Credit Spread News and Financial Market Risk*

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March 22, 2026

Abstract

This paper shows that credit spread news, defined by changes and absolute changes in corporate bond credit spreads, predict a substantial share of future variation in financial market risk. I first document a strong and robust predictive relationship between credit spread news and financial market risk, establishing the former as statistically significant and economically meaningful predictors of the latter. I then investigate the economic mechanism underlying this relationship and provide both theoretical and empirical evidence highlighting a central role for financial intermediaries' risk constraints. My findings have important policy implications, as they indicate that intermediary constraints endogenously propagate and amplify financial market risk.

Keywords: Credit Spreads; Financial Market Risk; Macro-Finance; Uncertainty

*I am deeply thankful to Allan Timmermann and Rossen Valkanov for the many discussions, their guidance, and the example they set as role models. Thanks also go to Carlos Avenancio-Leon, Joey Engelberg, Jim Hamilton, Giorgio Ottonello, John-Henry Pezzuto, Michael Reher, and to seminar participants at the Rady School of Management.

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1 Introduction

Volatility and risk are central concepts in finance. Periods of elevated volatility can have dramatic consequences for investors, as seen during the collapse of Long-Term Capital Management and the Global Financial Crisis. The time variation in volatility has been extensively documented in the academic literature, beginning with the seminal works of Officer (1973) and Schwert (1989). Time-varying volatility has implications for nearly every aspect of financial economics. From portfolio theory to tests of asset pricing models, it is a feature that must be accounted for. Despite this relevance, explaining why volatility fluctuates over time remains an open question (see Engle (2004) in his Nobel Prize discussion).

In parallel, a separate and growing literature has shown that indicators of credit market conditions, such as credit spreads and credit risk premia, predict future economic activity.[1] The bulk of this work, however, focuses on the relationship between levels of credit spreads and levels of economic activity, as measured by GDP or industrial production growth. The success of credit spreads in forecasting economic activity poses a natural question: do credit markets also contain information relevant for understanding and predicting financial market risk?

In this paper, I show the importance of credit spread news for predicting and explaining time variation in financial market risk. The key finding is that credit spread news, defined as changes and absolute changes in credit spreads, are robust and powerful predictors of aggregate financial risk, complementing the macro-finance literature that has primarily focused on credit spread levels as indicators of business cycle conditions.

The main results of my study are summarized by Table 1. The table reports two baseline predictive regressions for the realized volatility of the S&P 500 Index using credit spread news. These predictive regressions are based on monthly data from January 1973 to December 2023, and include several major economic events, such as financial crises, normal recessions, and a pandemic. These results establish a robust fact: credit spread news predict financial market risk. The robust t-statistics of the coefficients of credit spread news are significant at the 1% level, even after controlling for the first lag of realized volatility. Beyond illustrating the predictive power of credit spread news for aggregate risk, these results suggest that this predictive power is complementary to the information already contained in the lagged values of the risk proxy considered.

I show that the predictive power of credit spread news is consistent and robust

[1] E.g., Stock and Watson (2003), Gilchrist and Zakrajšek (2012), Faust et al. (2013).

across alternative proxies for financial risk, such as the VIX and GARCH-based volatility. Moreover, when compared with several classical macro-finance predictors, such as the default spread and the term spread, credit spread news emerge as the only predictor capable of achieving sizable improvements in terms of out-of-sample R^2 and statistical significance. I further orthogonalize the risk series by the predictive power embedded in their past values and decompose credit spread news into negative and positive components, corresponding to a widening and tightening of spreads, respectively. These transformations reveal that the predictive power in credit spread news is additional to that of the lagged values of the risk series, and that most of the forecasting power arises from negative news, consistent with the evidence that widening credit spreads signal a deteriorating financial landscape. Subsample analyses, out-of-sample forecast evaluations, and multi-step-ahead predictive regressions further corroborate these findings and underscore their robustness.

After establishing the empirical link between credit spread news and financial market risk, I explore why credit spread news are informative about it. I investigate three possible mechanisms.

Motivated by the observation that financial intermediaries represent more than two-thirds of the clientele in the corporate bond market, I begin by considering a mechanism based on time variation in their risk appetite. The theoretical foundation for this mechanism comes from the intermediary-based asset pricing literature.[2] In these models, risk premia are inversely related to intermediaries' risk appetite, which is time varying and depends on the shadow price of the financial constraints the intermediaries face. Credit spread news may reflect intermediaries' forecasts of future risk—shaped by their risk constraints—and the way these expectations are incorporated into the risk premium component of credit spreads. Consistent with this interpretation, I derive the main forecasting relationship of the paper within an intermediary-based asset pricing framework. To further corroborate this channel, I empirically link credit spread news to intermediaries' risk appetite using the risk perception measure of Pflueger et al. (2020) and the leverage factor of Adrian et al. (2014). I finally show that the predictive power of credit spread news for financial risk is robust to the inclusion of these measures. Taken together, the theoretical derivations and the empirical results, provide support to the hypothesis that credit spread news are related to financial intermediaries' risk appetite and expectations.

A second, complementary mechanism operates through credit market frictions. These frictions have been a central mechanism in models of aggregate fluctuations

[2]See, e.g., Vayanos (2004), Adrian et al. (2014), and Adrian et al. (2019)

since Bernanke and Gertler (1989) and Kiyotaki and Moore (1997).[3] Building on these works, I investigate whether credit market frictions, interpreted as shocks to firms' financing conditions, could be one of the possible mechanisms underlying my findings. I find that credit spread news and financing conditions are linked by a two-way lead-lag relationship, with credit spread news showing strong predictive power for future financial conditions. This pattern is consistent with the presence of credit market frictions and an amplification mechanism.

Finally, I examine a mechanism that relies on credit market sentiment. Behavioral theories build on the narratives of Minsky (1977) and Kindleberger (1978) and have attracted considerable attention in recent years.[4] As argued by López-Salido et al. (2017), periods of high credit market sentiment are characterized by underpriced risk in credit markets. Changes in credit spreads may therefore reflect shifts in credit market sentiment. Using the measure proposed by Greenwood and Hanson (2013) as a proxy for credit market sentiment, I show that while credit spread news predict sentiment, and changes in sentiment, the opposite does not hold. This one-way predictability suggests that sentiment does not play a primary role in explaining my findings.

$$RV_{t+1} = \mu + \gamma_i \; CS_{i,t}^{\mathbf{NEWS}} + \phi RV_t + \epsilon_{t+1}$$

	μ	$CS_{1,t}^{\text{NEWS}}$	$CS_{2,t}^{\text{NEWS}}$	RV_t
coeff.	0.002	0.472		0.242
t-stat	4.359	2.738		2.176
coeff.	0.001		0.623	0.232
t-stat	3.027		2.912	2.251

Table 1: Predictive Regressions. This table shows the results from predictive regressions of the S&P 500 Index realized volatility using credit spread news. Credit spread news are defined as the first difference of the Gilchrist and Zakrajšek (2012) credit spread index ($CS_{1,t}^{\text{NEWS}} := \Delta CS_t$) and by its absolute value ($CS_{2,t}^{\text{NEWS}} := |\Delta CS_t|$). RV_{t+1} is the monthly realized volatility of the S&P 500 Index, computed using daily squared returns. The sample spans January 1973 to December 2023 and is at monthly frequency. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

[3] Quadrini (2011) provides a comprehensive review of this literature.
[4] See, for an example related to credit cycles, Greenwood et al. (2019).

Related Literature. This paper contributes to the growing field of macro-finance that examines the link between asset prices and the broader macroeconomy. Specifically, I add to three main strands of literature. First, I document a new stylized fact, contributing to the literature that seeks to quantify and explain financial risk using macroeconomic variables. Second, I contribute to the intermediary-based asset pricing literature by showing that the predictor embeds information about intermediaries' risk appetite and risk expectations. Finally, by constructing the predictor from corporate credit spreads, I provide novel evidence on the information content of credit markets.

The first literature has faced numerous empirical challenges in linking financial market risk to economic variables. Although there has been considerable success on the statistical front, the literature still falls short of identifying robust economic predictors of aggregate stock market volatility. For example, in a comprehensive study, Paye (2012) evaluates the out-of-sample performance of a large set of macroeconomic predictors for stock market volatility and finds limited evidence of predictive power among standard financial and macroeconomic variables. Even sophisticated econometric methodologies (Engle and Rangel (2008), Engle et al. (2013)) and structural approaches (David and Veronesi (2013)) have yielded limited progress in advancing our understanding of risk and its time variation.

More recently, interest in the topic has surged, with several papers incorporating stochastic volatility into macro-finance models (see, among others, Bansal et al. (2014), Dew-Becker et al. (2017), Berger et al. (2020), and Dew-Becker et al. (2021)). Within this literature, Campbell et al. (2018) shows that the default spread—the difference between the yields of BAA and AAA bonds—has predictive power for future stock market volatility. However, this finding has been questioned by Andersen and Varneskov (2021), who caution that the observed predictability may be spurious—driven by the high persistence of the default spread, which leads to important size distortions.[5] Establishing credit spread news as robust predictors of financial market risk, this paper makes an important step forward for this literature.[6]

By showing that the forecasting power of credit spread news is linked to financial intermediaries' risk appetite and risk expectations, I contribute to the literature on intermediary-based asset pricing. This class of models (Brunnermeier and Pedersen (2009), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and

[5]The literature on stock return predictability has extensively documented the problem of spurious inference arising from near–unit-root predictors, such as accounting ratios (see, e.g., Ferson et al. (2003)).

[6]As discussed in Section 2, the credit spread news measures considered in this paper are model-free and exhibit weak serial correlation. This means that they are not based on parametric assumptions, do not require a model for credit spreads, and mitigate concerns about spurious predictability.

Adrian et al. (2014)), has shown considerable promise in explaining asset pricing puzzles across several markets.[7] In this framework, the marginal agent is a financial intermediary who prices assets subject to margin constraints. The presence of binding constraints is a central pillar of these models. In particular, these constraints determine the risk premia that intermediaries require to hold risky assets and, as shown by Vayanos (2004) and Adrian et al. (2019), depend on intermediaries' risk appetite and the amount of financial risk in the economy.

In this paper, I link changes in credit spreads to intermediaries' risk expectations. Specifically, I show that investors' required compensation for holding corporate bonds is informative about financial market risk, as it indirectly reflects the risk expectations of participants in the corporate bond market. Starting from the observation that financial intermediaries represent over 70% of the clientele in the corporate bond market, I provide theoretical and empirical evidence illustrating a novel information channel within intermediary-based asset pricing models.

Finally, I contribute to the literature on the information content of credit spreads. Beginning with Bernanke (1983), a substantial body of work has examined the predictive power of credit markets for macroeconomic fluctuations.[8] Gilchrist and Zakrajšek (2012) develop a highly informative credit spread index with strong predictive power for future economic activity, while Boons et al. (2023) investigate the reverse channel, from macroeconomic shocks to credit spreads, finding evidence of a negative relationship from economic activity shocks to future credit spreads.

My paper differs from this previous work in that its main focus is on financial market risk, rather than levels of economic activity (e.g., GDP or industrial production growth). In addition, unlike most of the existing literature, which focuses on levels of credit spreads, I study measures of changes in credit spreads, following a more recent and emerging strand of research. Two important contributions within this emerging literature are López-Salido et al. (2017) and Krishnamurthy and Muir (2025), although they primarily focus on changes in the default spread for macroeconomic aggregates.

The outline of the paper is as follows. Section 2 defines credit spread news, introduces the data, and documents their empirical properties. Section 3 presents the main results, Section 4 explores the possible economic mechanisms, and Section 5 concludes the paper.

[7] See, e.g., He et al. (2017), Adrian et al. (2019), and Haddad and Muir (2021).

[8] See, for example, Faust et al. (2013), Favara et al. (2016), and Greenwood et al. (2019), while Stock and Watson (2003) surveys the earlier literature.

2 Credit Spread News

In this section, I begin by formally defining credit spread news, introduce the data used throughout the paper, and illustrate key empirical features of the series.

2.1 Formal Definitions

I begin by defining the following two measures of credit spread news:

Definition. *Given a credit spread index of interest, CS_t, credit spread news at time t are defined by the first difference of the credit spread index and by its absolute value:*

$$\eta_{1,t}^{CS} := \Delta CS_t = CS_t - CS_{t-1}, \tag{1}$$

$$\eta_{2,t}^{CS} := |\Delta CS_t| = |CS_t - CS_{t-1}|, \tag{2}$$

where I refer to $\eta_{1,t}^{CS}$ as the credit spread innovation and to $\eta_{2,t}^{CS}$ as the credit spread magnitude.

