustness with manufacturing orders



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

Instead of mean impulse responses, we now turn to quantile impulse responses to explore the potential distributional effect on risks to future industrial production or unsecured credit growth.

6.2 Non-linear quantile-augmented VAR

The previous section estimates a mean impulse response, that is, the mean impact of stress shocks that are assumed to propagate linearly in the system. However, stress shocks may impact higher order moments of the macroeconomic variables of interest. For instance, Adrian et al. (2019) use a quantile regression to show that a change in financial stress has a stronger impact on the tail of future GDP one year later. Boire et al. (2025) confirm that structurally identified financial stress shocks create a downside skew in the impulse response of future GDP.

Non-linear specification. We now estimate quantile impulse response after a stress shock following Boire et al. (2025) who provide a simple extension of the linear VAR to a quantile setup, called Quantile-augmented VAR (QAVAR). The framework relaxes the linear propagation assumption of the VAR for *one* variable of interest, while maintaining the standard VAR structural shock identification property. We therefore estimate the analog of our linear VAR with the Quantile-augmented VAR and employ the same Cholesky shock identification

strategy as before. We display the quantile impulse response functions for each variable of interest coming from a different Quantile-augmented VAR, allowing for a distributional response of one variable at a time. We contrast the quantile impulse with the equivalent mean impulse response functions from an equivalent linear VAR.[17]

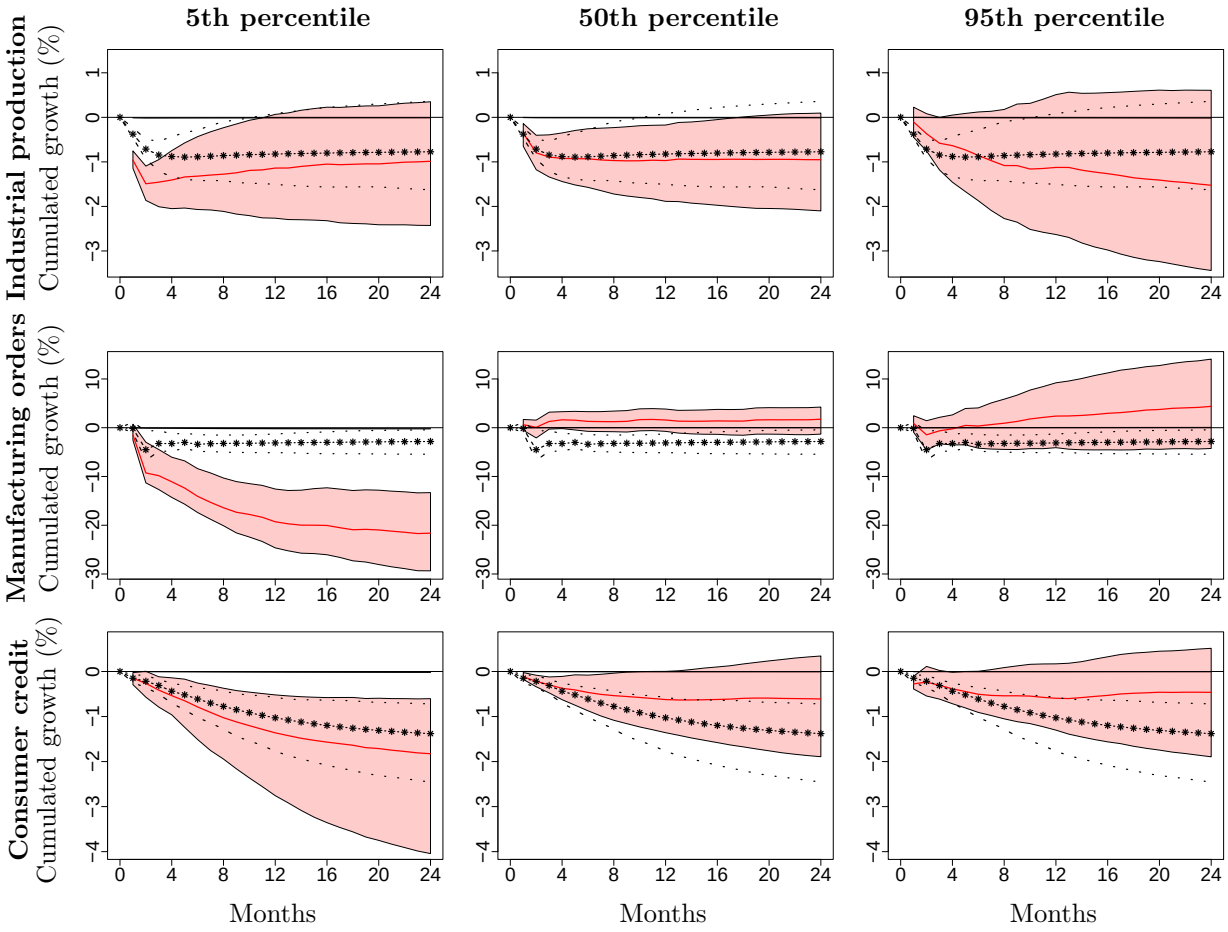
Distributional impact of financial stress shock not driven by the news. Figure 9 shows that financial stress shocks not originating in the news worsen the left tail of industrial production growth, manufacturing orders growth and consumer credit growth. However the right tail remains unaffected. This left-skewness after a financial shock highlights a possible channel of amplification for financial stress shocks, via the decrease in the provision of consumer credit when financial markets face a sharp repricing of risks, together with the reduction in manufacturing orders when the economy is expected to face a downturn. This is consistent with Boire et al. (2025) who find a negative skewness impact on GDP after financial stress shocks, although they do not control for news perceptions with the news-based stress index. This is also consistent with the seminal results on GDP growth by Adrian et al., 2019, although they focus on financial stress changes, not shocks, and do not control for news information. The impact on credit is also consistent with Duprey and Ueberfeldt (2020) and Adrian et al. (2022) who find a correlation between lower credit and future downside risks to growth.

More limited distributional impact of a news shock. We now turn to the impact of a news-based stress shock reflecting the attention to risks as perceived via the media that is not simply reflecting the financial market prices. Figure 10 (middle column) shows that the median effect (plain line) is close to the mean effect (starred line). The top row also shows that a news-based stress shock does not significantly impact the distribution of industrial production growth. However, news shocks do worsen risks to manufacturing orders (second row, left column), but possibly less abruptly than financial stress shocks. In addition, news shocks worsen the distribution of future consumer credit uniformly across quantiles: by shifting the distribution entirely to the left, it is a location rather than a skewness effect. This confirms our hypothesis that perception shocks derived from news have a disproportionately larger impact on unsecured consumer credit. Worried households reading the news are more likely to limit their use of unsecured credit. By doing so, this increases the risk of lower manufacturing orders, but those are buffered by firms with no change in industrial production in the absence of further broadening of financial stress beyond the news perception. [18]

[17]The financial or news shock impulse is virtually identical between the Quantile-augmented VAR and the linear VAR equivalent, such that differences in the responses are driven by the distributional aspect, not by the shock identification, the shock persistence, or its uncertainty.

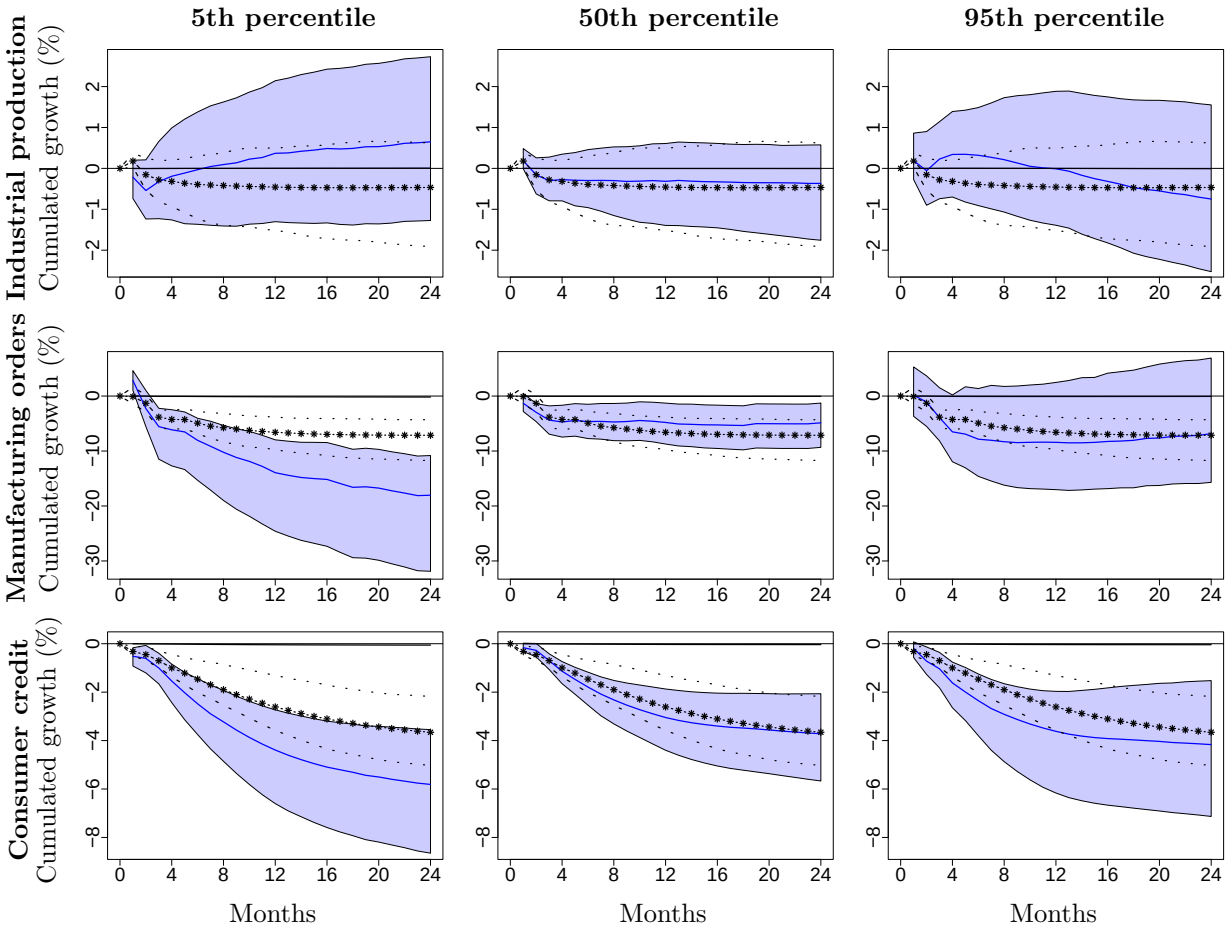
[18]Similar results emerge after filtering out COVID-related effects that may influence the tails of the estimated conditional distributions. In Internet Appendix Figure C.1, all variables are pre-filtered using changes in the COVID-19 policy stringency index from Hale et al. (2021) and excess COVID-19 mortality from Mathieu et al. (2020). This confirms that the estimated tail dynamics are not driven by the extraordinary macro-financial swings observed during the pandemic.

Figure 9: Quantile impulse response to a financial stress shock



Notes: Monthly Quantile-augmented VAR (QAVAR, following the method of Boire et al. (2025)) with three lags over 1981m1-2025m7; one model per row. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in log-difference cumulated since period zero over the horizon. Stress shocks identified using Cholesky ordering: news-based stress shocks are not reflected in financial prices on impact, while news-based and financial stress shocks are not reflected in macroeconomic variables on impact. The financial stress shock is scaled such that the financial stress index increases to 0.1 on impact. The quantile-augmented VAR model is represented by the plain red line and the red-shaded confidence bands. The mean response from the equivalent linear VAR is in the starred black line with the confidence bands in dashed black. The confidence bands are the 10th and 90th percentiles produced with 53500 replications (100*535): 100 block bootstrapped replications with block sizes of two years for 535 possible initial conditions (we have 535 monthly observations).