These definitions of credit spread news offer a number of advantages.

A first key advantage of these measures of credit spread news is that they can be computed without specifying a parametric model for the conditional mean of the credit spread index; that is, they are model free. As a result, no functional form needs to be specified, and no additional predictors or parameters have to be estimated.

Second, since both CS_t and CS_{t-1} are directly observable at time t, also $\eta_{1,t}^{CS}$ and $\eta_{2,t}^{CS}$ are observable. This ensures that real-time forecasting models, which only include information available up to the point when the forecast is produced, can be implemented.

Finally, several credit spread indices exhibit finite-sample behavior that is close to a unit-root process. This is the case for the credit spread index underlying my empirical analysis—namely, the index proposed by Gilchrist and Zakrajšek (2012). Thus, constructing credit spread news as in (1)–(2) ensures that these series are stationary and weakly dependent. This is important for assessing their predictive power, because stationarity and weak dependence help prevent spurious predictability arising from highly persistent predictors, as cautioned by, among others, Andersen and Varneskov (2021).

To examine whether news associated with widening spreads (i.e., negative news) have a different impact on aggregate risk than those associated with tightening spreads (positive news), I define measures of downside and upside credit spread

news:

Definition. *Let CS_t be the credit spread index of interest, the downside credit spread news at time t is defined as:*

$$\eta^{CS}_{\mathcal{D},t} := |\Delta CS_t|^+ = |CS_t - CS_{t-1}|I(\Delta CS_t > 0), \tag{3}$$

where $I(\Delta CS_t > 0)$ is the indicator function that takes value 1 if the credit spread index widens and 0 otherwise. The upside credit spread news at time t is defined as:

$$\eta^{CS}_{\mathcal{U},t} := |\Delta CS_t|^- = |CS_t - CS_{t-1}|I(\Delta CS_t < 0), \tag{4}$$

where $I(\Delta CS_t < 0)$ is the indicator function that takes value 1 if the credit spread tightens and 0 otherwise.

These two measures allow me to study the relationship between the direction of credit spread news and financial risk, and to assess whether this relationship is asymmetric, as suggested by the literature on downside and left-tail risk.[9]

2.2 Data

The empirical analysis relies on data on credit spreads and financial risk measures. In this subsection, I introduce the main data and refer the reader to the data appendix for further details.

Credit Spreads. To quantify credit spreads I use the monthly credit spread index developed by Gilchrist and Zakrajšek (2012) (the *GZ* index). The *GZ* index is constructed as the cross-sectional average of a large number of individual bond spreads of nonfinancial firms over duration-matched risk-free securities.[10] It has been shown to possess strong predictive power for future economic activity (see Gilchrist and Zakrajšek (2012) for the original contribution and Boons et al. (2023) for a recent validation). The large cross-section and the risk-free matching methodology ensure that it represents a broader spectrum of risk profiles than those captured by the default spread (commonly measured by the BAA–AAA spread) and to avoid the "duration mismatch".

I obtain the updated series of the *GZ* index from the FED's website, where it has been made available by Favara et al. (2016).[11] The series is at monthly frequency starting from January 1973.[12]

[9] See, e.g., Ang et al. (2006), Brunnermeier and Sannikov (2014).

[10] See the data appendix for details on the construction and granularity of this index.

[11] https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html

[12] Importantly, the updated version contains data revisions to the original series used in Gilchrist

Financial Market Risk. I measure financial risk by considering several series that have been widely employed in the literature: the monthly realized volatility of the S&P 500 Index (RV), the VIX, and a GARCH-based volatility estimate (GARCH).[13] All measures are expressed in squared terms (i.e., in variance units) and are sampled at a monthly frequency. Further details on their construction are as follows.[14]

Monthly realized volatility (expressed in variance units) is calculated by summing the squared daily log returns within each trading month. Daily returns are computed using closing prices obtained from CRSP, which are available from the 1920s onward. The VIX is obtained directly from the Chicago Board Options Exchange (CBOE). Since the index is reported in annualized volatility units, I square it and divide by 12 to obtain a monthly variance measure. The GARCH-based risk measure is constructed by fitting a GARCH(1,1) model to the monthly log returns of the S&P 500 over the full sample period from January 1871 to December 2023. The estimated model is then used to construct a time series of estimated time-varying conditional volatility.[15]

Variables for the Economic Mechanism. To investigate the economic mechanism behind my findings, I consider proxies for intermediaries' risk appetite; a measure of credit market conditions; and a measure of credit market sentiment. To assess the intermediaries' risk appetite channel, I use the price of volatile stocks (PVS) introduced by Pflueger et al. (2020),[16] and the broker-dealer leverage factor of Adrian et al. (2014).[17] To measure credit market conditions, I use the Chicago Fed National Financial Conditions Index, which is constructed as a weighted average of several indicators of financial activity and includes measures of credit and leverage conditions.[18] Finally, credit market sentiment is measured using the high-yield share measure proposed by Greenwood and Hanson (2013).[19]

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and Zakrajšek (2012).

[13] Although this involves some abuse of terminology, I use the term volatility interchangeably to refer to variance, following a convention common in the volatility literature (see, for instance, Drechsler and Yaron (2011)).

[14] The data appendix contains further details on these series along with their summary statistics.

[15] As an additional robustness test, I also estimate the parameters of the GARCH(1,1) using only data up to January 1973 and generate a pseudo-OoS volatility measure. Results are essentially unchanged.

[16] The data series on the PVS is sourced from Caroline Pflueger's website: https://sites.google.com/view/carolin-pflueger/home

[17] The data series is downloaded from Table L.130 (Q) from the financial release of the board https://www.federalreserve.gov/datadownload/Choose.aspx?rel=Z1.

[18] See https://www.chicagofed.org/research/data/nfci/current-data

[19] The series is sourced from Harvard Business School's Behavioral Finance and Financial Stability webpage: https://www.hbs.edu/behavioral-finance-and-financial-stability/data/Pages/sentiment.aspx

Additional Variables. Financial and non-financial predictors considered are from Welch and Goyal (2008) and Goyal et al. (2024), and are obtained from Amit Goyal's website.[20] The macroeconomic data used are sourced from the FRED database, maintained by the St. Louis FED.[21] Additional predictors and variables of interest are introduced as needed, with further details of the data and sources provided in the appendix.

2.3 Empirical Properties of Credit Spread News

I construct series of credit spread news by substituting the GZ index in equations (1)-(4), and refer to them as $\eta_{1,t}^{GZ}$, $\eta_{2,t}^{GZ}$, $\eta_{\mathcal{D},t}^{GZ}$, and $\eta_{\mathcal{U},t}^{GZ}$, respectively.[22]

Table 2 presents summary statistics for the credit spread news measures over the full sample period (January 1973 to December 2023), as well as for a subsample spanning January 1985 to December 2023. Panel A reports the summary statistics for the innovation and the magnitude series. The innovation series, $\eta_{1,t}^{GZ}$, has a mean of zero and an annualized standard deviation of approximately 78 basis points over the full sample and about 85 basis points over the subsample. The magnitude series, $\eta_{2,t}^{GZ}$, exhibits a slightly lower standard deviation, approximately 65 basis points for the full sample and 70 basis points for the subsample, and a non-zero mean of around 45 basis points in both samples. Both series exhibit weak first-order autocorrelation, with $\eta_{2,t}^{GZ}$ showing slightly higher values of ρ.[23] In any case, the degree of persistence in the predictors is not strong enough to raise concerns about spurious inference, thereby guarding against the issues emphasized by Andersen and Varneskov (2021). Panel B reports summary statistics for downside and upside credit spread news. In the full sample, from January 1973 to December 2023, negative and positive news are approximately evenly split: about 53% of observations correspond to positive news, while the remaining 47% correspond to negative news. The two series have non-zero means—about 50 basis points for downside news and 40 basis points for upside news—exhibit higher volatility in the downside series, and display weak first-order autocorrelation, which is slightly higher for downside than for upside news.

In Figure 1, I plot the time series of credit spread innovations and credit spread magnitudes over the full sample. A first notable pattern is that credit spread news alternate between periods of small movements and clusters of large news. This behavior mirrors the well-documented dynamics of stock market volatility, where

[20] https://sites.google.com/view/agoyal145

[21] https://fred.stlouisfed.org/ .

[22] Whenever the notation becomes burdensome and the GZ superscript is not needed, I drop it, clarifying now that it will be intended.

[23] This higher first-order autocorrelation suggests a relationship with volatility clustering.

episodes of high volatility tend to cluster over time. The top panel shows that credit spread innovations exhibit particularly pronounced movements during episodes of financial and economic stress, such as the collapse of Long-Term Capital Management (LTCM), the Global Financial Crises (GFC), and the COVID-19 pandemic. This is further emphasized in the bottom panel, which displays the time series of credit spread magnitudes. Similar to innovations, the magnitude series becomes more volatile following the collapse of LTCM and remains elevated thereafter, with sharp spikes during the GFC and the COVID-19 pandemic.

To conclude this section, I summarize the advantages of the credit spread news measures I propose. First, they avoid the specification and estimation of a parametric model. Second, they exhibit weak persistence and stationarity, making them suitable predictors in predictive regressions. Finally, they are available in real time, facilitating practical implementation.

Further results on the properties of credit spread news are reported in Appendix B.2.1, where I compare them with the excess bond premium of Gilchrist and Zakrajšek (2012) and show that the relationship between the two is weak, highlighting that credit spread news capture different information.[24]

3 Forecasting Financial Market Risk

In this section, I establish the forecasting power of credit spread news for financial market risk. I start by presenting the main empirical results and discuss their implications. Next, I consider a number of additional evaluation exercises and robustness checks. All reported results are based on heteroskedasticity- and autocorrelation-robust t-statistics, computed using the automatic lag-length selection method of Newey and West (1994).

3.1 Main Results

I begin by reporting the main empirical findings of my study in Table 3. This table extends Table 1 from the introduction and presents the statistics from the predictive regressions

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+1}^{RV}, \quad i = 1, 2, \tag{5}$$

[24]Moreover, like the GZ index, the series of the excess bond premium is highly persistent, raising issues related to valid inference when used as a predictor.

which are estimated over the full sample spanning January 1973 to December 2023, and include up to three lags of the realized volatility as additional control variables.[25]

The left panel of Table 3 shows the results for the predictive regressions related to credit spread innovations, $\eta_{1,t}^{GZ}$. Innovations to credit spreads, alone, explain about nine percent of the monthly variation in future aggregate realized volatility. The finding remains robust and stable when lagged values of the realized volatility are incorporated into the predictability specification, further providing evidence that $\eta_{1,t}^{GZ}$ captures systematic information beyond that already contained in the past values of realized volatility. The coefficient for the credit spread innovation γ_1 is estimated to be positive. This is consistent with the ex-ante expectation that a widening of the corporate spreads precedes periods of higher realized volatility, and therefore higher risk going forward.

Turning to the right panel of Table 3, the results for $\eta_{2,t}$ further strengthen the finding that credit spread news predict financial market risk. The robust t-statistic on γ_2 in the univariate regression is highly significant (3.68), and the adjusted R^2 exceeds 14%. In the augmented predictive regressions, the robust t-statistics of credit spread news are statistically significant at the 1% level, regardless of the included control variables. Even for the most comprehensive specification, which includes three lags of realized volatility, credit spread magnitudes have a robust t-statistic of about 2.75. The change in the coefficient γ_2 is small after including the first lag of the realized volatility, indicating that, while controlling for past volatility is important, it does not diminish the predictive power of credit spread news. Credit spread magnitudes also account for most of the explained variation in future aggregate volatility, as indicated by the adjusted R^2. The adjusted R^2 increases only modestly—from 14% to 18%, an increase of about 4%—when moving from a model that includes only credit spread magnitudes to one that also incorporates three lags of past realized volatility.

The size of the coefficients allows us to quantify the expected change in risk given a change in credit spreads. Ceteris paribus, a 100-basis-point increase in credit spreads in month t is associated with an average increase in realized volatility of about 10.5% in month $t+1$.[26]

Figure 2 illustrates visual evidence of the relationship between credit spread news and realized volatility. The figure plots the time series of credit spread news alongside the realized volatility of the S&P 500 Index to illustrate their joint dy-

[25]The volatility forecasting literature has extensively documented the importance of incorporating the first lag of volatility (see, e.g., Andersen et al. (2003)). Incorporating up to three lags allows for greater robustness.