Figure 10: Quantile impulse response to a news stress shock



Notes: Monthly Quantile-augmented VAR (QAVAR, following the method of Boire et al. (2025)) with three lags over 1981m1-2025m7; one model per row. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in log-difference cumulated since period zero over the horizon. Stress shocks identified using Cholesky ordering: news-based stress shocks are not reflected in financial prices on impact, while news-based and financial stress shocks are not reflected in macroeconomic variables on impact. The news-based stress shock is scaled such that the news-based stress index increases to 0.01 on impact. The quantile-augmented VAR model is represented by the plain blue line and the blue shaded confidence bands. The mean response from the equivalent linear VAR is in the starred black line with the confidence bands in dashed black. The confidence bands are the 10th and 90th percentiles produced with 53500 replications (100*535): 100 block bootstrapped replications with block sizes of two years for 535 possible initial conditions (we have 535 monthly observations).

7 Robustness: alternative news-based stress indices

We explore three measurement concerns. First, whether the machine-learning expansion contributes information beyond the initial expert-curated terms. Second, whether the index benefits from look-ahead information unavailable in real time. Third, whether the equal-weighting scheme drives the results. We show that our findings are robust to each concern.

7.1 The benefit of the expanded dictionary over initial keywords

The financial stress dictionary combines the 116 initial keywords of Table 2 with 1,000 additional bigrams discovered by the keyword algorithm of Section 4. To assess the contribution of the discovered bigrams, we compare the baseline NSI with an index constructed identically but using only the initial terms, NSI^{IT}.

The initial-keyword index performs substantially worse than the baseline index. It tracks fewer historical stress episodes (Figure D.1) and loses most relationships with macro-financial variables (Table D.1).

These results reflect the limitation of purely human-curated dictionaries documented by King et al. (2017): the initial keywords are precise but sparse. Each term appears in relatively few articles, so an index built on them alone produces a noisy signal of stress attention, dominated by the handful of episodes described in exactly those words. This confirms the value-added of our NSI derived from machine learning algorithms.[19]

7.2 Chronologically consistent index

The baseline dictionary is estimated over the full sample, which embeds information (e.g. the timing of recession periods) that would not have been available to an observer in real time. To address this look-ahead concern, we construct a chronologically consistent variant of the index, NSI^{CC}.

Rather than estimating the dictionary once, we re-estimate it recursively: after each recession ends, the keyword-selection algorithm is re-run using only the recession periods observed up to that date, and the resulting dictionary $\mathcal{C}_{\tau}^{NSI}$, reflecting only information up to that date, is used to score all articles until the end of the subsequent recession, at which point the dictionary is updated again. Formally,

$$\text{NSI}_{i,t}^{\text{CC}} = \frac{1}{B_{i,t}} \sum_{b}^{B_{i,t}} \mathcal{I}\left[b \in \mathcal{C}_{\tau(t)}^{NSI}\right], \tag{7}$$

where $\tau(t)$ denotes the most recent dictionary available at month t. The monthly index is the equal-weighted average across articles, as in the baseline.

Figure D.2 compares the NSI and NSI^{CC}. The two series co-move closely, with a pairwise correlation of 64.8%. The correlation strengthens over time as the recursive dictionary is estimated on a growing history of recessions. While NSI^{CC} lags the onset of the GFC, it identifies the major post-GFC stress episodes, including the 2014–15 oil price collapse, the COVID-19 pandemic, and the 2025 tariff episode, despite relying only on information available before those events occurred. This suggests that the language of financial stress

[19] We can alternatively show the value added of our expanded dictionary derived from the news by comparing the NSI with a measure of public attention to financial stress constructed from Canadian Google Trends search volumes on the initial set of keywords (Internet Appendix E). The search-based index begins only in 2004, can be built only from the initial keywords, and shows little response to the 2014-15 oil price collapse, an episode of first-order importance for a commodity-exporting economy.

in Canadian news coverage is sufficiently stable for a historically estimated dictionary to identify new crises in real time.

The main empirical findings are largely unchanged. Table D.2 reports the lead-lag regressions of Section 5.3 with the NSI^{CC} in place of the baseline index. Higher NSI^{CC} remains associated with weaker consumer confidence and lower consumer credit growth. The main difference is that lagged NSI^{CC} is no longer significantly associated with the FSI at horizons $h > 0$. Early in the sample, the recursive dictionary draws on few recessions, so the real-time index provides a noisier estimate of stress attention. The two dictionaries converge as recessions accumulate, and the difference in the early sample measures the estimation error in the recursive construction rather than a difference in the underlying construct.

Figure D.3 presents impulse responses from the VAR of Section 6.1, but re-estimated with the NSI^{CC} as the stress measure. Similar to the baseline index, news shocks continue to generate declines in consumer credit. The main difference is that the response of manufacturing orders is no longer statistically significant.

Overall, the results indicate that the predictive content of the baseline NSI is not an artifact of look-ahead information embedded in the full-sample dictionary construction.

7.3 TF-IDF–weighted index

The baseline NSI weights all dictionary bigrams equally. While this simplicity aids interpretation, it may allow a handful of frequent but relatively uninformative terms to exert disproportionate influence on the index. To address this concern, we construct a variant of the NSI that weights each bigram by its distinctiveness in the corpus using term frequency–inverse document frequency (TF-IDF) weights. Under this scheme, bigrams that appear in relatively few articles receive larger weights, because their occurrence is more indicative of stress-related content:

$$\text{NSI}_{i,t}^{\text{TFIDF}} = \frac{\sum_{b \in \mathcal{C}^{NSI}} tf_{b,i,t} \times idf_b}{\sqrt{\sum_{b' \in \mathcal{C}^{NSI}} \left(tf_{b',i,t} \times idf_{b'}\right)^2}}, \qquad idf_b = \ln\left(\frac{1+N}{1+n_b}\right) + 1, \tag{8}$$

where $tf_{b,i,t}$ is the number of occurrences of bigram b in article i in month t, N is the total number of articles in the corpus, n_b is the number of articles containing bigram b, and the denominator is the Euclidean (L^2) norm of article i's vector of tf–idf weights over the dictionary vocabulary $\mathcal{C}^{NSI}$.[20] The idf_b weights are estimated once on the full corpus and held fixed, so that variation in the index reflects changes in the text rather than changes in the weighting scheme. Normalizing by the L^2 norm bounds the contribution of each article and removes the mechanical effect of article length, so that an article's score reflects the composition of its stress-related language.

[20] We compute the weights using the `TfidfVectorizer` implementation in the `scikit-learn` Python library (Pedregosa et al., 2011), with smoothed inverse document frequencies and L^2 normalization.

Figure D.4 compares the NSI and NSI^{TF-IDF}. The two series track each other closely throughout the sample, with a pairwise correlation of 79.0%, and identify the same major stress episodes. This similarity suggests that the baseline index is not driven by a handful of frequent but uninformative terms, with the advantage of being simpler and independent of any corpus-wide weight estimation.

The main empirical findings are largely unchanged. Table D.3 reports the corresponding lead-lag regressions. Higher NSI^{TFIDF} remains associated with greater financial stress, weaker consumer confidence, and lower future credit growth. Likewise, news shocks from the VAR in Figure D.5 re-estimated with NSI^{TFIDF} generate declines in consumer credit and manufacturing orders. Overall, the results indicate that the main findings are not sensitive to the equal-weighting scheme used in the construction of the baseline NSI.

Taken together, the robustness exercises suggest that the main findings are not driven by the choice of dictionary, look-ahead bias in dictionary construction, or the equal-weighting scheme used to aggregate keywords.

8 Conclusion

This paper introduces a news-based measure of perceived financial stress, applied to Canada using nearly five decades of business news. Unlike traditional measures based on financial market prices, the News-based Stress Index captures shifts in attention to financial risks as reflected in media coverage. The index tracks major episodes of financial stress and correlates strongly with macro-financial conditions.

Our results show that perceived financial stress and realized financial stress are distinct phenomena with different macroeconomic consequences. While financial stress reflected in market prices primarily increases downside risks to economic activity, news-based stress mainly affects household behavior, consistent with precautionary motives. News-based stress leads to reductions in unsecured credit and weaker future demand even when financial market conditions remain relatively benign. The distinction is particularly relevant during recent periods of high uncertainty in which households express heightened concerns despite limited signs of stress in asset prices.

More broadly, our findings suggest that monitoring financial vulnerabilities may benefit from incorporating measures of perceived stress alongside traditional market-based indicators. News narratives provide information about attention, expectations, and concerns that are not fully reflected in asset prices, yet may influence economic decisions and ultimately shape macro-financial outcomes.

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A Appendix: additional NSI information

Table A.1: Hyperparameter specification and tuning ranges

Model	**Parameter**	**Tuning Range**	**Description**
Naive Bayes	α	{0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100}	Laplace smoothing parameter
SVM	C	{0.1, 1, 10, 100, 200}	Regularization parameter
	Kernel	Linear, rbf	Controls the shape of the decision boundary
	max_iter	1000	Maximum number of optimization iterations allowed
Random Forest	n_estimators	150	Number of decision trees in the ensemble
	max_depth	{1, 5, 10, 30}	Maximum depth allowed for each decision tree
	max_features	{`sqrt`, 0.1, 0.2}	Number of features randomly selected at each split

Table A.2: Top 100 most frequent keywords

Keyword	Count	Keyword	Count	Keyword	Count
united state	212125	fund manager	12296	high rate	8420
interest rate	96389	high interest	11955	canadian bond	8339
long term	70935	bond market	11854	rate cut	8321
real estate	65539	bond yield	11629	york base	8306
bank canada	62003	dominion bank	11442	price high	8025
prime minister	60393	emerge market	11385	big bank	7907
stock market	46022	nesbitt burn	11285	portfolio manager	7773
central bank	36930	commodity price	11201	bank commerce	7743
nova scotia	35255	monetary policy	11171	goldman sachs	7676
royal bank	34443	hedge fund	11066	institutional investor	7646
short term	30909	hold company	10978	imperial bank	7534
mutual fund	30158	private equity	10871	george bush	7508
finance minister	28494	high yield	10851	canadian imperial	7494
oil price	27020	rbc dominion	10766	morgan stanley	7324
financial service	22799	standard poor	10671	global economy	7319
bank montreal	22732	housing market	10350	precious metal	7319
cibc world	22686	money market	10253	world bank	7294
economic growth	21597	reserve board	10002	record high	7245
federal reserve	20837	dominion security	9941	preferred share	7184
stock price	20791	equity fund	9857	canadian stock	7083
financial institution	18142	middle east	9832	td bank	6836
capital market	16658	insurance company	9743	bank financial	6772
high level	16380	financial crisis	9703	canada big	6748
national bank	16060	canadian bank	9696	cut cost	6674
chief economist	14801	foreign exchange	9420	raise money	6618
credit card	14759	commercial paper	9286	investment banking	6613
balance sheet	14416	rate high	9109	price fall	6467
crude oil	13820	state canada	9063	euro zone	6436
basis point	13533	european union	8938	investment bank	6434
merrill lynch	13120	total return	8645	public offering	6410
toronto dominion	12761	government bond	8644	fixed income	6400
financial market	12663	bmo nesbitt	8631	foreign investor	6382
world market	12452	analyst expect	8574	country large	6298
bank nova	12343				

Table A.3: Top 90 keywords grouped into seven macro-financial categories from Duprey (2020)

Category	Keywords
Equity	stock market, stock price, mutual fund, equity fund, hedge fund, private equity, fund manager, portfolio manager, institutional investor, standard poor, high yield, world market, canadian stock, preferred share, total return, record high, analyst expect
Government	bank canada, central bank, federal reserve, reserve board, monetary policy, interest rate, rate cut, government bond, canadian bond, finance minister, prime minister, george bush, national bank, high level
Foreign Exchange	united state, state canada, foreign exchange, emerge market, middle east, european union, world bank, global economy
Money / Credit	money market, commercial paper, credit card, basis point, high interest, high rate, rate high, bond market, bond yield, long term, short term
Banking / Corporate Finance	financial institution, financial service, financial market, financial crisis, capital market, balance sheet, chief economist, insurance company, hold company, canadian bank, big bank, canada big, royal bank, bank montreal, nova scotia, bank nova, toronto dominion, dominion bank, td bank, bank commerce, imperial bank, canadian imperial, bank financial, cibc world, rbc dominion, dominion security, nesbitt burn, bmo nesbitt, merrill lynch, goldman sachs, morgan stanley, york base
Housing / Real Estate	real estate, housing market
Corporate / Commodities	oil price, crude oil, commodity price, precious metal, price high, economic growth

Figure A.1: ROC curves: NSI across alternative stress definitions

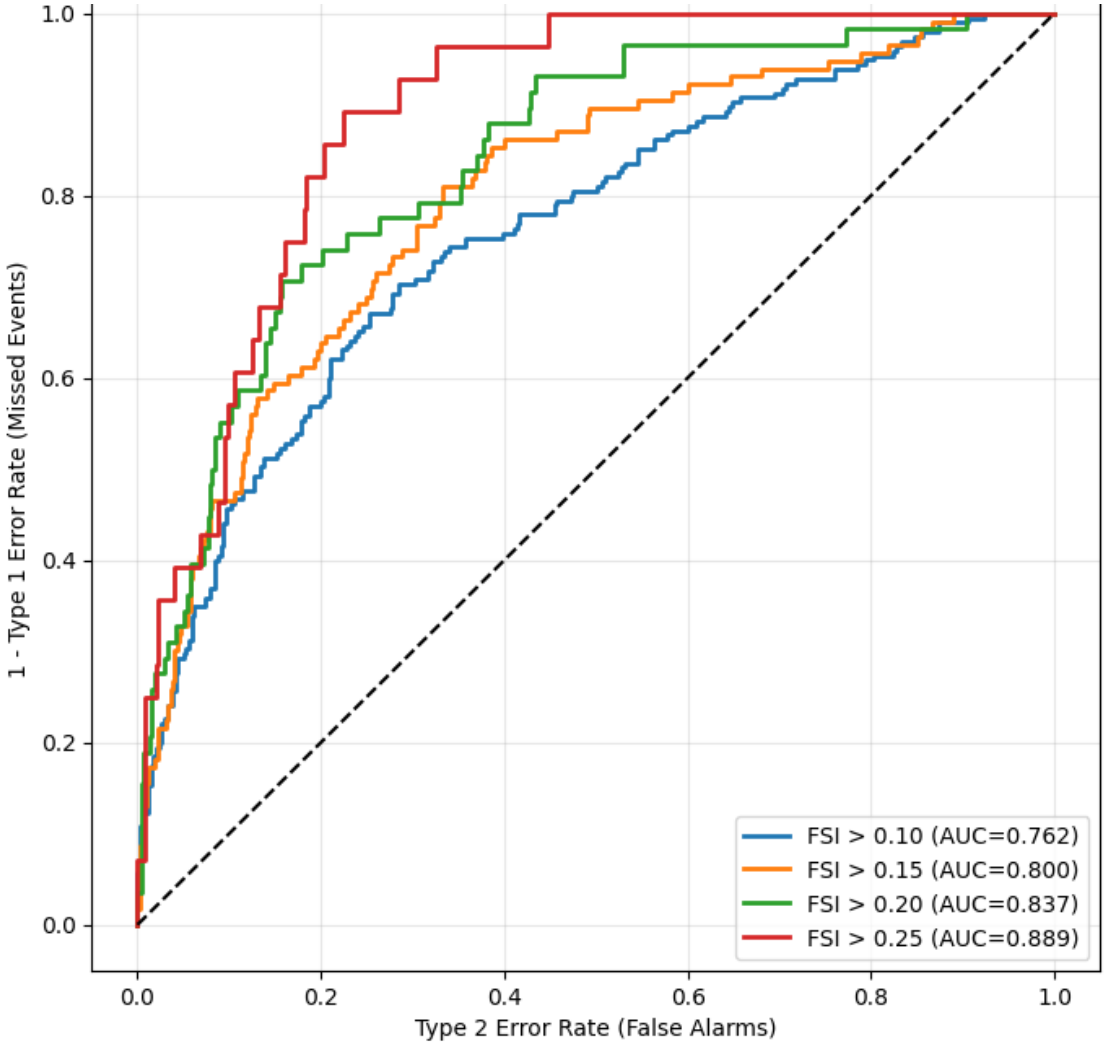


Figure A.1 presents receiver operating characteristic (ROC) curves evaluating the ability of NSI to contemporaneously signal periods of elevated financial stress under alternative stress definitions. Stress episodes are defined as months in which the Canadian Financial Stress Index (FSI) exceeds various thresholds (0.10, 0.15, 0.20, and 0.25). For each definition, we compute the true positive rate (1 minus the missed-event rate) against the false positive rate (false alarms) across all possible NSI thresholds.

Across all stress definitions, the ROC curves lie well above the 45-degree line corresponding to a random classifier, indicating substantial discriminatory power. The area under the curve (AUC) ranges from 0.762 to 0.889, implying that NSI assigns higher values to stress months than to non-stress months approximately 76–89 percent of the time. Notably, performance improves as the stress threshold increases, with the highest AUC observed when stress is defined more restrictively (FSI $>$ 0.25). This pattern suggests that NSI is particularly effective at identifying episodes of more severe financial stress.

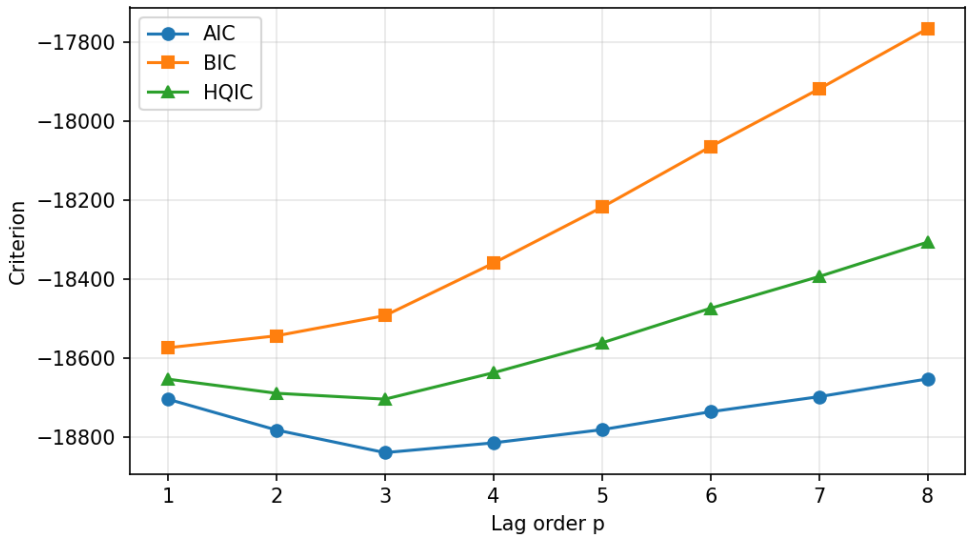
Table A.4: Variable definitions

Variable	Description	Source
NSI	Canadian News Stress Index	Authors' calculations
NSI^{CC}	Chronologically consistent NSI	
NSI^{TF-IDF}	TF-IDF weighted NSI	
FSI	Canadian Financial Stress Index	Duprey (2020)*
VIX (US)	U.S. VIX volatility index	FRED
Corp Spread (US)	U.S. corporate bond spread (average spread)	
MES (Banks, CA)	Marginal Expected Shortfall of Canadian bank equities (average across banks)	MacDonald et al. (2016)
Distance-to-Default (Banks, CA)	Distance-to-default measure for Canadian banks (average across banks)	
Δ log Bank Equity Index (CA)	Log difference of the Canadian bank stock index	Datastream
Δ log TSX (SA)	Log difference of the seasonally adjusted TSX index	
T-bill 3M (CA)	3-month Government of Canada Treasury bill yield	
Term Spread 5Y–3M (CA)	Term spread: 5-year minus 3-month Government of Canada yield	
Interbank Spread (CA)	Spread between interbank lending rate and 3-month Treasury bill	
Credit Spread BBB–A (CA)	Corporate credit spread between BBB and A rated bonds	Merrill-Lynch
Overnight Repo (CA)	Overnight repo rate for Canada	Datastream
Corp Paper–Tbill Spread 3M (CA)	Spread between 3-month commercial paper and 3-month Treasury bill	
Δ log Oil (WCS/WCC)	Log difference of Canadian oil prices	
Δ log REER (CA)	Log difference of the real effective exchange rate (REER) of Canada	
Δ log House Prices (CA)	Log difference of real residential house prices in Canada	
Mortgage Spread	Spread between 5-year mortgage rate and 5-year Government of Canada yield	
Consumer Confidence (CA)	Consumer confidence index	Conference board
Consumer Confidence (CA)	Consumer confidence index (discontinued in 2017 but starting in 1980, for Figure 5)	OECD (2025)
Monetary Policy Shock	Monetary policy surprise estimated from a VAR	Champagne and Sekkel (2018)
Δ log CPI (SA, CA)	Log difference of seasonally adjusted CPI (Canada)	Fortin-Gagnon et al. (2022)
Δ log IPI (SA, CA)	Log difference of seasonally adjusted industrial production	
Δ log GDP (SA, CA)	Log difference of Canadian GDP (seasonally adjusted)	
Δ log Real Credit (Cons, SA)	Log difference of real non-mortgage consumer credit (seasonally adjusted)	
Δ log Real Credit (Bus, SA)	Log difference of real business credit (seasonally adjusted)	
Δ log Real Credit (Mortgage, SA)	Log difference of real mortgage credit (seasonally adjusted)	
Δ log New Orders (Mfg, SA)	Log difference of real manufacturing new orders (seasonally adjusted)	
Δ log New Orders (Durables, SA)	Log difference of real durable goods new orders (seasonally adjusted)	

* Publicly available at https://www.bankofcanada.ca/rates/indicators/financial-stability-indicators/