[26]The percentage reported corresponds to standard deviation units.

namics. Both the top panel, for credit spread innovations, and the bottom panel, for credit spread magnitudes, show pronounced comovement, with periods of elevated volatility coinciding with large movements in credit spreads.

Together, this first set of results provides initial evidence that credit spread news are a strong predictor of financial market risk, as measured by aggregate stock market volatility. To fully establish this finding, I now examine whether the results hold when financial risk is measured using alternative series. Specifically, I begin with results for the VIX series and then turn to a GARCH-based volatility measure.

VIX. The VIX is a widely used measure to proxy for financial risk. Often referred to as the 'fear gauge' by industry participants (Whaley (2000)), it embeds forward-looking information about financial risk.[27]

To evaluate the predictive power of credit spread news for the VIX, I consider the following predictive regressions:

$$VIX_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j VIX_{t+1-j} + \epsilon_{t+1}^{VIX}, \quad i = 1, 2, \tag{6}$$

estimated over the sample that extends from January 1990 to December 2023, where the shorter length of this sample is dictated by the availability of the VIX series.

Table 4 reports the results of predictive regressions of the VIX on credit spread news, including an additional set of control variables. The results show a strong degree of predictability coming from both credit spread magnitudes and credit spread innovations.

The main conclusion from the t-statistics in Table 4 is that credit spread news have robust predictive power for the VIX. Analogously to the RV, the predictability is stronger for credit spread magnitudes, with an adjusted R^2 that, in the univariate regression, is 43.5%. In other words, credit spread magnitudes, alone, can explain about half of the predictive variation in the VIX. The magnitude of the coefficient of credit spread magnitudes diminishes after the addition of the first lag of the VIX, highlighting once more the importance of accounting for past financial risk, but stays relatively stable when the second and third lags of the VIX are added. The associated t-statistics remain strongly statistically significant after the inclusion of the lagged VIX values as control variables. Credit spread innovations have a similar behavior, with the coefficient showing strong statistical significance that is robust to the addition of the past values of the VIX.

The coefficients of these predictive regressions allow to draw some conclusions

[27] This offers an interesting comparison with respect to the realized volatility, which can be interpreted as a realized-risk measure, see Berger et al. (2020).

about expected future volatility. For example, a 100 basis points change in credit spreads at time t predicts a movement in the VIX in month $t+1$ of about 10.2%, when measured in standard deviation units.

In contrast to realized volatility, which measures realized risk, the VIX offers a forward-looking measure that embeds investors' expectation of future financial risk. The fact that credit spread news can predict a significant proportion of the variation in the VIX suggests that they are linked to risk expectations. This is the first hint that one possible mechanism at work may be related to investors' risk expectations, as reflected in their risk appetite.

GARCH. As a final measure of financial market risk, I consider a GARCH-based filtered conditional volatility. As detailed in Section 2.2, I construct it by fitting a GARCH(1,1) model to monthly returns on the S&P 500. GARCH-based volatility is constructed under the physical probability measure and remains one of the workhorse measures employed for volatility forecasting to this day, see, e.g., Bekaert et al. (2025).

Analogously to the previous risk measures, the predictive regressions that I consider for the GARCH are given by

$$\sigma_{t+1}^{GARCH} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j \sigma_{t+1-j}^{GARCH} + \epsilon_{t+1}^{GARCH}, \quad i = 1, 2. \tag{7}$$

I estimate these predictive regressions over the full sample January 1973 to December 2023, and I report the results in Table 5.

Starting with credit spread magnitudes, their coefficient, γ_2, is both statistically and economically significant: its t-statistic is about 8.75, and its economic value implies that a credit spread magnitude of 100 basis points in the current month, t, predicts an increase in GARCH-based volatility of about 5.5% at time $t+1$.

The left panel of Table 5 (the η_1 panel) shows that including only $\eta_{1,t}^{GZ}$, provides no statistically significant evidence of predictive power for risk. The t-statistic of γ_1 is insignificant at all conventional levels, and the adjusted R^2 is close to zero. This result likely arises because positive and negative innovations offset each other, thereby confounding the effect of the γ_1 coefficient. This fact is clear when considering the results for credit spread magnitudes, in the right panel of Table 5.

The highly significant t-statistics of the lagged GARCH terms in the predictive regressions is not surprising, as, by construction, a GARCH recurrence equation is updated using its past values.[28] When lags of the GARCH model are included, γ_1 becomes strongly statistically significant, with an average t-statistic exceeding 3.

[28]Moreover, by unfolding the process it shows that a GARCH depends on its full past history.

To address concerns about multicollinearity, it is worth noting that the correlation between $\eta_{1,t}$ and the lagged GARCH terms is close to zero.

3.2 Discussion

To provide context for my results, Table 6 summarizes the empirical challenges the literature has faced in establishing a relationship between macroeconomic variables and financial risk. I consider a set of ten macro-finance variables identified as key predictors of financial market risk. I estimate predictive regressions in which each predictor is added individually to a benchmark AR(1) model for realized volatility, and I report the average t-statistics and out-of-sample R^2 (R^2_{OoS}) over two subsamples, which span 25 and 15 years of out-of-sample validation, respectively.

All the macro-finance variables considered display insignificant (average) t-statistics, and most of them have negative R^2_{OoS}. The only predictor that shows an improvement in terms of R^2_{OoS} is the default spread (DS), consistent with the findings of Campbell et al. (2018), although its t-statistic is not significant, regardless of the sample considered. Moreover, several of these predictors, and particularly the DS, are highly persistent, with AR(1) coefficients close to unity. This introduces the well-known statistical issue of testing with persistent predictors, see Andersen and Varneskov (2021) for a recent review of the literature of this problem within the framework of predictive regressions for realized volatility.

In the final two columns of Table 6, I report the main variables of interest in this paper: credit spread news. These columns show that credit spread news are the only predictors with statistically significant t-statistics and sizable improvements in the out-of-sample R^2, reaching nearly 9% in the longest sample for $\eta^{GZ}_{2,t}$.

These results highlight this paper's main contribution relative to prior research. I examine the economic mechanisms that may explain why credit spread news are robust predictors of financial market risk in Section 4, while the remaining part of this section is devoted to establish additional results and conduct a number of robustness checks.

3.3 Further Results and Robustness Checks

In this subsection, I present several exercises designed to further illustrate the role of credit spread news as predictors of financial market risk, along with a set of robustness checks. Additional robustness checks and results are reported in Appendix C.

3.3.1 Good and Bad News

The previous results have shown that credit spread magnitudes, $\eta^{GZ}_{2,t}$, have stronger predictive power. This is consistent with anecdotal evidence that a widening of spreads signals a deterioration in financial conditions. In addition, a large body of literature indicates that investors are more averse to downside and left-tail risks, as discussed in works such as Ang et al. (2006), Brunnermeier and Pedersen (2009), and Adrian et al. (2019).

To examine whether a similar mechanism operates here, I use the downside and upside credit spread news defined in equations (3)–(4), and estimate the following regressions:

$$RV_{t+1} = \mu + \gamma^{-}\eta^{GZ}_{\mathcal{D},t} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon^{RV}_{t+1},$$
$$RV_{t+1} = \mu + \gamma^{+}\eta^{GZ}_{\mathcal{U},t} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon^{RV}_{t+1},$$

where $\eta^{GZ}_{\mathcal{D},t}$ and $\eta^{GZ}_{\mathcal{U},t}$ are the downside and upside credit spread news, respectively. These regressions allow me to dissect γ into a *downside gamma*, denoted by γ^{-}:

$$\gamma^{-} = \frac{Cov(\eta^{GZ}_{\mathcal{D},t}, RV_{t+1})}{Var(\eta^{GZ}_{\mathcal{D},t})}, \tag{8}$$

and an *upside gamma*, denoted by γ^{+}:

$$\gamma^{+} = \frac{Cov(\eta^{GZ}_{\mathcal{U},t}, RV_{t+1})}{Var(\eta^{GZ}_{\mathcal{U},t})}. \tag{9}$$

I report the results of these regressions in Table 7.

Starting from the left panel, the results show a strong role for negative news, $\eta^{GZ}_{\mathcal{D},t}$, which corresponds to a widening of credit spreads. The robust t-statistics for the downside gamma remain above conventional significance thresholds, even after controlling for past realized volatility. Interestingly, when adding the time t value of the realized volatility, the estimate of the downside gamma is close to unity, the intercept value stays near zero and the t-statistic highly significant. The adjusted R^2 for the downside regression starts at a substantial 17.26%, when the downside measure is considered alone, and increases only modestly to 21.28% when current and past lags of realized volatility, up to two lags, are included, highlighting the importance of negative credit spread news in forecasting risk.

Conversely, the upside gamma does not exhibit significant values, although the t-

statistic becomes significant after the inclusion of the second lag of realized volatility. For these specifications, the sign of γ^+ is estimated to be negative. The adjusted R^2 for the upside regression is also lower than that of the downside regression, with the highest value reaching 15.82%.

Consistent with prevailing narratives of investors' aversion to downside risk, these results show that periods of widening credit spreads are associated with higher financial risk. Moreover, they further emphasize the role of investors' risk appetite, providing additional insights into the possible economic mechanism behind the predictive power of credit spread news.

3.3.2 Orthogonalized Risk Series

In the regressions, the predictive power of credit spread news remained significant even after controlling for the lagged values of the risk measures used as proxies for financial market risk. These findings suggest that credit spread news forecast a component of risk not captured by the lagged risk measures.

The literature has argued that volatility is driven by two components: a persistent component, linked in equilibrium models to the volatility of fundamentals, and a strongly mean-reverting, nearly serially uncorrelated component, associated with volatility-of-volatility.[29] If credit spread news reflect financial market risk, they should forecast the component of risk associated with volatility-of-volatility.

To test this hypothesis, I assess whether credit spread news predict the component of financial risk not captured by the lagged risk proxies. Specifically, I construct financial risk measures orthogonalized with respect to their predictable component based on past values as

$$\sigma^{\perp}_{t+1} = \sqrt{\left(\sigma_{t+1} - \widehat{\sigma}_{t+1}\right)^2},$$

where $\widehat{\sigma}_{t+1}$ is the component of the risk proxy predictable using past values of the proxy itself, i.e., $\widehat{\sigma}_{t+1} = \widehat{\mu} + \sum_{j=1}^{l} \widehat{\beta}_j \, \widehat{\sigma}_{t+1-j}$.[30]

Once I obtain $\sigma^{\perp}_{t+1}$, I run predictive regressions of the orthogonalized measures on credit spread news:

$$\sigma^{\perp}_{j,t+1} = \gamma_i \; \eta_{i,t} + \epsilon_{j,t+1}, \;\; j = RV, \text{VIX}, GARCH. \tag{10}$$

I report the results of these predictive regressions in Table 8. The results indicate that credit spread innovations, magnitudes, and downside news have strong

[29] See, e.g., Guo and Whitelaw (2006), Adrian and Rosenberg (2008), and Bollerslev et al. (2009).

[30] In the empirical implementation I use 3 lags in the estimation of $\widehat{\sigma}_{t+1}$, accounting for approximately one quarter of information.

predictive power for the orthogonalized risk component. The effect is strongest for downside news, with HAC robust t-statistics exceeding 4 for all financial risk proxies and an adjusted R^2 of nearly 20% for both the VIX and GARCH measures.

Upside news (i.e., tightening of the credit spreads), do not have predictive power for the orthogonalized component. This is consistent with the findings reported in the previous section, based on the intuition that volatility shocks are triggered by 'bad' events, which are associated with negative news (i.e., widening of the credit spreads).

In summary, these results support the hypothesis that credit spread news capture true financial market risk—specifically, volatility-of-volatility—rather than merely reflecting information contained in lagged values of the volatility proxy.

3.3.3 Subsample Analysis

An important robustness check involves assessing the stability over time of the results presented so far. To this end, I report the results of subsample regressions in Table 9. Specifically, I run the main predictive regressions of realized volatility on credit spread news and the control variables (see Table 3 for a detailed explanation of the specifications) over three subsamples: the first subsample goes from January 1985 to December 2023; the second subsample goes from January 1973 to June 2008; the third subsample goes from January 1985 to December 2019. The choice of these subsamples is motivated as follows.

The first subsample choice follows Gilchrist and Zakrajšek (2012), who split their original data by considering as a starting point January 1985, advocating for this split based on the shift in monetary policy that occurred around that period. The second subsample excludes both the GFC and the COVID pandemic. Since these periods were marked by extreme volatility spikes, omitting them provides evidence that the results are not driven by a few large outliers.[31] The third and final subsample starts at the same point as the first but ends before the onset of COVID-19, thereby accounting for both the change in monetary policy and the extreme volatility observed during the pandemic.