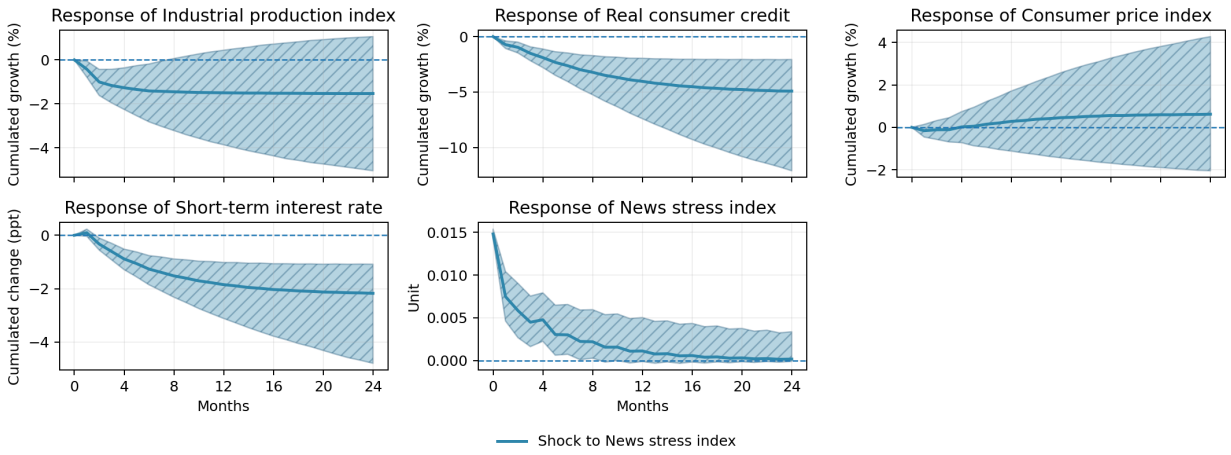
B Appendix: additional BVAR results

Figure B.1: Choice of the lag order for the benchmark vector autoregression



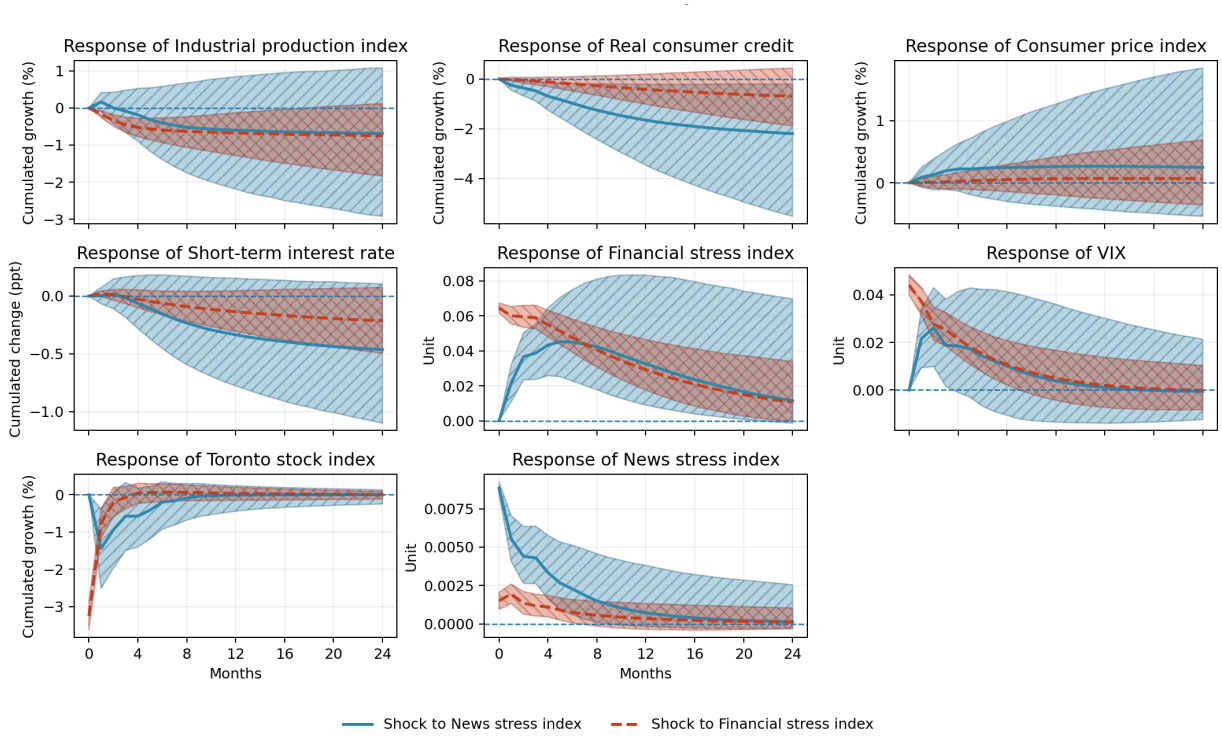
Note: Benchmark monthly Bayesian VAR with 1 to 8 lags over 1981m1-2025m7.

Figure B.2: Impulse response after a news shock: robustness without financial stress shocks



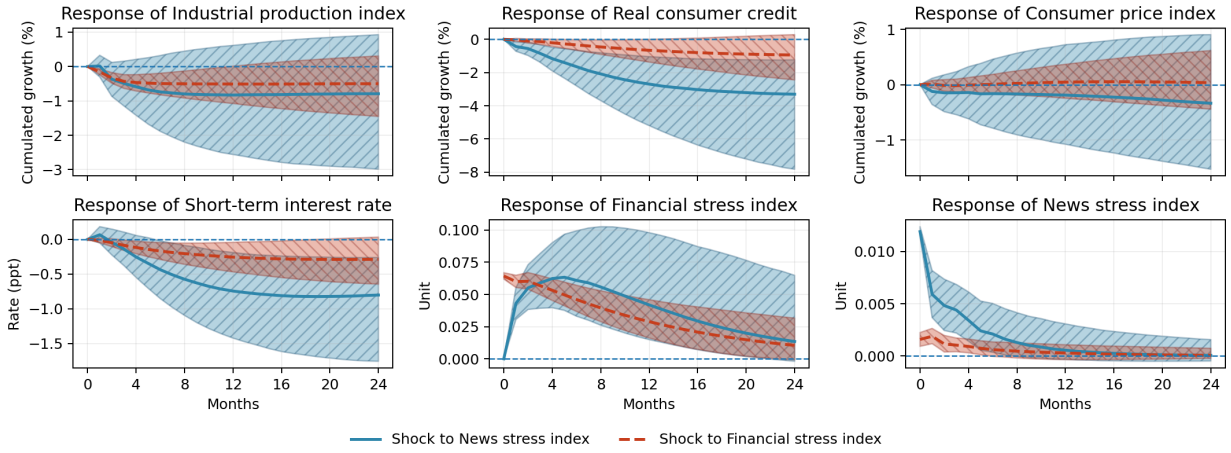
Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). Stress shocks identified using Cholesky ordering: news shocks are not reflected in macro variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

Figure B.3: Impulse response after a financial or news shock: robustness with stock price data



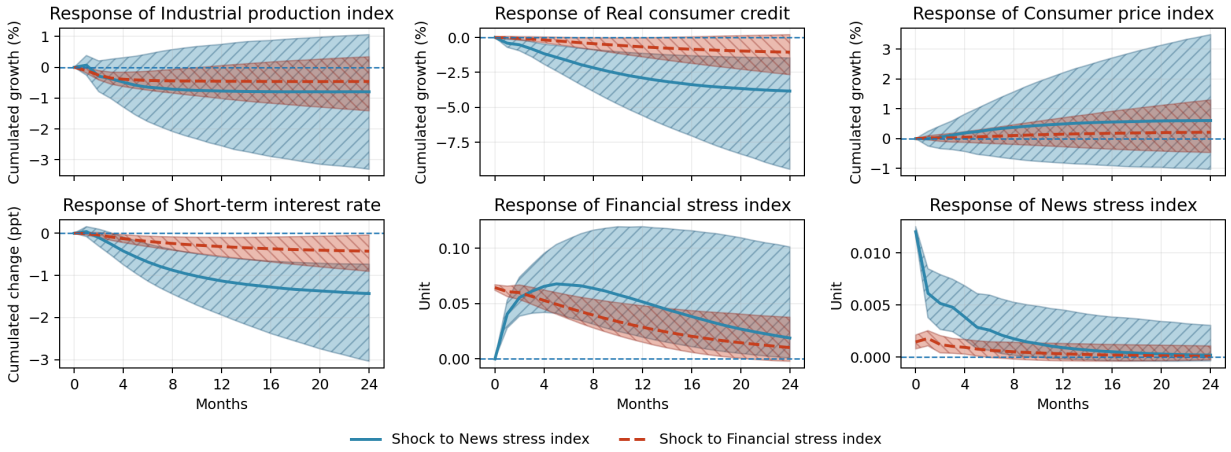
Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). Specification with the addition of the US VIX and the Canadian TSX. Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

Figure B.4: Impulse response after a financial or news shock: robustness with the short-term rate in level



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the level for the short-term rate). Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

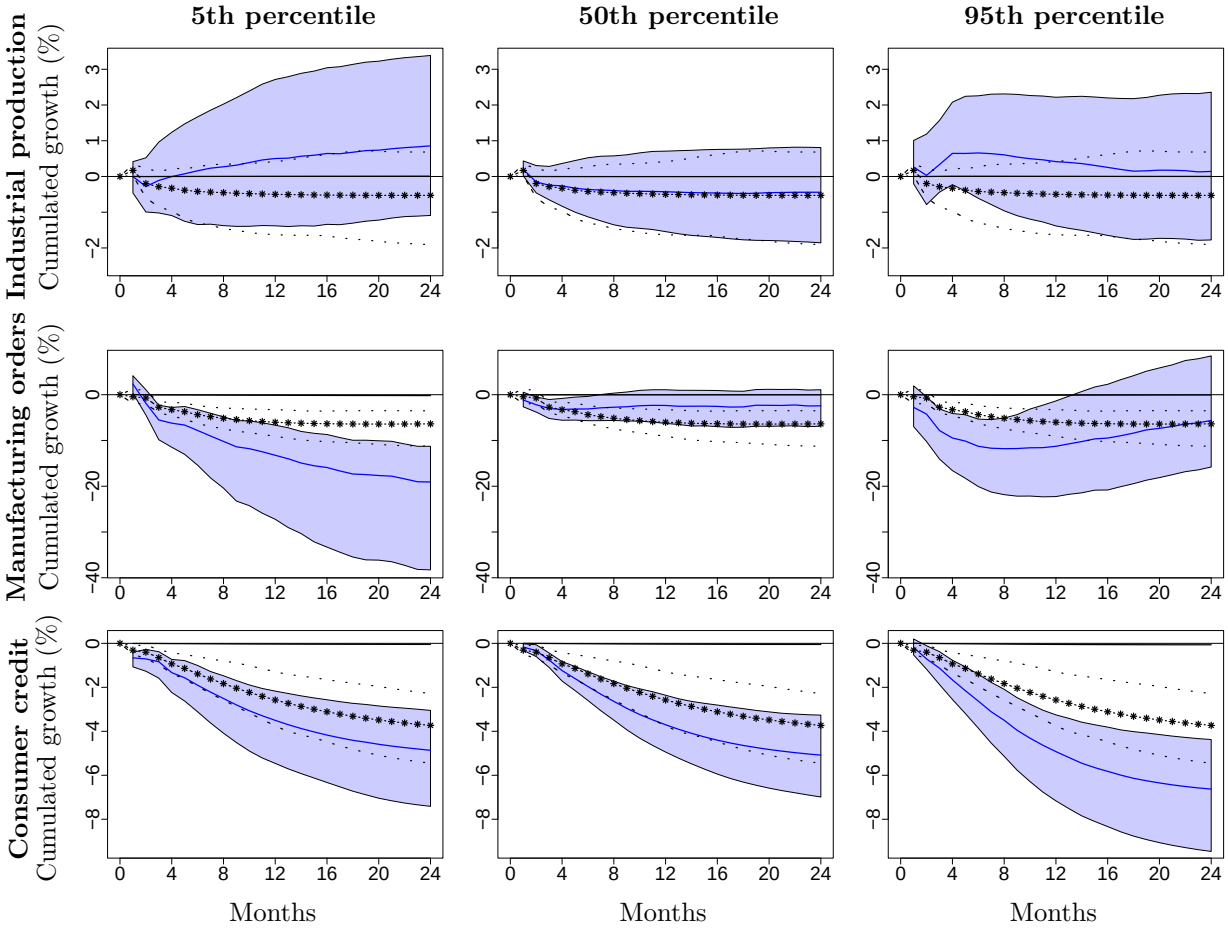
Figure B.5: Impulse response after a financial or news shock: filtering out the COVID shock



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). To correct for the spikes during the pandemic, we pre-filter all variables using the change in the COVID-19 policies stringency index from Hale et al. (2021) and the number of excess death due to COVID-19 from Mathieu et al. (2020). Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. Shock magnitudes of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

C Appendix: additional QAVAR results

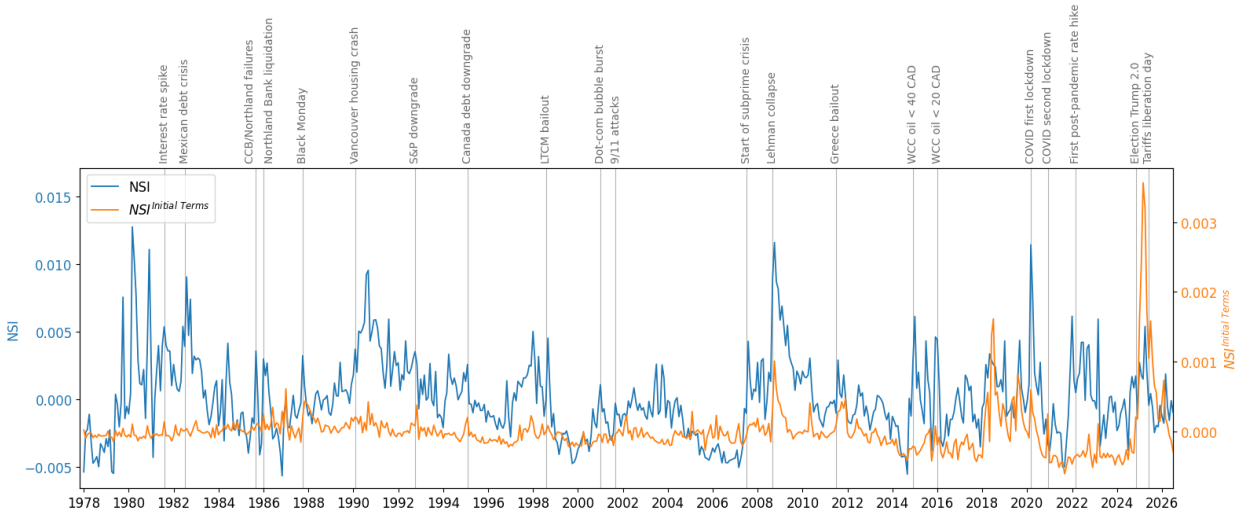
Figure C.1: Quantile impulse response to a news stress shock, adjusted for COVID spike



Notes: Monthly Quantile-augmented VAR (QAVAR, following the method of Boire et al. (2025)) with three lags over 1981m1-2025m7; one model per row. All variables are pre-filtered using the change in the COVID-19 policies stringency index from Hale et al. (2021) and the number of excess death due to COVID-19 from Mathieu et al. (2020). Macroeconomic variables are all seasonally adjusted, in real terms and expressed in log-difference cumulated since period zero over the horizon. Stress shocks identified using Cholesky ordering: news-based stress shocks are not reflected in financial prices on impact, while news-based and financial stress shocks are not reflected in macroeconomic variables on impact. The news-based stress shock is scaled such that the news-based stress index increases to 0.01 on impact. The quantile-augmented VAR model is represented by the plain blue line and the blue shaded confidence bands. The mean response from the equivalent linear VAR is in the starred black line with the confidence bands in dashed black. The confidence bands are the 10th and 90th percentiles produced with 53500 replications (100*535): 100 block bootstrapped replications with block sizes of two years for 535 possible initial conditions (we have 535 monthly observations).

D Appendix: alternative NSI measures

Figure D.1: NSI and NSI^{IT} monthly news attention to known stress events



Note: The initial-terms index applies Equations (1)-(2) using only the 116 initial expert-curated keywords of Table 2. Because these terms appear in far fewer articles, the index operates on a smaller scale and is plotted on the right axis. Vertical lines represent major Canadian and global stress events. The pairwise correlation between the two series is 27.9%.

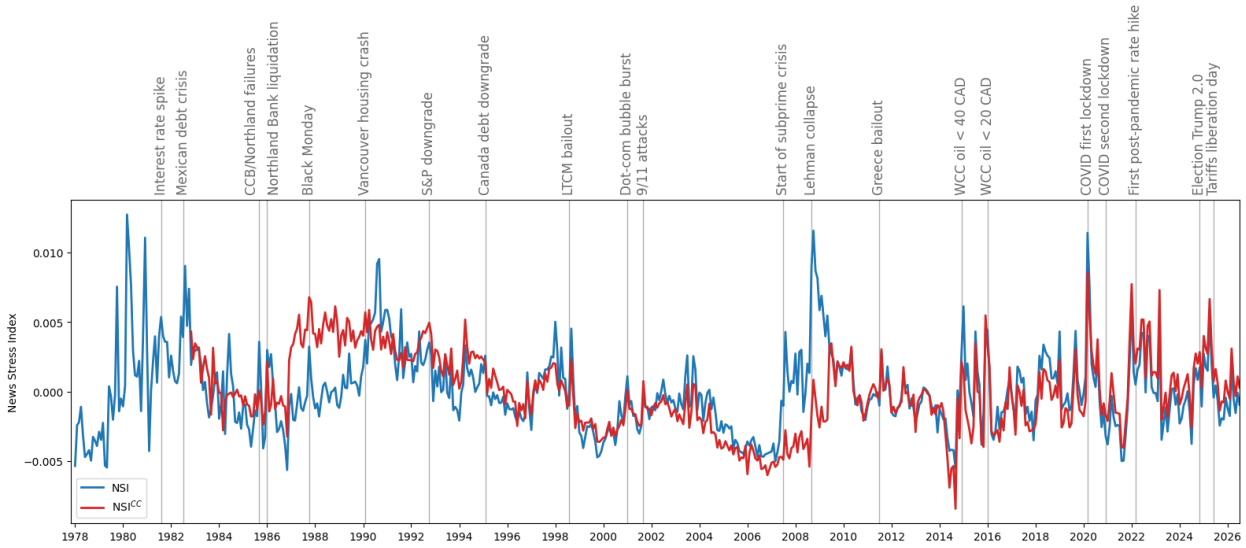
Table D.1: Lead-lag specification results (initial terms NSI)

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Panel A: Financial Stress & Risk											
FSI	19.17	2.26	4.49	19.40	22.24	3.90	-0.01	-0.03*	-0.04*	-0.03*	-0.04*
	(0.72)	(0.57)	(0.45)	(0.92)	(0.71)	(0.14)	(-1.47)	(-1.72)	(-1.91)	(-1.86)	(-1.95)
VIX (US)	3914.82*	-51.70	-549.65	-382.29	-607.31	-1124.63	-0.00	-0.00*	-0.00***	-0.00*	-0.00***
	(1.79)	(-0.09)	(-0.79)	(-0.38)	(-0.56)	(-0.60)	(-1.31)	(-1.73)	(-2.63)	(-1.91)	(-2.71)
Corp Spread (US)	1153.78*	67.33	84.10	226.96	132.96	83.62	0.00	-0.00	-0.00	-0.00	-0.00
	(1.95)	(1.35)	(0.87)	(1.62)	(0.84)	(0.45)	(1.12)	(-0.77)	(-1.23)	(-1.30)	(-1.09)
Panel B: Banking Sector											
MES (Banks, CA)	2529.32***	484.68*	422.89	113.29	-14.83	-274.78	0.00*	0.00	-0.00	-0.00	-0.00*
	(3.09)	(1.76)	(1.38)	(0.31)	(-0.05)	(-0.73)	(1.75)	(0.02)	(-1.10)	(-0.78)	(-1.69)
Distance-to-Default (Banks, CA)	-187.84	-31.34	-52.68	-112.18	-136.63	72.82	0.00	0.00	0.00	0.00	0.00
	(-0.64)	(-1.47)	(-1.03)	(-1.17)	(-0.94)	(0.23)	(0.50)	(0.48)	(0.38)	(0.38)	(0.65)
Δ log Bank Equity Index (CA)	-15.41*	2.75	7.08	8.14	4.48	2.04	0.01	0.01	0.05	0.00	0.03
	(-1.95)	(0.56)	(1.41)	(1.41)	(0.83)	(0.38)	(0.33)	(0.61)	(1.49)	(0.02)	(1.07)
Panel C: Equity Markets											
Δ log TSX (SA)	-12.82	5.08	6.80**	4.30	1.20	3.90	-0.02	0.00	0.05	0.02	0.06**
	(-1.51)	(1.51)	(2.11)	(0.97)	(0.34)	(0.81)	(-0.82)	(0.02)	(1.39)	(0.60)	(2.28)
Panel D: Government Bond Markets											
Monetary Policy Shock	-120.59	68.93	115.13	157.16	171.78	18.81	0.00	-0.00	0.00	0.00	0.00
	(-0.70)	(0.46)	(1.11)	(1.45)	(1.52)	(0.21)	(0.70)	(-0.21)	(0.47)	(0.15)	(0.00)
T-bill 3M (CA)	525.61	-22.88	-126.46	-258.24*	-371.42*	-675.50	0.00	0.00	0.00	0.00**	0.00**
	(0.58)	(-0.89)	(-1.58)	(-1.80)	(-1.79)	(-1.57)	(0.53)	(0.85)	(1.48)	(2.04)	(2.27)
Term Spread 5Y–3M (CA)	-55.25	-37.61	-31.50	-86.45	-115.43	-274.58	-0.00	0.00	0.00	0.00	0.01
	(-0.74)	(-1.06)	(-1.02)	(-1.54)	(-1.53)	(-1.52)	(-0.85)	(0.43)	(1.29)	(1.32)	(1.33)
Panel E: Money Markets											
Interbank Spread (CA)	560.31***	22.27	61.92	158.89	171.01	-144.30	0.01*	0.01	0.01	0.01	0.00
	(4.36)	(0.83)	(1.05)	(1.28)	(0.87)	(-0.57)	(1.67)	(1.14)	(1.01)	(0.95)	(0.81)
Panel F: Corporate Sector											
Credit Spread BBB-A (CA)	-21.97	3.40	-5.26	-12.65	-10.02	32.09	-0.00*	-0.00*	-0.00**	-0.00***	-0.00***
	(-0.76)	(0.44)	(-0.28)	(-0.41)	(-0.25)	(0.58)	(-1.85)	(-1.90)	(-2.13)	(-2.83)	(-2.70)
Corp Paper–Tbill Spread 3M (CA)	-52.12*	-30.77	-61.44	-71.26**	-38.19	-83.45	0.00	-0.00	-0.00	-0.00	-0.00
	(-1.75)	(-1.14)	(-1.45)	(-2.03)	(-1.11)	(-1.45)	(0.05)	(-1.25)	(-1.19)	(-1.44)	(-1.46)
Panel G: Commodity Markets											