The results reported in Table 9 show the stability and consistency over time of my findings. The t-statistics of the credit spread news coefficients are significant across all specifications. The smallest t-statistic is 1.81, corresponding to the coefficient on $\eta_{1,t}^{GZ}$ in the specification that includes one lag of realized volatility for the third subsample. All other t-statistics are well above 2, irrespective of the sample or

[31] In unreported results, I also consider an exercise in which volatility spikes are included but trimmed. The results are qualitatively unchanged.

specification considered.

The table shows that the coefficients are larger when the GFC is included in the sample, indicating a measurable effect of the crisis. Following Adrian et al. (2019), this finding can be interpreted as evidence that the financial crisis intensified the link between credit and equity markets, making credit spread news a more economically important predictor of financial risk. One possible explanation is that, during the GFC, a shock to financial conditions led to a severe contraction in expected risk by financial intermediaries, constrained by their risk-bearing capacity. This, in turn, may have contributed to a further widening of credit spreads and the emergence of a volatility spiral. I further investigate this mechanism in Section 4.

3.3.4 Multi-Step-Ahead Predictions

In Table 10, I report the results from multi-step-ahead regressions forecasting monthly realized volatility at horizons of 2 and 3 months, displayed in the upper and lower panels, respectively.[32]

This exercise is intended to mimic the situation of an investor who at time t forecasts time $t+h$, for $h = 2, 3$, using only information available at the time the forecast is made. Formally, the multi-step-ahead regressions are given by:

$$RV_{t+h} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+h}^{RV}, \;\; h = 2, 3. \tag{11}$$

As Table 10 shows, there is evidence of predictive power, although both its economic and statistical magnitudes are somewhat lower compared to the one-step-ahead regressions. In the multi-step ahead univariate regressions, $\eta_{2,t}^{GZ}$ has strongly significant robust t-statistics, that are equal to 3.80 for the two-month-ahead and 4.16 for the three-month-ahead horizon. These t-statistics are slightly reduced when I include the full set of control variables, decreasing to 3.16 and 2.17, respectively. The adjusted R^2 exceeds 6% for the two-step-ahead regression and is approximately 3% for the three-step-ahead regression. The economic magnitude of the coefficient is also sizable: γ_2 equals 0.47 in the two-step-ahead regression with the full set of controls, and 0.21 for the three-step-ahead regression with the full set of controls. On the other hand, credit spread innovations exhibit weaker predictive power, with t-statistics that are significant at lower confidence levels. The adjusted R^2 values are also lower. The loss of predictive power also applies to past values of realized volatility.

[32] An important remark is that these multi-step-ahead regressions do not involve overlapping observations.

These results show that credit spread news—albeit to a lesser extent—contain information about future realized volatility, beyond one-month horizon and can improve risk prediction up to three months ahead.[33]

3.3.5 Relationship with Macroeconomic Variables

Given the success of the *GZ* index as predictor of economic activity, a question that naturally arises is: what is the relationship between credit spread news and macroeconomic variables? In this subsection, I present empirical results that address this question.

Specifically, in Tables 11 and 12, I assess the role of credit spread news in forecasting the level and volatility of macroeconomic variables. Formally, I run:

$$y_{t+1}^{\text{macro}} = \mu + \gamma_i \eta_{i,t}^{GZ} + \beta_1 RV_t + \phi y_t^{\text{macro}} + \epsilon_{y,t+1}, \tag{12}$$

and

$$\sigma_{t+1}^{\text{macro}} = \mu + \gamma_i \eta_{i,t}^{GZ} + \beta_1 RV_t + \phi \sigma_t^{\text{macro}} + \epsilon_{\sigma_y,t+1}, \tag{13}$$

where both specifications control for the lagged macroeconomic variable (or its volatility) and realized volatility of the S&P 500 Index.

The macroeconomic variables I consider are the growth of industrial production, the growth of nonfarm payroll employment, and the change in the unemployment rate. The choice of these three variables follows Gilchrist and Zakrajšek (2012), who use them to establish their main result.

Starting from the levels of macroeconomic variables, the central panel of Table 11 shows that credit spread news do not have predictive power for any of the macroeconomic variables considered. For credit spread innovations, the coefficient γ_1 has the correct economic sign: it is negative for industrial production and payroll growth, but positive for unemployment changes, indicating that a widening of credit spreads is associated with a contraction in economic activity, while a tightening corresponds to an expansion. However, the associated t-statistics are not significant at any reasonable significance level. Analogous conclusions hold for credit spread magnitudes, which display insignificant t-statistics across all macroeconomic variables. Thus, contrary to the levels of credit spreads, credit spread news do not forecast levels of economic activity.

In Table 12, I report the results for the volatility of the macroeconomic variables,

[33] Dew-Becker et al. (2017) show that volatility risk is not priced beyond the quarterly horizon. The corresponding loss of predictive power of credit spread news at longer horizons is again indicative of a mechnanism based on risk expectations.

computed using a GARCH(1,1) model. The central panel of the table shows that credit spread news have no predictive power for the volatility of the macroeconomic series. All the t-statistics associated to the coefficients of the credit spread news are insignificant, ruling out a role for credit spread news in predicting one-month-ahead macroeconomic volatility.

These results show that credit spread news have no forecasting power for macroeconomic variables, either for growth (levels) or for their volatility. These findings, which contrast sharply with the predictive power of the GZ index for macroeconomic levels, suggest that credit spread news are devoid of any lead–lag relationship with real economic activity, reinforcing their interpretation as indicators of financial system strains rather than real economic conditions..

3.3.6 Out-of-Sample Validation

As a final robustness check, I conclude this section by presenting an out-of-sample analysis.

I evaluate the out-of-sample forecasting power of credit spread news following Welch and Goyal (2008). Starting from the full sample—January 1973 to December 2023—I split it into an initial warm-up window of length 25 years (300 months), which corresponds to the period January 1973 to December 1998, and keep the remaining 25 years (January 1999 to December 2023) as the evaluation sample. I then proceed as follows.

I use a rolling window estimation scheme of length 25 years. For every month in the evaluation sample, t_{OoS}, I use the previous 300 observations to estimate the predictive regression coefficients and construct a forecast for $t_{OoS}+1$, using the predictors up to t_{OoS}. Next, I obtain the out-of-sample forecast error for $t_{OoS}+1$, denoted by $\widehat{e}_{t_{OoS}+1}$, store it and move to $t_{OoS}+2$. I iterate this scheme up to $T_{OoS}-1$, which yields the last prediction error $\widehat{e}_{T_{OoS}}$. This evaluation method ensures that the forecasts are computed recursively using only real-time information, available at the time the forecast is made.

To denote the forecasting errors corresponding to different models, I write the forecasting error as a function of the model considered, so that $\widehat{e}_{t_{OoS}}(bmk)$ is the out-of-sample prediction error from the benchmark model, while $\widehat{e}_{t_{OoS}}(\mathcal{M})$ is the out-of-sample prediction error from model $\mathcal{M}$. The benchmark model is taken to be the following forecasting model: $\widehat{RV}_{t+1} = \widehat{\mu} + \widehat{\beta_1} RV_t$, which aligns with the current state of the art, namely that the best forecast of next-period realized volatility is a linear transformation of its current value.[34]

[34] See Bekaert et al. (2025) for a recent overview of volatility forecasting models.

For a given loss function, $\mathcal{L}(\cdot\ ;\ \cdot)$, define the loss error difference (LED) between the benchmark and a competing forecasting model, $\mathcal{M}$, by:

$$LED_{t_{OoS}}(bmk, \mathcal{M}) := \mathcal{L}(\widehat{e}_{t_{OoS}}(bmk)) - \mathcal{L}(\widehat{e}_{t_{OoS}}(\mathcal{M})). \tag{14}$$

Whenever the loss error difference is greater than zero, that is, $LED_{t_{OoS}}(bmk, \mathcal{M}) > 0$, model $\mathcal{M}$ provides a better forecast than the benchmark, in terms of the loss function $\mathcal{L}$. Following the volatility forecasting literature (see, e.g., Patton (2011)), I consider two loss functions that are robust to the empirical properties of volatility: the absolute error loss and the QLIKE loss. I then report the cumulative sum of the loss error differences ($CuSLED$).[35]

Figure 3 shows the $CuSLED$ plot of the model incorporating credit spread news compared with the benchmark, over the full out-of-sample period from January 1999 to December 2023. The top panel plots the $CuSLED$ for the absolute error loss, while the lower panel plots the $CuSLED$ for the QLIKE loss function. The figure shows that incorporating credit spread news into the forecasting model leads to sustained gains, irrespective of the loss function considered. Over the out-of-sample period, the gains are consistent, exhibiting a stable upward trend, only occasionally interrupted by brief periods where the benchmark model performs better. For example, under the absolute error loss, the periods where the benchmark model is ahead of the competing model are after the Dot.Com bubble and after the GFC. Nevertheless, the overall trend remains positive, consistently increasing the cumulative differential of the errors. This highlights the out-of-sample stability of the predictive power of credit spread news. The QLIKE loss function plotted in the bottom panel, further establishes this point: the $CuSLED$ increases steadily, indicating stable gains from incorporating credit spread news. Abnormal gains, consistent with the patterns observed in the subsample analysis, emerge during the Global Financial Crisis (GFC). However, even if these gains were removed, the improvements attributable to credit spread news would remain sizable.

To provide additional insights on the out-of-sample performance, I compute the out-of-sample R^2 and the Clark and West (2007) statistic to compare the performance of the baseline AR(1) to those of the model augmented with credit spread news. The R^2_{OoS} averages about 6%, and the Clark and West (2007) statistic returns a value of 1.872, which is significant beyond the 5% level. These results denote important improvements in terms of out-of-sample accuracy gains, consistent with the results discussed in Section 3.2.

[35] See Appendix D for additional details on the cumulative sum plots and their computation.

4 Exploring the Economic Mechanisms

In this section, I examine three potential mechanisms that could account for the empirical facts documented in the paper. I first consider financial intermediaries' risk appetite and expectations. I then investigate credit market frictions. Finally, I assess a role for credit market sentiment.

4.1 Intermediaries' Risk Appetite

According to the intermediary-based asset pricing literature (e.g., Vayanos (2004), Adrian et al. (2014) and Adrian et al. (2019)), financial risk affects asset correlations and betas, thereby influencing assets' risk premia. For example, Vayanos (2004) develops a theoretical model in which equilibrium expected returns depend on aggregate risk proxies, with volatility serving as a state variable that influences investors' risk appetite. As a result, expected future volatility is a determinant of the returns demanded by investors through their risk appetite. Indirect empirical support for a similar mechanism comes from Haddad et al. (2021), who show that disruptions in the corporate bond market are closely linked to the financial health and liquidity needs of intermediaries, such as mutual funds.

If credit spread news reflect the compensation that intermediaries require to hold corporate bonds rather than risk-free assets, following the intermediary-based asset pricing literature, these measures should then embed intermediaries' expectations of future risk, which, in turn, shape the financial constraints they face.[36]

Why should credit markets specifically reflect the risk expectations of financial intermediaries? An answer to this question is given by Table L.214 of the Financial Accounts of the United States available from the Federal Reserve Board.[37] The table shows that the corporate bond market is dominated by financial intermediaries and institutional investors, in contrast to the equity market, where households play a dominant role.[38]

These theoretical and empirical observations provide a fertile ground to conjecture that prices and risk premia of corporate bonds reflect the underlying expectations of financial intermediaries.

Appendix A provides formal derivations of the main forecasting regressions within the intermediary-based asset-pricing framework, including the theoretical relation-

[36] As documented in Section 3, the stronger predictability for the forward-looking VIX series, together with their predictive power for volatility news, suggests that credit spread news contain information about intermediaries' expectations of future risk.

[37] https://www.federalreserve.gov/releases/z1/

[38] See Table L.224 of the Financial Accounts for the equity market data.

ship between credit spread news and intermediaries' risk expectations. The remainder of this subsection presents the corresponding empirical evidence linking credit spread news to intermediaries' risk perception and risk appetite. The analysis proceeds in two steps. First, I show that credit spread news are linked to the price of volatile stocks (PVS) measure proposed by Pflueger et al. (2020). Given that the PVS is interpreted as a macroeconomic risk appetite measure, I then demonstrate that credit spread news are specifically related to intermediaries' risk appetite using the leverage factor of Adrian et al. (2014). After establishing this link, I show that the predictive power of credit spread news for financial market risk remains robust when including alternative risk appetite proxies. Taken together, these results highlight intermediaries' risk appetite as the primary channel through which credit spread news predict financial market risk.