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h=0$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Δ log Oil (WCS/WCC)	-35.30*	-31.62*	-11.79	1.23	35.68	37.64	0.00	0.00	-0.00	-0.00	0.01
	(-1.85)	(-1.78)	(-0.87)	(0.05)	(1.06)	(1.08)	(0.53)	(0.23)	(-0.11)	(-0.16)	(0.70)
Panel H: Foreign Exchange Markets											
Δ log REER (CA)	-2.90	2.50**	2.96**	2.59	-0.06	5.71**	-0.03	-0.06	-0.02	0.05	0.14
	(-1.14)	(2.13)	(2.30)	(1.39)	(-0.03)	(2.16)	(-0.63)	(-0.58)	(-0.30)	(0.68)	(1.20)
Panel I: Housing Markets											
Δ log House Prices (CA)	-2.89	0.13	3.25	0.69	5.62	7.22*	-0.04	-0.05	-0.07	-0.05	-0.04
	(-1.26)	(0.06)	(1.46)	(0.27)	(1.29)	(1.72)	(-0.67)	(-0.83)	(-1.07)	(-0.79)	(-0.53)
Mortgage Spread	128.34	15.19	-38.23	-60.36	-80.46	-162.53	-0.00	0.00	0.00	0.00*	0.00
	(0.94)	(0.66)	(-1.11)	(-1.00)	(-1.08)	(-1.18)	(-0.37)	(0.22)	(1.24)	(1.65)	(1.51)
Panel J: Real Economy											
Consumer Confidence (CA)	-8788.53*	-1057.09	-177.28	-530.81	-83.43	3450.92	-0.00	-0.00	0.00	-0.00	-0.00
	(-1.90)	(-1.36)	(-0.16)	(-0.35)	(-0.03)	(0.71)	(-0.13)	(-0.04)	(0.06)	(-0.12)	(-0.18)
Δ log Real Credit (Cons, SA)	0.51	0.26	0.11	0.29	0.07	-0.17	0.12	0.20	0.07	0.26	0.32
	(0.71)	(0.53)	(0.24)	(0.28)	(0.06)	(-0.17)	(0.88)	(1.44)	(0.37)	(1.25)	(1.56)
Δ log Real Credit (Bus, SA)	0.03	-1.19**	-0.42	-0.57	1.42	0.22	-0.16	-0.11	-0.04	-0.02	-0.13
	(0.04)	(-1.98)	(-0.74)	(-0.47)	(1.03)	(0.16)	(-1.55)	(-0.65)	(-0.22)	(-0.14)	(-0.82)
Δ log Real Credit (Mortgage, SA)	1.20	0.16	0.21	1.48**	1.79*	2.44**	-0.12	0.09	0.03	0.18	-0.03
	(1.25)	(0.45)	(0.50)	(2.09)	(1.66)	(2.54)	(-0.81)	(0.56)	(0.13)	(0.82)	(-0.11)
Δ log CPI (SA, CA)	-1.00**	-0.23	-0.11	-0.40	-0.16	0.10	0.27	0.16	0.42	-0.13	0.03
	(-2.42)	(-0.92)	(-0.42)	(-0.76)	(-0.25)	(0.15)	(1.28)	(0.75)	(1.06)	(-0.38)	(0.09)
Δ log New Orders (Mfg, SA)	-0.14	-11.73**	-4.19	-3.96	0.95	-4.13	-0.03	-0.01	-0.00	-0.02	-0.03
	(-0.04)	(-2.13)	(-0.83)	(-1.20)	(0.10)	(-0.51)	(-1.60)	(-0.66)	(-0.05)	(-0.56)	(-1.28)
Δ log IPI (SA, CA)	-2.44**	-2.42**	-0.70	-2.48	0.12	-0.05	0.10	0.23	0.16	0.08	-0.10
	(-2.34)	(-2.50)	(-0.50)	(-1.33)	(0.07)	(-0.03)	(0.66)	(0.81)	(0.66)	(0.38)	(-0.41)
Δ log GDP (CA, SA)	-2.55*	-1.65**	-1.01*	-1.93	0.64	3.86	0.09	0.06	0.26**	-0.09	0.01
	(-1.70)	(-2.33)	(-1.85)	(-1.20)	(0.27)	(1.29)	(1.05)	(0.46)	(2.27)	(-0.57)	(0.06)

Notes: Coefficient estimates are multiplied by 100 for the right panel columns with t-statistics in parentheses below each coefficient. * p<0.10, ** p<0.05, *** p<0.01. Variables definition and sources are listed in Appendix C Table A.4.

Figure D.2: NSI and NSI^{CC} monthly news attention to known stress events



Note: Vertical lines represent major Canadian and global stress events. The NSI pairwise correlation with the chronologically consistent NSI^{CC} of Equation (7) is 64.8%. The NSI^{CC} starts only in 1982 as we do not have prior recessions in our dataset so we cannot identify the stress keywords in real time prior when the first recession entering our data.

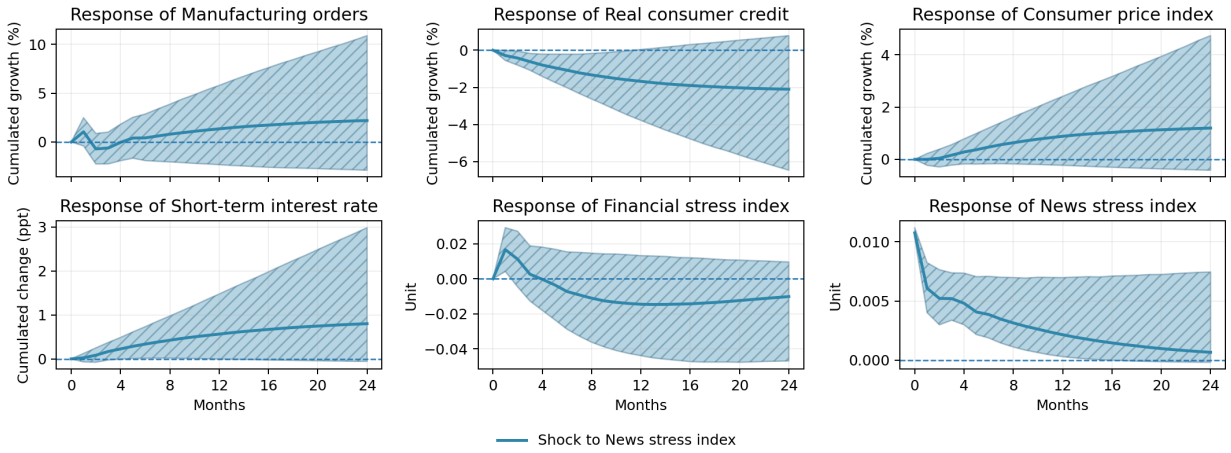
Table D.2: Lead-lag specification results (chronologically consistent NSI)

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Panel A: Financial Stress & Risk											
FSI	7.97***	-0.13	-1.40	-1.78	-3.02	-3.93	-0.00	-0.04	-0.00	0.06	0.15
	(3.24)	(-0.25)	(-0.88)	(-0.63)	(-0.88)	(-1.06)	(-0.01)	(-0.24)	(-0.02)	(0.28)	(0.70)
VIX (US)	527.76**	-107.21	-317.74*	-285.67	-544.92**	-787.29***	-0.00	-0.00	-0.00	-0.00	0.00
	(2.40)	(-1.54)	(-1.86)	(-1.29)	(-2.31)	(-3.24)	(-1.33)	(-1.35)	(-1.01)	(-0.03)	(0.12)
Corp Spread (US)	32.76	-4.76	-32.48*	-47.17	-72.57**	-89.80**	0.00	0.01	0.03	0.05**	0.06***
	(1.50)	(-0.91)	(-1.79)	(-1.60)	(-2.01)	(-2.32)	(0.10)	(0.50)	(1.09)	(2.43)	(3.06)
Panel B: Banking Sector											
MES (Banks, CA)	46.62**	1.97	-22.87	-29.89	-44.37	-58.48	-0.01	-0.01	0.00	0.01	0.01
	(2.21)	(0.24)	(-1.07)	(-1.02)	(-1.31)	(-1.63)	(-1.58)	(-0.35)	(0.12)	(0.72)	(0.62)
Distance-to-Default (Banks, CA)	-10.90	3.77	15.97	35.10*	63.67**	109.97***	0.00	0.00	0.01	0.00	-0.00
	(-0.25)	(0.92)	(1.40)	(1.66)	(2.27)	(3.42)	(0.60)	(0.57)	(0.51)	(0.08)	(-0.07)
Δ log Bank Equity Index (CA)	-1.93**	0.22	0.29	-0.37	0.76	0.94	0.25	0.58***	0.54**	0.53*	0.04
	(-2.12)	(0.40)	(0.36)	(-0.44)	(0.90)	(1.15)	(1.46)	(2.98)	(2.47)	(1.86)	(0.17)
Panel C: Equity Markets											
Δ log TSX (SA)	-2.15***	0.32	0.52	-0.48	0.32	1.05	0.37**	0.63***	0.98***	0.48	0.29
	(-2.90)	(0.52)	(0.69)	(-0.68)	(0.42)	(1.43)	(2.23)	(2.74)	(4.26)	(1.19)	(0.84)
Panel D: Government Bond Markets											
Monetary Policy Shock	8.62	10.46	11.63**	4.72	7.14	8.62	0.02	0.02	0.04**	-0.03	-0.02
	(1.34)	(1.49)	(2.00)	(0.84)	(1.23)	(1.47)	(1.27)	(1.03)	(2.05)	(-1.08)	(-0.54)
T-bill 3M (CA)	500.79***	9.56	36.69*	74.06**	107.14**	139.97***	0.01***	0.01***	0.01**	0.01**	0.02***
	(4.90)	(1.33)	(1.89)	(2.30)	(2.54)	(2.75)	(3.37)	(2.89)	(2.32)	(2.43)	(2.86)
Term Spread 5Y–3M (CA)	17.68	4.85	9.26	7.93	4.96	9.79	0.02	0.04*	0.05	0.05	0.05
	(1.54)	(1.07)	(1.30)	(0.93)	(0.49)	(0.90)	(0.96)	(1.74)	(1.61)	(1.43)	(1.56)
Panel E: Money Markets											
Interbank Spread (CA)	7.57	-2.30	-3.42	-2.97	-6.05	-9.72	-0.00	-0.02	-0.06*	-0.07	-0.03
	(0.70)	(-0.99)	(-1.01)	(-0.52)	(-0.85)	(-1.16)	(-0.03)	(-0.59)	(-1.77)	(-1.52)	(-0.49)
Panel F: Corporate Sector											
Credit Spread BBB-A (CA)	28.24**	4.60**	7.99*	10.52	15.41*	22.69**	0.01	0.02	0.03	0.03	0.04
	(2.09)	(2.37)	(1.86)	(1.57)	(1.88)	(2.24)	(1.31)	(1.00)	(1.11)	(1.13)	(1.60)
Corp Paper–Tbill Spread 3M (CA)	2.56	1.94	6.09	1.73	2.76	0.47	0.00	-0.01	-0.01	-0.07*	-0.07*
	(0.33)	(0.39)	(0.89)	(0.25)	(0.40)	(0.07)	(0.09)	(-0.32)	(-0.32)	(-1.88)	(-1.86)
Panel G: Commodity Markets											