I begin by assessing the link between credit spread news and investors' risk perception using the PVS measure of Pflueger et al. (2020). The PVS is constructed as the difference between the average book-to-market ratio of low-volatility stocks and the average book-to-market ratio of high-volatility stocks, and, as Pflueger et al. (2020) show, it is related to the willingness of investors to hold risky assets. As the original PVS is constructed using accounting data, it is only available at quarterly frequency. To avoid reducing the forecasts to lower frequencies, I construct a monthly PVS series (PVS_t) by interpolating the original quarterly data.[39]

In Figures 4a-5a, I plot the time series of the credit spread news together with the PVS_t series. Figure 5a shows that declines in the PVS_t occur during periods of large credit spread magnitudes. This negative relationship is confirmed by both the contemporaneous and lead–lag correlations between PVS_t and $\eta_{2,t}^{GZ}$, which are around -0.3 over the full sample from January 1973 to December 2023.

In Table 13, I report the contemporaneous and predictive relationship between credit spread news and PVS_t. This table establishes a negative relationship between the two variables, with the strongest effects arising in the predictive regressions of the PVS_{t+1} on lagged credit spread news (central panel). Except for credit spread innovations, all other measures of credit spread news lead the measure of Pflueger et al. (2020), with predictive t-statistics significant beyond the 1% level. Finally, the right panel of Table 13 shows evidence of a predictive relation from PVS_t to credit spread news. Given that intermediaries also participate in the stock market, this reverse predictability does not contradict the proposed mechanism. The stronger predictive power of credit spread news may reflect the greater sophistication of

[39] I report the results based on a spline interpolator. Robustness checks using other methodologies yield almost identical results.

corporate bond investors, whose risk appetite and expectations adjust earlier than those of other market participants. Because the measure of Pflueger et al. (2020) is designed to proxy macroeconomic risk appetite, it incorporates preferences and perceptions of agents beyond financial intermediaries.

To provide direct evidence that credit spread news are specifically linked to intermediaries' risk appetite, I thus consider the broker-dealer leverage factor of Adrian et al. (2014), which offers a direct proxy for intermediaries' risk appetite (see Haddad and Muir (2021)).

Table 14 reports the relationship between credit spread news and the monthly change in broker-dealer leverage (ΔLev_t). The left panel of the table shows a contemporaneous negative relation between changes in leverage and credit spread news. The relationship is weaker for credit spread innovations and positive magnitudes (with t-statistics around –1.55), but stronger for credit spread magnitudes and downside news (with t-statistics of –2.67 and –2.46, respectively). Turning to the central panel of Table 14, there is a strong predictive relationship for all news measures except upside news, which has a t-statistic close to zero. The right panel of the table reports the predictive regressions of credit spread news on the lagged change in leverage. The results show evidence of predictability for credit spread magnitudes and the signed measures, although the latter is weaker.

These results establish a negative relationship between credit spread news and changes in intermediaries' leverage. The sign is consistent with the proposed mechanism: deleveraging episodes are associated with larger credit spread news. The insignificance of the upside measure reinforces this interpretation. Since positive news is not linked to changes in intermediary leverage, intermediaries' risk appetite appears unchanged in response to upside news. These findings support a link between credit spread news and proxies of intermediaries' risk appetite, showing specifically that credit spread news are inversely related to their risk appetite.

At this stage, it remains to determine whether credit spread news contain information about financial risk beyond that is captured by PVS_t or ΔLev_t.[40] To assess this, I run the volatility forecasting regressions including as additional controls PVS_t and ΔLev_t. Formally, I run:

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + b_{PVS} PVS_t + b_{\Delta Lev} \Delta Lev_t + \phi RV_t + \epsilon_{t+1}^{RV}, \;\; i = 1, 2.$$

Table 15 reports the results of these regressions. Credit spread news remain highly significant across all specifications, with robust t-statistics exceeding conventional

[40] Given that PVS_t is a broader measure of risk appetite, its predictive power is expected to disappear in the joint regressions.

significance levels. Among the additional risk-appetite proxies, PVS_t is significant only in the regressions using credit spread innovations, while ΔLev_t shows little evidence of predictive power in any of the specifications.

Taken together, the empirical evidence in this subsection links credit spread news to intermediaries' risk appetite. When combined with the theoretical derivations in Appendix A, these results are consistent with credit spread news capturing variation in intermediaries' risk perceptions and expectations.

4.2 Credit Market Frictions

Credit market frictions have become a leading framework for explaining the well-documented importance of credit markets for economic activity, as argued by Gilchrist and Zakrajšek (2012) and Boons et al. (2023), among others. More broadly, macroeconomic models incorporating financial frictions date back to Fisher (1933). Recent applications include Brunnermeier and Pedersen (2009), Jermann and Quadrini (2012), Brunnermeier and Sannikov (2014) and Caldara et al. (2016), whereas Quadrini (2011) provides a comprehensive review of the literature.

Building on this work, I explore the potential role of credit market frictions, interpreted as shocks to credit conditions. Such shocks influence firms' investment decisions by altering the cost of external finance and, hence, enter directly into the investment function. If levels of credit spreads reflect the prevailing funding conditions faced by firms in the corporate bond market (i.e., borrowing conditions), then news in credit spreads capture changes in those conditions. When these conditions deteriorate, firms may reduce investment, leading to lower economic growth and higher aggregate risk.

In Figures 4b-5b, I plot credit spread news alongside a proxy for credit market conditions, represented by the Chicago FED National Financial Condition Index (CFNFCI). Positive values of the CFNFCI correspond to tighter-than-average credit conditions, while negative values are associated with looser-than-average credit conditions.[41] The figures show that the series share common dynamics, with movements in credit spread news associated with movements in the credit conditions index.

This is further illustrated in Figure 6, which displays the scatterplot of the GZ index against the Chicago FED NFCI. The figure confirms a positive relationship between credit spreads and the credit condition index, with higher values of credit spreads corresponding to tighter-than-average funding conditions.

To formally corroborate the relationship between credit spread news and credit

[41] Where tighter refers to increased difficulty for firms to borrow in the credit market.

conditions, I estimate contemporaneous and predictive regressions of credit conditions on credit spread news, as well as the reverse regressions.

Since the CFNFCI exhibits near-unit-root behavior, I run these regressions using its first difference to avoid spurious predictability.[42] Formally, I consider:

$$\begin{aligned}
\Delta CC_t &= a + b\ \eta_{1,t}^{GZ} + \epsilon_t^{\Delta CC}, \\
\Delta CC_{t+1} &= a + b\ \eta_{1,t}^{GZ} + \epsilon_{t+1}^{\Delta CC}, \\
\eta_{1,t+1}^{GZ} &= a + b\ \Delta CC_t + \epsilon_{t+1}^{GZ},
\end{aligned}$$

where ΔCC_t is the first difference of the Chicago FED NFCI.

Table 16 reports the results of these regressions. Starting with the left column, which presents the contemporaneous regression of changes in credit conditions on credit spread news, there is a strong and positive relationship between the two variables. The robust t-statistic is close to 8, and the sign of the coefficient supports the economic interpretation that a widening of the spreads is associated with a contemporaneous deterioration in credit conditions, while a tightening corresponds to an improvement.

The central column shows the predictive regression of future changes in credit conditions on credit spread news. This relationship is again positive and statistically significant. The robust t-statistic of the coefficient of credit spread news is above 10, and its sign has the expected economic interpretation: a widening of credit spreads forecasts a deterioration in credit conditions, while a tightening forecasts an improvement. Finally, the right column reports the results of the reverse predictive regression of credit spread news on credit conditions. Although the statistical significance is weaker—the robust t-statistic is around 2.5—there is still evidence of a predictive relationship from credit conditions to credit spread news.

Together, these results indicate an amplification mechanism, in which changes in credit spreads and credit conditions reinforce each other. A shock to credit conditions immediately affects the external finance premium, which represents the wedge between the cost of internal and external funds arising from frictions. Credit spread news may capture changes in this premium and, consequently, firms' ability to borrow for financing new investments. As a result, future growth becomes more uncertain, with aggregate and financial risks increasing.

This mechanism is not mutually exclusive with the one discussed in subsection 4.1, where changes in intermediaries' risk aversion and risk expectations drive market

[42] The first-order autocorrelation of the CFNFCI is about 0.99 over the full sample from January 1973 to December 2023.

dynamics. By contrast, this mechanism based on credit market frictions operates on the demand side of the corporate bond market, reflecting firms' need for external financing, whereas intermediaries operate on the supply side, responding to investment opportunities.

4.3 Credit Market Sentiment

A recent strand of the literature builds on behavioral theories to study the role of credit market sentiment as a driver of credit markets and credit cycles (see, for example, López-Salido et al. (2017) and Bordalo et al. (2018)). This literature explains credit cycles through investors' beliefs and overreactions. Given that credit market sentiment has been linked to variables that forecast future returns to bearing credit risk, credit spread news may be related to sentiment, suggesting that sentiment could be one mechanism underlying the main findings documented.[43]

To explore this channel, I proxy for credit market sentiment using the high-yield share (HYS) measure proposed by Greenwood and Hanson (2013). The HYS is a popular, quantity-based credit market sentiment measure constructed as the high-yield share of nonfinancial corporate bonds issued during a given period.[44]

To study its relationship with credit spread news, I construct a monthly HYS series by interpolating the quarterly data with a spline and measure sentiment as the monthly demeaned HYS.[45]

Figures 4c-5c plot the time series of credit market sentiment and credit spread news. Although some common patterns can be noticed, the visual relationship between credit spread news and credit market sentiment appears weaker than that between credit spread news and the price of volatile stocks or the credit condition index. On average, periods characterized by larger credit spread news are associated with more negative sentiment, while periods with smaller news correspond to more positive sentiment.

To formally examine the relationship between credit spread news and credit market sentiment, I estimate both contemporaneous and predictive regressions of sentiment on credit spread news, as well as the reverse specification. To assess whether changes in credit market sentiment, rather than its level, are related to credit spread news, I consider the first difference of the HYS series.

[43] See Appendix A for derivations showing the link between credit spread news and risk premia on corporate bonds.

[44] Greenwood and Hanson (2013) use Moody's rating to distinguish between high-yield (BB+ or lower ratings) and investment-grade bonds (those with higher rating than BB).

[45] In untabulated results, I explore different types of interpolation and the results are essentially unchanged.

Table 17 reports the results of these predictive regressions. Starting with the regressions using the level of sentiment, from the left side of Panel A, the contemporaneous relationship between credit market sentiment and credit spread news is weak. Only credit spread magnitudes display a statistically significant coefficient ($|t|-$statistic of about 2.38), which is estimated to be negative. Moving to the central part of Panel A, the results of the predictive regressions of credit spread news for credit market sentiment show evidence of a predictive relationship. The strongest predictability arises from credit spread magnitudes and negative news, with robust t-statistics well in excess of 3, in absolute value. The sign of the coefficients provides a formal validation of what Figures 4c-5c suggested: credit spread news are negatively related to credit market sentiment. The results for credit spread innovations show that positive news (spreads narrowing) are associated with a more positive sentiment, while negative news (spreads widening) are associated with a more pessimistic sentiment. Finally, the right column of Panel A reports the predictive regressions for credit spread news on credit market sentiment. In this case, it is not possible to conclude that sentiment leads credit spread news. This result is important because it allows me to establish a one-way relationship between credit spread news and credit market sentiment, with sentiment that is predicted by credit spread news, and not vice versa.

Panel B of Table 17 repeats the regression analysis using changes in sentiment rather than levels. The results are qualitatively similar to those obtained using levels. The strongest relationship between credit market sentiment and credit spread news is the predictive specification in which current credit spread news predicts next-period changes in sentiment. In contrast, the reverse specification—current changes in credit sentiment predicting next-period credit spread news—shows no significant evidence of predictive power.

Taken together, these results indicate a one-way relationship that is hard to reconcile with a primary role for sentiment in explaining the main findings. Instead, credit spread news may serve as an early indicator of changes in credit market sentiment. Given the relatively recent theoretical and empirical literature that emphasize sentiment in explaining financial crises, credit spread news may provide informative signals in this context.

The main takeaway from this section is that financial intermediaries' risk expectations are a key driver of the predictive power of credit spread news. The results also indicate a complementary role for credit market frictions. In contrast, credit market sentiment appears to have no significant effect on the main findings.