Variable	$h=0$	Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
		$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Δ log Oil (WCS/WCC)	-5.25*	-2.02	1.31	-2.12	2.20	-0.16	0.01	0.14**	0.04	0.13*	0.02
	(-1.79)	(-0.82)	(0.54)	(-0.89)	(0.88)	(-0.08)	(0.33)	(2.51)	(0.67)	(1.82)	(0.37)
Panel H: Foreign Exchange Markets											
Δ log REER (CA)	-0.59**	-0.06	0.15	-0.08	0.04	0.11	-0.15	1.28*	0.43	1.74*	-0.05
	(-2.19)	(-0.30)	(0.54)	(-0.28)	(0.15)	(0.36)	(-0.28)	(1.86)	(0.56)	(1.87)	(-0.06)
Panel I: Housing Markets											
Δ log House Prices (CA)	-0.51	-0.46	-0.35	-0.39	-0.12	-0.25	-0.06	0.13	0.27	0.36	0.36
	(-1.57)	(-1.44)	(-0.69)	(-1.32)	(-0.34)	(-0.76)	(-0.15)	(0.24)	(0.46)	(0.69)	(0.55)
Mortgage Spread	77.43***	6.75*	9.57	3.46	5.51	8.79	0.03***	0.05***	0.08***	0.10***	0.13***
	(5.00)	(1.87)	(1.17)	(0.31)	(0.40)	(0.53)	(2.91)	(2.77)	(3.05)	(3.25)	(3.80)
Panel J: Real Economy											
Consumer Confidence (CA)	-3156.90***	-381.68***	-464.44**	-1032.18***	-1476.29***	-1556.19***	-0.00*	-0.00*	-0.00	-0.00	-0.00
	(-5.62)	(-2.81)	(-2.00)	(-2.73)	(-3.35)	(-3.19)	(-1.86)	(-1.82)	(-0.84)	(-1.36)	(-1.57)
Δ log Real Credit (Cons, SA)	-0.31**	-0.28***	-0.22**	-0.23**	-0.24**	-0.18*	-0.51	-1.44	-2.26	-2.56	-4.27
	(-2.47)	(-2.63)	(-2.57)	(-2.31)	(-2.45)	(-1.92)	(-0.41)	(-0.79)	(-0.93)	(-1.00)	(-1.51)
Δ log Real Credit (Bus, SA)	-0.17	-0.23**	-0.25**	-0.24**	-0.15	-0.17	-0.41	-1.32	-1.52	-2.42	-1.47
	(-1.26)	(-2.44)	(-1.96)	(-1.97)	(-1.16)	(-1.35)	(-0.41)	(-1.13)	(-1.05)	(-1.59)	(-0.79)
Δ log Real Credit (Mortgage, SA)	0.13	0.00	-0.05	-0.00	-0.10	-0.09	-0.47	2.25	2.22	2.49	3.50
	(1.09)	(0.02)	(-0.57)	(-0.01)	(-0.93)	(-0.88)	(-0.33)	(0.97)	(0.82)	(0.75)	(1.10)
Δ log CPI (SA, CA)	0.07	0.10**	0.16***	0.10*	0.12**	0.13**	3.85*	7.08**	12.26***	10.07**	10.71**
	(1.11)	(2.31)	(3.40)	(1.78)	(1.96)	(2.39)	(1.83)	(2.02)	(2.73)	(2.04)	(2.43)
Δ log New Orders (Mfg, SA)	1.00*	-0.44	0.58	0.32	0.22	-0.03	-0.35**	-0.36**	-0.37	-0.52*	-0.27
	(1.96)	(-0.48)	(0.85)	(0.57)	(0.44)	(-0.06)	(-1.97)	(-2.01)	(-1.33)	(-1.90)	(-1.25)
Δ log IPI (SA, CA)	0.00	-0.02	0.13	-0.01	0.20	0.04	0.21	0.48	2.33	0.49	2.63
	(0.01)	(-0.24)	(0.96)	(-0.06)	(1.21)	(0.28)	(0.22)	(0.32)	(1.30)	(0.23)	(1.16)
Δ log GDP (SA, CA)	-0.53	-0.19	0.31	-0.12	0.31	0.22**	1.42**	1.23	1.64	1.88	-0.71
	(-0.99)	(-0.88)	(1.38)	(-0.55)	(1.22)	(2.15)	(2.28)	(1.44)	(1.27)	(1.40)	(-0.63)

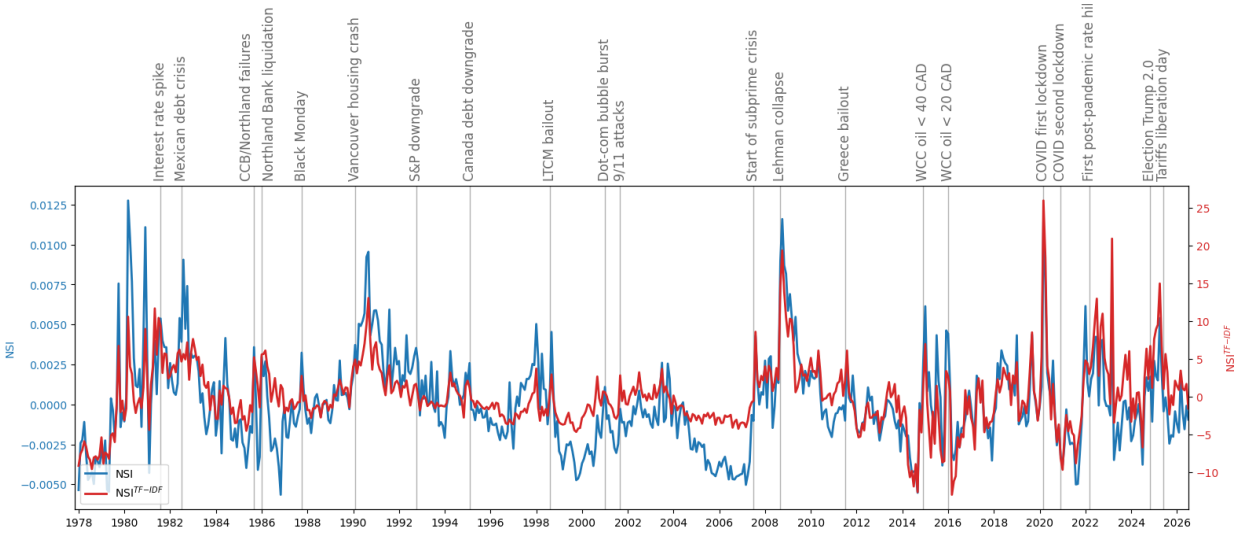
Notes: Coefficient estimates are multiplied by 100 for the right panel columns with t-statistics in parentheses below each coefficient. * p<0.10, ** p<0.05, *** p<0.01. Variables definition and sources are listed in Appendix C Table A.4.

Figure D.3: Impulse responses to an NSI^{CC} shock



Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). The chronologically consistent news-based stress index NSI^{CC} is computed recursively using the recession episodes known up until each point in time. Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. News shock magnitude of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

Figure D.4: NSI and NSI^{TF-IDF} monthly news attention to known stress events



Note: Vertical lines represent major Canadian and global stress events. The NSI pairwise correlation with the frequency weighted NSI^{TF-IDF} of Equation (8) is 79.0%.

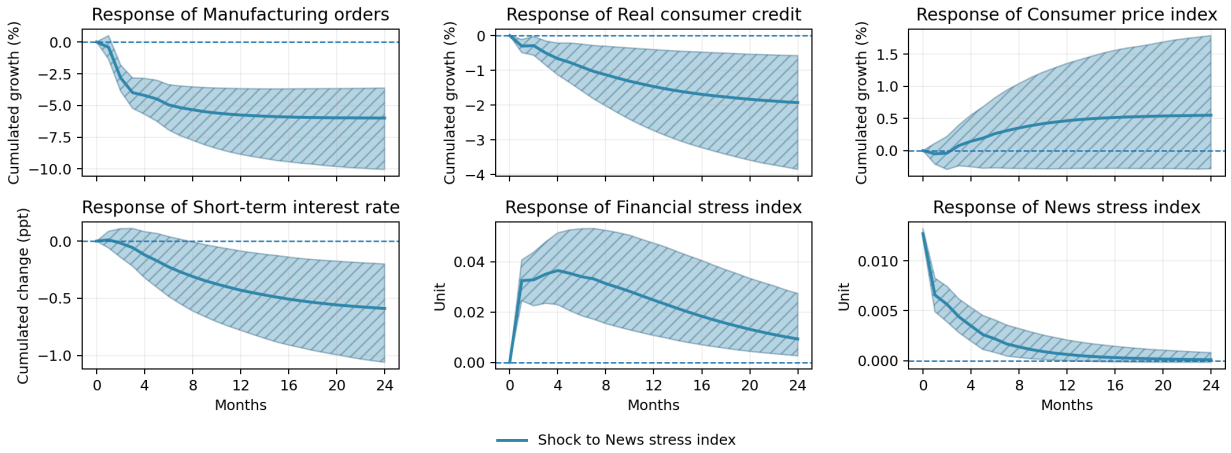
Table D.3: Lead-lag specification results (TF-IDF weighted NSI)

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h=0$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Panel A: Financial Stress & Risk											
FSI	1.06***	0.17***	0.24**	0.42**	0.40**	0.43***	1.87	0.55	-1.80	0.27	1.80
	(4.86)	(2.80)	(1.98)	(2.42)	(2.36)	(2.71)	(0.89)	(0.19)	(-0.49)	(0.08)	(0.57)
VIX (US)	85.00***	7.30	1.35	6.86	-7.66	-22.27**	0.01	-0.03	-0.07	0.00	0.03
	(4.58)	(0.96)	(0.13)	(0.55)	(-0.73)	(-2.03)	(0.45)	(-0.71)	(-1.64)	(0.07)	(0.63)
Corp Spread (US)	8.38***	0.94*	0.60	1.04	0.28	-0.04	0.43	0.60	0.14	0.45	0.53
	(2.70)	(1.95)	(0.67)	(0.88)	(0.26)	(-0.03)	(1.42)	(1.40)	(0.27)	(1.08)	(1.59)
Panel B: Banking Sector											
MES (Banks, CA)	9.90***	2.91**	2.89*	2.80	1.34	1.69	-0.16	-0.10	-0.40	-0.01	-0.08
	(3.21)	(2.52)	(1.81)	(1.51)	(0.91)	(1.01)	(-1.43)	(-0.49)	(-1.62)	(-0.06)	(-0.28)
Distance-to-Default (Banks, CA)	-6.13**	-0.77***	-1.50**	-2.59**	-2.83*	-1.22	-0.02	0.01	0.01	-0.12	-0.16
	(-2.20)	(-3.24)	(-2.45)	(-2.26)	(-1.85)	(-0.68)	(-0.19)	(0.03)	(0.04)	(-0.47)	(-0.67)
Δ log Bank Equity Index (CA)	-0.28***	-0.04	0.01	-0.01	0.05	0.03	-1.37	2.91	8.79**	3.84	-0.07
	(-4.64)	(-0.76)	(0.09)	(-0.11)	(1.07)	(0.68)	(-0.51)	(0.72)	(2.14)	(0.82)	(-0.02)
Panel C: Equity Markets											
Δ log TSX (SA)	-0.26***	-0.04	0.02	-0.05	-0.00	0.01	-2.80	4.98	13.40**	6.20	4.77
	(-4.14)	(-0.78)	(0.41)	(-1.08)	(-0.07)	(0.27)	(-0.87)	(1.02)	(2.48)	(1.20)	(0.99)
Panel D: Government Bond Markets											
Monetary Policy Shock	-0.48	-0.90*	-0.49	-0.62	0.72	0.26	0.14	0.30	0.16	0.16	-0.29
	(-0.76)	(-1.92)	(-1.11)	(-1.13)	(1.17)	(0.53)	(0.45)	(1.08)	(0.53)	(0.49)	(-0.91)
T-bill 3M (CA)	16.95*	-0.88**	-3.98***	-7.65***	-9.68***	-12.10***	0.06*	0.11**	0.14**	0.18***	0.21***
	(1.78)	(-2.01)	(-3.06)	(-3.42)	(-3.38)	(-3.51)	(1.85)	(1.96)	(2.03)	(2.61)	(3.15)
Term Spread 5Y–3M (CA)	0.76	0.28	0.13	-0.50	-0.84*	-1.18*	0.69**	1.69***	1.86***	1.92***	1.99***
	(0.94)	(0.78)	(0.27)	(-1.00)	(-1.67)	(-1.84)	(2.23)	(3.69)	(3.42)	(3.88)	(4.30)
Panel E: Money Markets											
Interbank Spread (CA)	1.04	-0.15	0.08	0.23	0.36	-0.16	0.01	-0.05	-0.42	-0.65	-0.15
	(0.83)	(-0.66)	(0.16)	(0.32)	(0.46)	(-0.25)	(0.05)	(-0.07)	(-0.60)	(-0.88)	(-0.16)
Panel F: Corporate Sector											
Credit Spread BBB-A (CA)	0.58	0.19*	0.17	0.31	0.12	0.32	-0.19	-0.30	-0.33	-0.48	-0.67*
	(1.45)	(1.68)	(0.77)	(0.93)	(0.33)	(0.84)	(-1.16)	(-1.04)	(-0.89)	(-1.28)	(-1.73)
Corp Paper–Tbill Spread 3M (CA)	-0.25	-1.04***	-1.82***	-1.65***	-0.67	-1.03**	-0.16	-0.19	-0.09	-0.02	-0.51
	(-0.36)	(-2.73)	(-3.16)	(-2.91)	(-1.30)	(-2.08)	(-0.74)	(-0.66)	(-0.22)	(-0.04)	(-1.16)
Panel G: Commodity Markets											