5 Conclusion

In this paper, I show that credit spread news—defined as changes and absolute changes of corporate bond credit spreads—are robust predictors of financial market risk. The predictive power of credit spread news is both statistically strong and economically meaningful. The findings are highly robust: they hold across multiple proxies for financial risk, remain significant after controlling for lagged risk measures, and persist in subsample and out-of-sample analyses. The economic interpretation highlights a central role for financial intermediaries' risk expectations. The results uncover a novel information channel operating through credit markets, emphasizing the importance of credit spread movements and intermediaries' risk appetite for understanding second-moment dynamics. Moreover, the evidence presented points to the existence of an amplification channel that depends on the tightness of intermediary constraints. The policy implication is that tightening financial intermediaries' risk constraints may produce the opposite of the intended effect. To conclude, this paper brings attention to how measures of credit spreads, other than the levels, can be used to understand macro-finance puzzles. These findings open promising avenues for further research.

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Tables and Figures

Summary Statistics

	Sample			
	Jan 1973 - Dec 2023		Jan 1985 - Dec 2023	
Panel a) Credit Spread News				
	$\eta_{1,t}^{GZ}$	$\eta_{2,t}^{GZ}$	$\eta_{1,t}^{GZ}$	$\eta_{2,t}^{GZ}$
Mean	0.019	44.128	0.059	46.959
Std. Dev.	77.959	64.242	83.663	69.207
ρ	0.211	0.406	0.267	0.405
Panel b) Downside and Upside News				
	$\eta_{\mathcal{D},t}^{GZ}$	$\eta_{\mathcal{U},t}^{GZ}$	$\eta_{\mathcal{D},t}^{GZ}$	$\eta_{\mathcal{U},t}^{GZ}$
Mean	47.997	40.834	52.280	42.612
Std. Dev.	76.915	50.926	85.170	52.480
ρ	0.368	0.292	0.359	0.312

Table 2: Summary Statistics. This table reports the summary statistics of credit spread news obtained from the *GZ* index. 'Mean' is the sample average, 'Std. Dev.' is the sample standard deviation, both expressed in annualized basis point, and 'ρ' is the first order autocorrelation coefficient.

Predictive Regressions for Monthly Realized Volatility

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+1}^{RV}$$

Regressor	η_1-Panel				η_2-Panel			
μ	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.001
t-stat	7.941	4.283	4.358	4.347	3.434	3.168	3.021	2.906
$\eta_{1,t}^{GZ}$	0.725	0.376	0.472	0.544				
t-stat	2.621	2.149	2.744	3.099				
$\eta_{2,t}^{GZ}$					1.103	0.654	0.621	0.610
t-stat					3.681	3.222	2.903	2.746
RV_t		0.314	0.242	0.214		0.247	0.232	0.228
t-stat		2.374	2.176	2.083		2.213	2.255	2.225
RV_{t-1}			0.139	0.103			0.056	0.032
t-stat			6.125	4.974			1.334	0.747
RV_{t-2}				0.124				0.069
t-stat				5.946				4.955
Adj. $R^2(\%)$	8.966	16.604	17.979	19.086	14.166	17.741	17.856	18.122

Table 3: *RV* Predictive Regressions. This table shows the results from predictive regressions on the realized volatility, including additional control variables. The sample spans January 1973 to December 2023. The data used for the construction of the credit spread news is from the FED, while the realized volatility is computed as the sum of daily squared returns within the trading month. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Predictive Regressions for Monthly VIX

$$VIX_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j VIX_{t+1-j} + \epsilon_{t+1}^{VIX}$$

Regressor	η_1−Panel				η_2−Panel			
μ	0.004	0.001	0.001	0.001	0.002	0.001	0.001	0.001
t-stat	10.461	4.996	4.901	6.866	7.802	5.346	6.029	5.412
$\eta_{1,t}^{GZ}$	0.513	0.267	0.271	0.332				
t-stat	2.086	3.046	2.574	3.114				
$\eta_{2,t}^{GZ}$					1.054	0.397	0.355	0.327
t-stat					4.924	2.605	2.643	2.675
VIX_t		0.798	0.789	0.798		0.697	0.821	0.874
t-stat		27.550	11.033	14.012		13.410	11.037	11.962
VIX_{t-1}			0.010	-0.229			-0.129	-0.294
t-stat			0.132	-2.022			-2.874	-3.770
VIX_{t-2}				0.281				0.151
t-stat				2.823				3.363
Adj. R^2(%)	14.740	74.922	74.861	76.876	43.479	75.151	75.519	76.067

Table 4: VIX Predictive Regressions. This table shows the results from predictive regressions on the VIX, including additional control variables. The sample spans January 1990 to December 2023. The data used for the construction of the credit spread innovations and magnitudes is from the FED, while the VIX data is from the CBOE. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Predictive Regressions for Monthly GARCH-based Volatility

$$GARCH_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j GARCH_{t+1-j} + \epsilon_{t+1}^{GARCH}$$

Regressor	η_1-Panel				η_2-Panel			
μ	0.002	0.000	0.000	0.000	0.002	0.000	0.000	0.000
t-stat	15.424	4.598	4.695	4.200	13.731	5.391	5.409	5.171
$\eta_{1,t}^{GZ}$	0.018	0.041	0.038	0.039				
t-stat	0.283	3.208	2.864	3.053				
$\eta_{2,t}^{GZ}$					0.316	0.064	0.060	0.060
t-stat					8.758	3.990	3.718	3.686
$GARCH_t$		0.911	0.950	0.952		0.873	0.910	0.911
t-stat		50.869	21.836	21.217		56.514	20.909	21.523
$GARCH_{t-1}$			-0.043	-0.078			-0.038	-0.050
t-stat			-1.093	-1.382			-0.952	-1.124
$GARCH_{t-2}$				0.037				0.013
t-stat				0.741				0.294
Adj. $R^2(\%)$	-0.078	82.984	82.968	82.949	18.803	83.158	83.136	83.098

Table 5: GARCH Predictive Regressions. This table shows the results of GARCH predictive regressions, including additional control variables. The sample spans January 1973 to December 2023. The data used for the construction of the credit spread innovations and magnitudes is from the FED, while the GARCH-based volatility series is constructed as detailed in the data section of the paper. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Out-of-Sample Challenges of Macro-Finance Predictive Regressions

$$RV_{t+1} = \mu + \beta_x x_t + \phi RV_t + \epsilon^{RV}_{t+1}$$

Sample	Predictor											
	INF.	INF. VOL	IP	IP VOL	tbl	lty	ltr	lty-tbl	ltr-lty	*DS*	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$
	Panel a) t-statistics											
1986M1-2023M12	0.059	-0.869	0.274	-0.167	0.086	0.017	0.493	-0.001	0.482	1.020	**2.001**	**1.937**
1973M1-2023M12	-0.049	-0.406	0.144	-0.342	-0.392	-0.212	-0.415	0.379	-0.204	1.355	**2.029**	**2.317**
	Panel b) R^2_{OoS}											
1986M1-2023M12	-5.352	-3.127	-1.760	-0.696	-6.655	-9.621	-6.221	-0.384	-12.333	2.406	**4.866**	**4.626**
1973M1-2023M12	-1.356	-0.257	-0.110	-0.161	0.049	-1.961	-2.207	0.101	-5.028	0.928	**4.013**	**8.729**

Table 6: Rolling Out-of-Sample Predictive Regressions. This table reports the average out-of-sample R^2 and t-statistics from predictive regressions of realized volatility on a range of predictors commonly used to study the relationship between macroeconomic predictors and financial risk. The benchmark model is $RV_{t+1} = \mu + \phi RV_t + \epsilon^{RV}_{t+1}$, and competing regressions are run by adding each individual predictor to the benchmark, as in the table's headline. The out-of-sample scheme follows a rolling window scheme, with a window length of 25 years (300 months) for the longer sample and 15 years (180 months) for the shorter sample. The R^2_{OoS} are expressed in % terms. The predictors used are from Welch and Goyal (2008). 'INF.'=inflation; 'IP'= industrial production growth; 'tbl'= treasury bill; 'lty' = long-term yield; 'ltr' = long-term return; '*DS*'= default spread. **Boldface** numbers highlight the performance of credit spread news.

Downside and Upside Predictive Regressions

$$RV_{t+1} = \mu + \gamma^{-}\ \eta^{GZ}_{\mathcal{D},t} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon^{RV}_{t+1}$$

$$RV_{t+1} = \mu + \gamma^{+}\ \eta^{GZ}_{\mathcal{U},t} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon^{RV}_{t+1}$$

	$\eta^{GZ}_{\mathcal{D},t}$−Panel				$\eta^{GZ}_{\mathcal{U},t}$−Panel			
μ	0.002	0.002	0.001	0.001	0.003	0.002	0.002	0.001
t-stat	7.008	4.412	4.208	3.871	6.826	3.860	3.846	3.905
$\eta^{GZ}_{\mathcal{D},t}$	1.362	0.937	0.995	1.065				
t-stat	4.479	3.487	3.725	3.724				
$\eta^{GZ}_{\mathcal{U},t}$					0.039	-0.043	-0.176	-0.258
t-stat					0.266	-0.395	-1.427	-2.139
RV_t		0.196	0.139	0.114		0.387	0.350	0.340
t-stat		1.781	1.538	1.348		2.635	2.503	2.414
RV_{t-1}			0.117	0.078			0.101	0.075
t-stat			4.644	4.083			3.096	2.302
RV_{t-2}				0.116				0.090
t-stat				5.099				5.753
Adj. R^2(%)	17.261	19.280	20.288	21.276	-0.157	14.677	15.303	15.817

Table 7: Predictive Regressions for Downside and Upside News. This table shows the results from predictive regressions of the realized volatility when credit spread news are separated into downside and upside news. The sample spans January 1973 to December 2023. The data used for the construction of the credit spread news is from the FED, while the realized volatility is computed as the sum of daily squared returns within the trading month. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Credit Spread News and Orthogonalized Risk

	$\sigma^{\perp}_{RV,t+1}$	$\sigma^{\perp}_{VIX,t+1}$	$\sigma^{\perp}_{GARCH,t+1}$
γ_1	0.433	0.267	0.053
t-stat	2.831	3.266	2.760
Adj. R^2	4.144	12.113	7.415
γ_2	0.546	0.331	0.097
t-stat	3.100	3.922	5.982
Adj. R^2	4.494	12.822	16.971
γ^-	0.743	0.437	0.109
t-stat	4.243	4.912	6.426
Adj. R^2	6.701	18.510	17.394
γ^+	-0.104	-0.070	0.021
t-stat	-1.302	-1.260	1.865
Adj. R^2	-0.091	-0.015	0.196

Table 8: Orthogonalized Risk. This table reports the results of predictive regressions of the orthogonalized risk component, i.e., the portion of risk not explained by its own past values. The sample spans January 1973 to December 2023 for RV and GARCH-based measures, and January 1990 to December 2023 for the VIX. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Subsample Predictive Regressions for Monthly Realized Volatility

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+1}^{RV}$$

		η_1-Panel				η_2-Panel			
RV Lags		0	1	2	3	0	1	2	3
	$\eta_{1,t}^{GZ}$	0.802	0.435	0.547	0.637				
	t-stat	2.666	2.055	2.667	3.123				
Jan 1985 - Dec 2023									
	$\eta_{2,t}^{GZ}$					1.163	0.711	0.678	0.668
	t-stat					3.672	3.035	2.717	2.576
	$\eta_{1,t}^{GZ}$	0.303	0.237	0.258	0.267				
	t-stat	2.682	2.545	2.723	2.853				
Jan 1973 - Jun 2008									
	$\eta_{2,t}^{GZ}$					0.492	0.374	0.353	0.330
	t-stat					2.698	2.524	2.440	2.265
	$\eta_{1,t}^{GZ}$	0.792	0.413	0.464	0.557				
	t-stat	2.105	1.805	2.283	2.691				
Jan 1985 - Dec 2019									
	$\eta_{2,t}^{GZ}$					1.233	0.728	0.696	0.686
	t-stat					3.287	2.874	2.658	2.545

Table 9: Subsample Predictive Regressions. This table reports the results of predictive regressions for realized volatility across different subsamples. The first subsample spans January 1985 to December 2023; the second subsample spans January 1973 to June 2008; the third subsample spans January 1985 to December 2019. The data used for the construction of the credit spread news is from the FED, while the realized volatility is computed as the sum of daily squared returns within each trading month. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

Multi-Step Ahead Predictive Regressions for Monthly Realized Volatility

$$RV_{t+h} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+h}^{RV}$$

	Intercept	$\eta_{1,t}^{GZ}$	$\eta_{2,t}^{GZ}$	RV_t	RV_{t-1}	RV_{t-2}	Adj. $R^2(\%)$
				$h = 2$			
coeff.	0.003	0.340					1.839
$t-$stat	7.746	1.869					
coeff.	0.002	0.224		0.124	0.114	0.038	5.818
$t-$stat	5.103	1.702		1.614	5.019	1.125	
coeff.	0.002		0.730				6.110
$t-$stat	5.643		3.804				
coeff.	0.002		0.471	0.086	0.070	0.007	6.820
$t-$stat	4.540		3.163	1.366	2.348	0.217	
				$h = 3$			
coeff.	0.003	0.287					1.263
$t-$stat	7.706	2.169					
coeff.	0.002	0.175		0.110	0.0	0.090	3.331
$t-$stat	5.497	1.636		3.782	0.021	1.495	
coeff.	0.002		0.479				2.540
$t-$stat	6.684		4.164				
coeff.	0.002		0.216	0.112	-0.022	0.053	3.227
$t-$stat	5.241		2.172	2.840	-0.779	1.130	

Table 10: Multi-Step Ahead Predictive Regressions. This table shows the results from the multi-step ahead predictive regressions of the realized volatility. The first panel presents the results for a two-step-ahead horizon, while the second panel reports the results for three-step-ahead horizon. The sample spans January 1973 to December 2023. The data used for the credit spread news is from the FED, while the realized volatility is computed as the sum of daily squared returns within each trading month. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Credit Spread News and Macroeconomic Variables: Levels

$$y_{t+1}^{\text{macro}} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \beta_1 RV_t + \phi y_t^{\text{macro}} + \epsilon_{y,t+1}$$

	Δip		ΔPAY		$\Delta UNRATE$	
	η_1	η_2	η_1	η_2	η_1	η_2
μ	0.003	0.003	0.003	0.003	-0.001	-0.001
$t-$stat	2.958	2.854	2.617	2.524	-1.570	-1.680
γ_1	-0.707		-0.377		0.307	
$t-$stat	-1.124		-0.784		0.855	
γ_2		-0.491		-0.500		0.292
$t-$stat		-0.719		-0.823		0.679
β_1	-0.545	-0.589	-0.580	-0.556	0.395	0.398
$t-$stat	-1.720	-1.372	-1.417	-1.222	1.379	1.197
ϕ	0.214	0.178	-0.003	-0.055	-0.029	-0.072
$t-$stat	2.770	2.030	-0.035	-0.520	-0.390	-0.795
Adj. $R^2(\%)$	22.481	20.967	30.436	30.344	27.141	26.323

Table 11: Credit Spread News and the Macroeconomy. This table reports the results of predictive regressions of macroeconomic variables on credit spread news. The data is monthly and span the period from January 1973 to December 2023. The macroeconomic variables are sourced from FRED. Δip denotes the log growth of industrial production, ΔPAY denotes the log growth of nonfarm payroll employment, and $\Delta UNRATE$ denotes the change in the unemployment rate. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Credit Spread News and Macroeconomic Variables: Volatility

$$\sigma_{t+1}^{\text{macro}} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + \beta_1 RV_t + \phi \sigma_t^{\text{macro}} + \epsilon_{\sigma_y, t+1}$$

	$\sigma(\Delta ip)$		$\sigma(\Delta PAY)$		$\sigma(\Delta UNRATE)$	
	η_1	η_2	η_1	η_2	η_1	η_2
μ	0.000	0.000	0.000	0.000	0.000	0.000
t-stat	-0.236	-0.550	-0.849	-0.939	-0.294	-0.596
γ_1	-0.038		-0.086		-0.003	
t-stat	-1.013		-1.031		-1.035	
γ_2		0.038		0.077		0.002
t-stat		1.098		1.002		1.027
β_1	0.017	0.001	0.029	-0.004	0.001	0.000
t-stat	1.209	0.534	1.055	-0.496	1.059	-0.525
ϕ	0.686	0.697	0.178	0.192	0.903	0.912
t-stat	23.538	32.564	6.882	13.884	81.426	229.420
Adj. R^2(%)	54.785	53.652	10.071	6.843	84.635	84.099

Table 12: Credit Spread News and the Macroeconomy. This table reports the results of predictive regressions of the volatility of macroeconomic variables on credit spread news. The data is monthly and span the period from January 1973 to December 2023. The macroeconomic variables are sourced from FRED. $\sigma(\cdot)$ denotes the conditional volatility, obtained by fitting a GARCH(1,1) model to the corresponding macroeconomic series. For example, $\sigma(\Delta ip)$ is obtained by fitting a GARCH(1,1) model to the log growth of industrial production; analogous definitions apply to the log growth of nonfarm payroll employment and to the change in the unemployment rate. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection procedure of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Credit Spread News and Risk Perception

	$PVS_t = a + b\ \eta^{GZ}_{i,t} + \epsilon_t$				$PVS_{t+1} = a + b\ \eta^{GZ}_{i,t} + \epsilon_{t+1}$				$\eta^{GZ}_{i,t+1} = a + b\ PVS_t\ + \epsilon_{t+1}$			
	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$
a	-0.192	-0.117	-0.185	-0.118	-0.192	-0.109	-0.180	-0.120	0.020	0.105	0.062	-0.043
t-stat	-4.967	-3.052	-4.618	-3.373	-4.945	-2.896	-4.546	-3.403	2.106	11.375	8.168	-8.048
b	0.288	-0.588	-0.102	-1.151	0.237	-0.654	-0.192	-1.141	0.101	-0.122	-0.010	0.112
t-stat	1.727	-3.380	-1.250	-5.497	1.457	-4.178	-2.407	-6.220	2.287	-3.364	-0.504	3.192

Table 13: Credit Spread News and Risk Perception. This table reports the contemporaneous and predictive regressions between credit spread news and the risk perception measure of Pflueger et al. (2020). The left panel reports the contemporaneous relationship between several measures of credit spread news and the monthly PVS_t. The central panel reports the predictive relationship between several measures of credit spread news and the monthly PVS_{t+1}. The right panel reports the predictive relationships of PVS_t on measures of credit spread news at month $t+1$. The sample goes from January 1973 to December 2023. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

Credit Spread News and ΔLev of Adrian et al. (2014)

	$\Delta Lev_t = a + b\ \eta^{GZ}_{i,t} + \epsilon_t$				$\Delta Lev_{t+1} = a + b\ \eta^{GZ}_{i,t} + \epsilon_{t+1}$				$\eta^{GZ}_{i,t+1} = a + b\ \Delta Lev_t\ + \epsilon_{t+1}$			
	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$
a	0.008	0.139	0.083	0.022	0.010	0.107	0.070	0.011	0.001	0.129	0.065	-0.064
t-stat	0.253	3.474	2.965	0.610	0.288	3.986	2.727	0.285	0.089	12.191	8.372	-8.878
b	-0.565	-1.027	-1.166	-0.222	-0.506	-0.771	-0.950	-0.030	-0.080	-0.148	-0.114	0.034
t-stat	-1.590	-2.670	-2.468	-1.513	-2.247	-3.599	-3.649	-0.132	-1.059	-2.649	-1.777	1.967

Table 14: Credit Spread News and Broker-Dealer Leverage. This table reports the contemporaneous and predictive regressions between credit spread news and the ΔLev factor of Adrian et al. (2014). The left panel reports the contemporaneous relationship between several measures of credit spread news and the monthly ΔLev_t. The central panel reports the predictive relationship between several measures of credit spread news and the monthly ΔLev_{t+1}. The right panel reports the predictive relationships of ΔLev_t on measures of credit spread news at month $t+1$. The sample goes from January 1973 to December 2023. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

Intermediaries' Risk Appetite Regressions

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + b_{PVS} PVS_t + b_{\Delta Lev} \Delta Lev_t + \beta_1 RV_t + \epsilon_{t+1}^{RV}$$

	η_1-panel			η_2-panel		
μ	0.002	0.001	0.001	0.001	0.001	0
t-stat	4.060	1.322	0.900	3.060	0.592	0.525
$\eta_{1,t}^{GZ}$	0.452	0.367	0.446			
t-stat	2.555	2.176	2.625			
$\eta_{2,t}^{GZ}$				0.649	0.6414	0.6281
t-stat				3.115	3.337	3.197
PVS_t	-0.002		-0.002	0.000		0.000
t-stat	-2.075		-2.135	-0.231		-0.402
ΔLev_t		0.003	0.004		0.003	0.003
t-stat		1.131	1.283		1.126	1.134
RV_t	0.285	0.312	0.209	0.246	0.245	0.246
t-stat	2.408	2.441	2.495	2.209	2.255	2.261
R^2	17.399	16.769	17.658	17.617	17.878	17.756

Table 15: Risk Appetite Regression. This table reports the volatility forecasting regression with the inclusion of the PVS_t from Pflueger et al. (2020) and the ΔLev_t from Adrian et al. (2014) as control variables. The left panel reports the forecasting regressions using credit spread innovations. The right panel reports the results for credit spread magnitudes. The sample is monthly and goes from January 1973 to December 2023. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Credit Spread News and Credit Tightening

	$\Delta CC_t = a + b\ \eta^{GZ}_{1,t} + \epsilon_t$	$\Delta CC_{t+1} = a + b\ \eta^{GZ}_{1,t} + \epsilon_{t+1}$	$\eta^{GZ}_{1,t+1} = a + b\ \Delta CC_t + \epsilon_{t+1}$
a	0.005	0.005	-0.002
t-stat	0.642	0.630	-0.156
b	0.278	0.239	0.329
t-stat	7.878	10.689	2.486

Table 16: Credit Spread Innovations and Credit Tightening. This table reports the results on the relationship between credit spread news and credit tightening, proxied using the first difference of the Chicago Fed National Financial Condition Index, denoted by ΔCC_t. The sample goes from January 1973 to December 2023. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

Credit Spread News and Credit Market Sentiment

Panel a) Level of Credit Market Sentiment

	$\widetilde{HYS}_t = a + b\,\eta^{GZ}_{i,t} + \epsilon_t$				$\widetilde{HYS}_{t+1} = a + b\,\eta^{GZ}_{i,t} + \epsilon_{t+1}$				$\eta^{GZ}_{i,t+1} = a + b\,\widetilde{HYS}_t + \epsilon_{t+1}$			
	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t+1}$	$\eta^{GZ}_{2,t+1}$	$\eta^{GZ}_{\mathcal{D},t+1}$	$\eta^{GZ}_{\mathcal{U},t+1}$
a	0.327	0.339	0.331	0.334	0.327	0.344	0.336	0.330	-0.035	0.176	0.071	0.105
t-stat	19.695	18.142	18.899	19.270	19.984	18.789	19.512	19.019	-0.905	4.548	4.374	3.022
b	-0.001	-0.095	-0.060	-0.109	-0.061	-0.125	-0.134	-0.041	0.118	-0.133	-0.008	-0.126
t-stat	-0.025	-2.378	-1.612	-1.578	-1.905	-3.562	-3.117	-0.542	1.167	-1.592	-0.183	-1.522

Panel b) Changes in Credit Market Sentiment

	$\Delta\widetilde{HYS}_t = a + b\,\eta^{GZ}_{i,t} + \epsilon_t$				$\Delta\widetilde{HYS}_{t+1} = a + b\,\eta^{GZ}_{i,t} + \epsilon_{t+1}$				$\eta^{GZ}_{i,t+1} = a + b\,\Delta\widetilde{HYS}_t + \epsilon_{t+1}$			
	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t}$	$\eta^{GZ}_{2,t}$	$\eta^{GZ}_{\mathcal{D},t}$	$\eta^{GZ}_{\mathcal{U},t}$	$\eta^{GZ}_{1,t+1}$	$\eta^{GZ}_{2,t+1}$	$\eta^{GZ}_{\mathcal{D},t+1}$	$\eta^{GZ}_{\mathcal{U},t+1}$
a	0.001	0.003	0.004	-0.003	0.001	0.004	0.005	-0.004	0.004	0.133	0.069	0.064
t-stat	0.177	0.922	1.253	-0.820	0.189	1.121	1.670	-1.241	0.273	7.643	5.283	6.135
b	-0.044	-0.022	-0.054	0.049	-0.061	-0.030	-0.074	0.068	-0.135	-0.027	-0.081	0.054
t-stat	-3.345	-1.239	-3.213	1.790	-6.981	-1.452	-5.818	4.071	-0.478	-0.139	-0.600	0.268

Table 17: Credit Spread News and Credit Market Sentiment. This table reports the results on the contemporaneous and predictive relationships between credit spread news and the demeaned monthly interpolated high-yield share ($\widetilde{HYS}_t$), and its first difference ($\Delta\widetilde{HYS}_t$), credit market sentiment measure from Greenwood and Hanson (2013). The left panel reports the contemporaneous relationship between several measures of credit spread news and the monthly $\widetilde{HYS}_t$. The central panel reports the predictive relationship between several measures of credit spread news and the monthly $\widetilde{HYS}_{t+1}$. The right panel reports the results for the predictability of credit spread news using $\widetilde{HYS}_t$. The sample goes from January 1985 to December 2015. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection method of Newey and West (1994).