		Explaining macro-financial indicators with lagged NSI					Explaining NSI with lagged macro-financial indicators				
Variable	$h=0$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Δ log Oil (WCS/WCC)	-0.70**	-0.29	0.19	-0.13	0.13	-0.05	0.60	3.07**	2.35	3.97**	2.60*
	(-2.14)	(-1.10)	(0.96)	(-0.89)	(0.93)	(-0.50)	(0.66)	(2.45)	(1.55)	(2.20)	(1.82)
Panel H: Foreign Exchange Markets											
Δ log REER (CA)	-0.05**	-0.00	0.03**	0.02	0.03**	0.02	-7.55	23.23*	23.81*	34.76**	16.16
	(-2.46)	(-0.07)	(2.12)	(1.05)	(2.04)	(1.64)	(-0.89)	(1.83)	(1.85)	(2.30)	(1.08)
Panel I: Housing Markets											
Δ log House Prices (CA)	-0.06***	-0.04*	0.01	-0.01	0.01	-0.01	-4.79	-10.40	-14.09	-8.14	-7.89
	(-3.08)	(-1.78)	(0.23)	(-0.34)	(0.35)	(-0.75)	(-0.61)	(-0.97)	(-1.21)	(-0.76)	(-0.83)
Mortgage Spread	6.36***	0.48	-0.45	-1.93**	-2.57***	-3.80***	0.52***	0.93***	1.12***	1.53***	1.63***
	(4.72)	(1.38)	(-0.80)	(-2.46)	(-2.97)	(-3.80)	(3.36)	(3.70)	(4.03)	(5.45)	(5.93)
Panel J: Real Economy											
Consumer Confidence (CA)	-144.56***	-28.41***	-36.51***	-46.90**	-50.32**	-33.43	-0.01	-0.01	0.00	-0.00	0.00
	(-5.50)	(-2.90)	(-2.82)	(-2.45)	(-1.99)	(-1.10)	(-0.91)	(-1.09)	(0.19)	(-0.10)	(0.05)
Δ log Real Credit (Cons, SA)	-0.02***	-0.02***	-0.02***	-0.02**	-0.02**	-0.01	-12.74	-29.08	-69.63**	-49.90	-60.20
	(-2.82)	(-3.19)	(-3.18)	(-2.46)	(-2.45)	(-1.61)	(-0.71)	(-1.06)	(-2.17)	(-1.22)	(-1.49)
Δ log Real Credit (Bus, SA)	-0.01	-0.01*	-0.02**	-0.03***	-0.03***	-0.03***	-17.11	-32.46	-42.27	-43.55	2.62
	(-0.90)	(-1.68)	(-2.55)	(-3.95)	(-4.16)	(-4.22)	(-0.91)	(-1.20)	(-1.42)	(-1.50)	(0.08)
Δ log Real Credit (Mortgage, SA)	-0.01	-0.01**	-0.02***	-0.01*	-0.01	-0.00	-29.08	-69.25*	-106.46**	-92.11	-90.95*
	(-0.99)	(-2.51)	(-3.68)	(-1.80)	(-1.47)	(-0.66)	(-1.33)	(-1.86)	(-2.38)	(-1.48)	(-1.67)
Δ log CPI (SA, CA)	-0.00	0.00	0.01*	0.00	0.00	-0.00	46.53	127.30**	270.35***	272.11***	292.09***
	(-0.52)	(0.42)	(1.70)	(0.27)	(0.11)	(-0.82)	(1.28)	(2.19)	(3.84)	(3.50)	(4.50)
Δ log New Orders (Mfg, SA)	-0.02	-0.19**	-0.05	-0.00	-0.03	0.01	-4.22	-1.73	-1.28	-5.80	-0.39
	(-0.46)	(-2.17)	(-0.73)	(-0.07)	(-0.94)	(0.29)	(-1.37)	(-0.54)	(-0.30)	(-1.31)	(-0.09)
Δ log IPI (SA, CA)	-0.03***	-0.02**	-0.01	-0.02*	-0.01	-0.02	7.13	32.56	84.68**	64.65*	107.71***
	(-2.91)	(-2.57)	(-0.93)	(-1.77)	(-0.60)	(-1.59)	(0.34)	(0.96)	(2.30)	(1.69)	(3.22)
Δ log GDP (SA, CA)	-0.06	-0.03*	0.01	-0.02	0.00	-0.00	27.11	47.39	62.18	70.78**	18.21
	(-1.55)	(-1.76)	(0.29)	(-1.48)	(0.37)	(-0.11)	(1.37)	(1.53)	(1.49)	(2.13)	(0.66)

Notes: Coefficient estimates are multiplied by 100 for the left panel columns with t-statistics in parentheses below each coefficient. * p<0.10, ** p<0.05, *** p<0.01. Variables definition and sources are listed in Appendix C Table A.4.

Figure D.5: Impulse responses to an NSI^{TF-IDF} shock



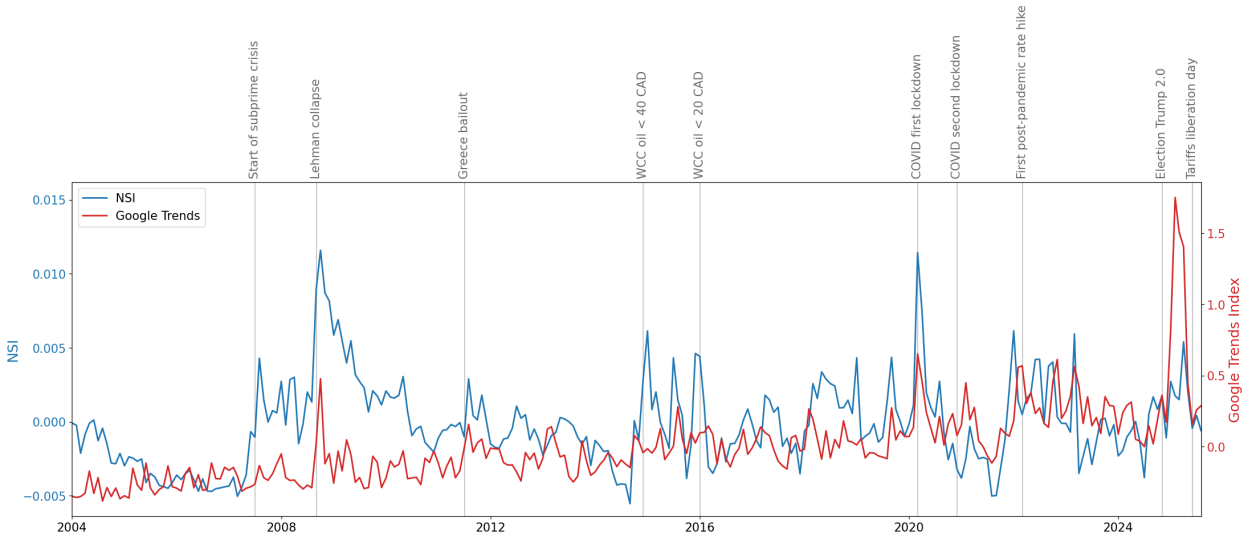
Note: Monthly Bayesian VAR with three lags over 1981m1-2025m7. Macroeconomic variables are all seasonally adjusted, in real terms and expressed in cumulated log-difference over the horizon (or simply the cumulated difference for the short-term rate). The weighted news-based stress index NSI$^{T}F - IDF$ uses term frequency–inverse document frequency weights. Stress shocks identified using Cholesky ordering: news shocks are not reflected in financial prices on impact, while news and financial shocks are not reflected in macroeconomic variables on impact. News shock magnitude of 2 standard deviations on impact. Confidence intervals represent the 10th and 90th percentile.

E Appendix: news coverage versus public attention

To assess how news-based stress attention relates to the broader public's awareness of financial stress, we compare the NSI with a measure constructed from Google Trends, which reports the relative intensity of Google search queries for a given term, region, and period. We retrieve monthly Canadian search volumes for the 116 initial expert-curated keywords of Table 2 and aggregate them into a single search-based stress index available from 2004 onward.

Three features of the search-based index shape this comparison. First, Google Trends data begin only in 2004, whereas the NSI extends back to 1977, limiting the historical coverage of a search-based measure and preventing its use in the VAR analysis of Section 6. Second, the search-based index can only be constructed from the 116 initial keywords, whereas the NSI also incorporates the 1,000 additional bigrams identified by the keyword discovery algorithm. Those phrases reflect the language of news coverage rather than the terms the public enters into a search box. Third, Google Trends rescales each query to its own maximum and returns sparse or empty series for low-volume terms, implying that the aggregate index is often driven by a relatively small subset of keywords. The comparison therefore contrasts the NSI with the best search-based alternative available to a researcher.

Figure E.1: NSI versus Google Trends search attention



Note: The search-based index aggregates Canadian Google Trends search volumes for the 116 initial expert-curated keywords of Table 2. Google Trends data are available from 2004 onward. The NSI is plotted on the left axis and the search-based index on the right axis. Vertical lines represent major Canadian and global stress events.

Figure E.1 compares the two measures. News-based and search-based stress attention move together around major stress episodes, including the GFC, the COVID-19 pandemic, and the 2025 tariff episode, indicating that severe financial stress is reflected both in news coverage and in public search behavior.

The measures nevertheless differ in how they rank those episodes. The NSI peaks during the GFC and again at the onset of the pandemic, whereas the Google Trends index reaches its maximum in 2025 and shows little response to the 2014–15 oil price collapse, despite Canada's important oil-production. Public search behavior therefore appears to be more sensitive to specific keywords and may put greater weight on recent and highly salient events, while the NSI more consistently reflects financially important episodes over time. Thus we view Google Trends as external validation of the NSI around major crises rather than as a substitute for it.