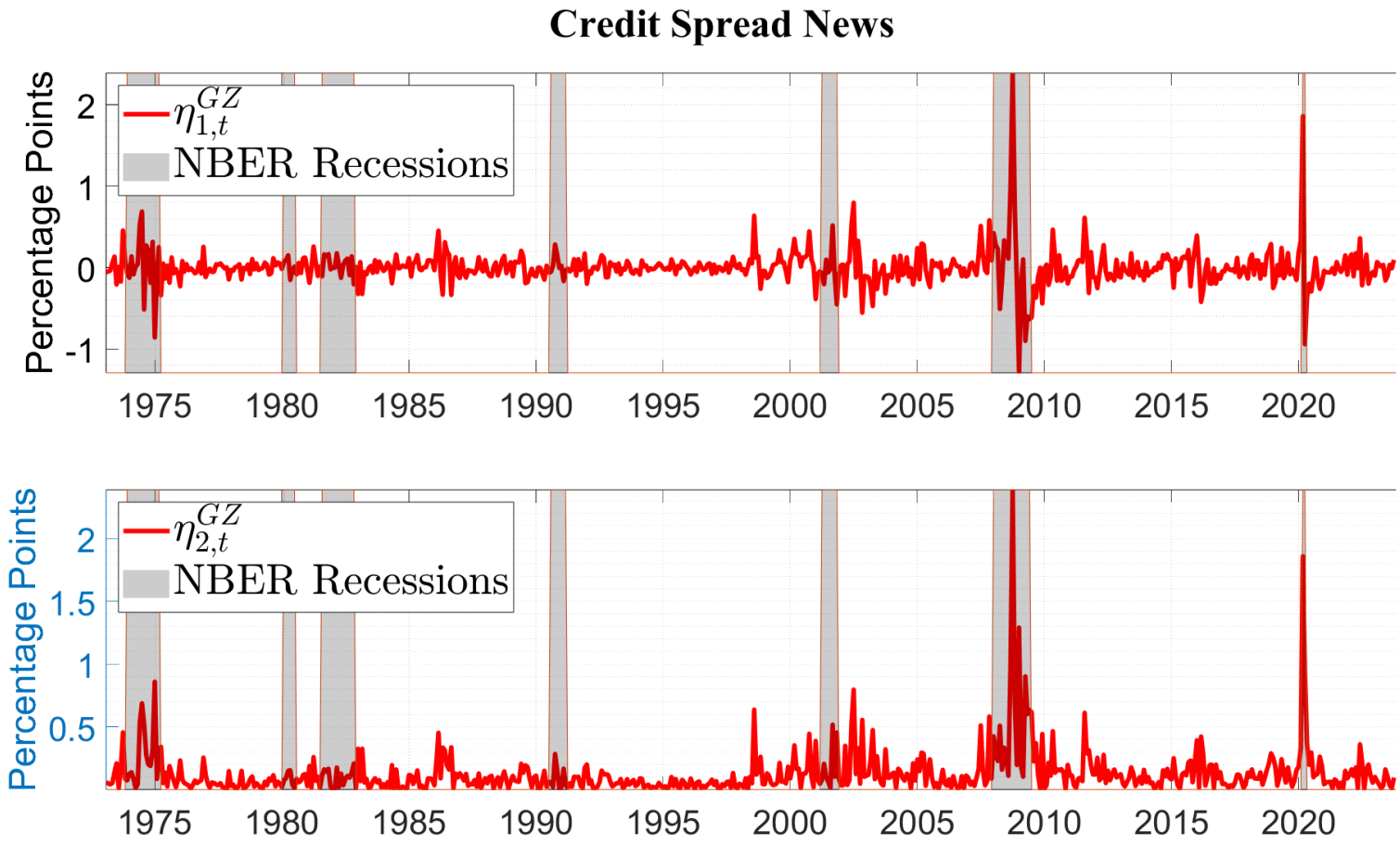
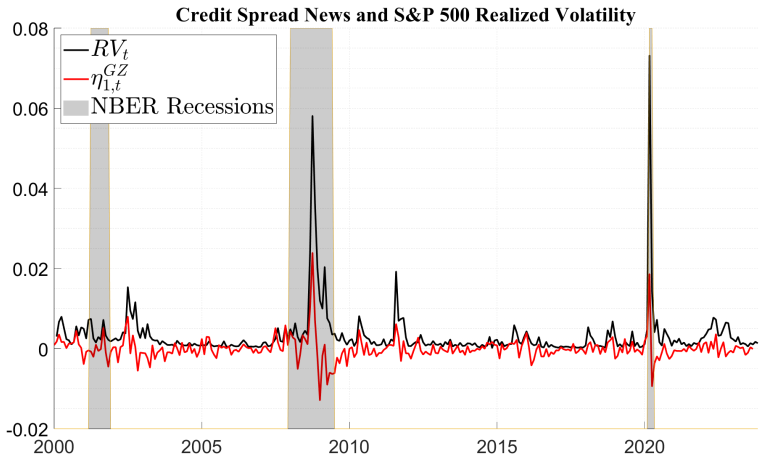
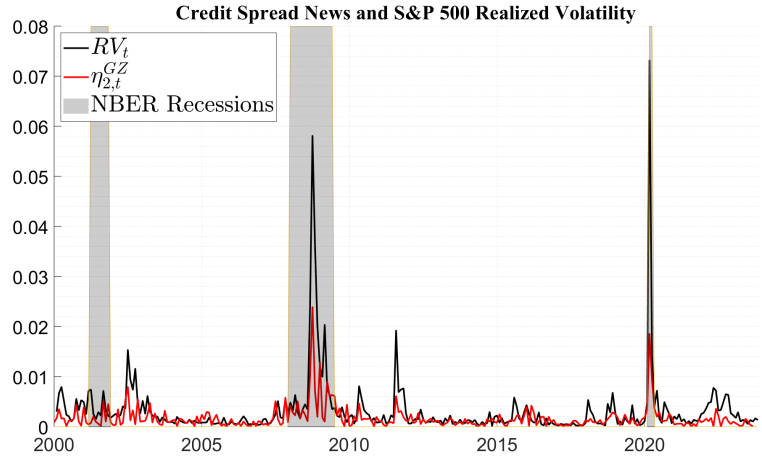


Figure 1: Credit Spread News. This figure plots the time series of the credit spread innovations and the credit spread magnitudes constructed using the GZ credit spread index. The innovations are constructed as $\eta^{GZ}_{1,t} = \Delta GZ_t$, while the magnitudes as $\eta^{GZ}_{2,t} = |\Delta GZ_t|$. The frequency of the series is monthly, and the sample goes from January 1973 to December 2023. Shaded areas denote NBER-declared recession dates.



(a) Credit Spread Innovations and Realized Volatility. This figure plots the time series of credit spread innovations, constructed as $\eta^{GZ}_{1,t} = \Delta GZ_t$, and the time series of the monthly realized volatility of the S&P 500 Index, computed using daily squared returns. The frequency of the series is monthly, and the sample goes from January 2000 to December 2023. Shaded areas denote NBER recession dates.



(b) Credit Spread Magnitudes and Realized Volatility. This figure plots the time series of credit spread magnitudes constructed as $\eta^{GZ}_{2,t} = |\Delta GZ_t|$, and the time series of the monthly realized volatility of the S&P 500 Index, computed using daily squared returns. The frequency of the series is monthly, and the sample goes from January 2000 to December 2023. Shaded areas denote NBER recession dates.

Figure 2: Credit Spread News and S&P 500 Index Realized Volatility

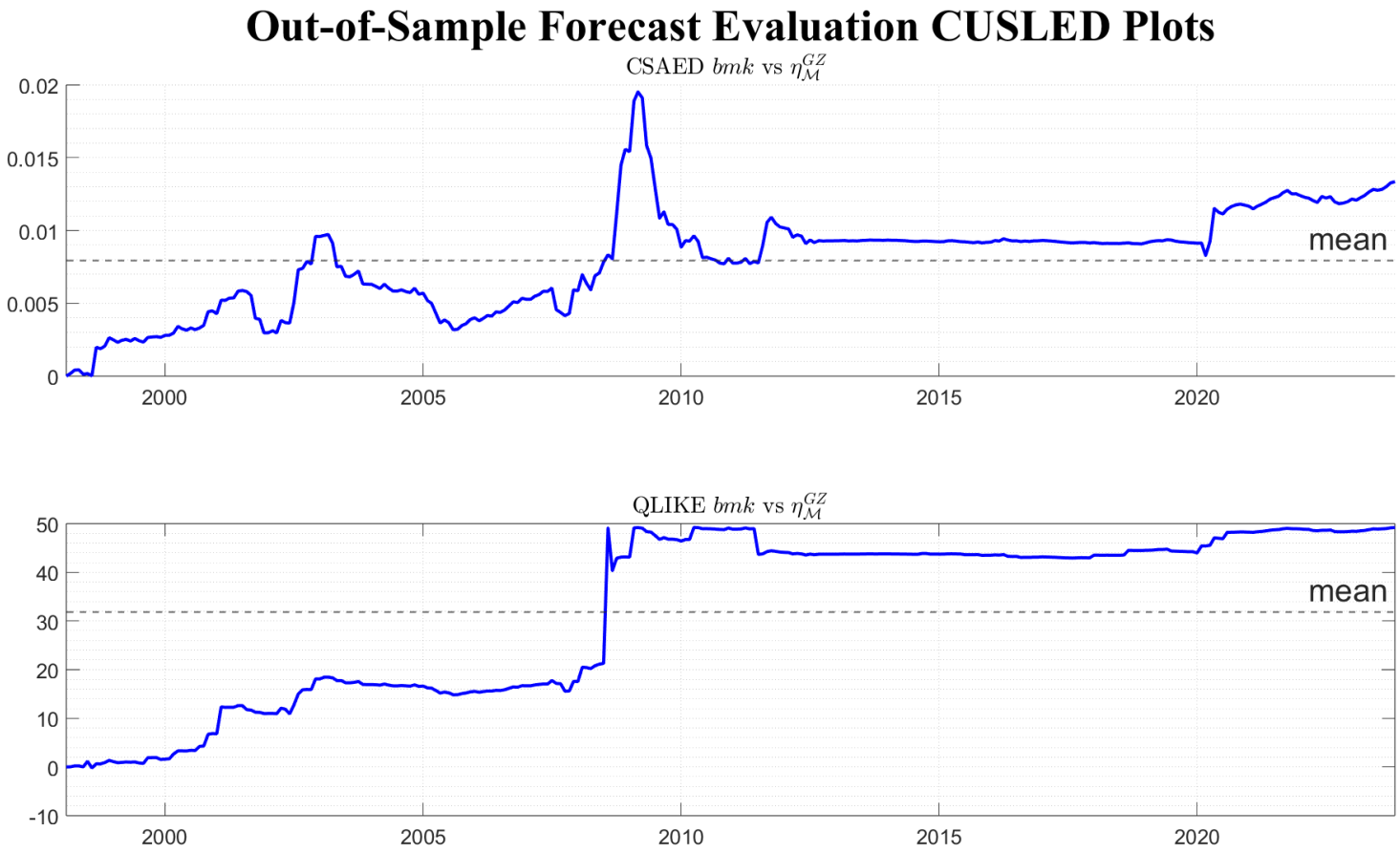


Figure 3: CuSLED Plots. This figure plots the out-of-sample cumulative sum of loss error differences ($CuSLED$) for the model which includes credit spread news versus the benchmark model without credit spread news. The out-of-sample period goes from January 1999 to December 2023, and the data frequency is monthly. The top panel reports the result for the absolute loss error difference. The bottom panel reports the results for the QLIKE function. The dotted lines report the out-of-sample average loss error differences.

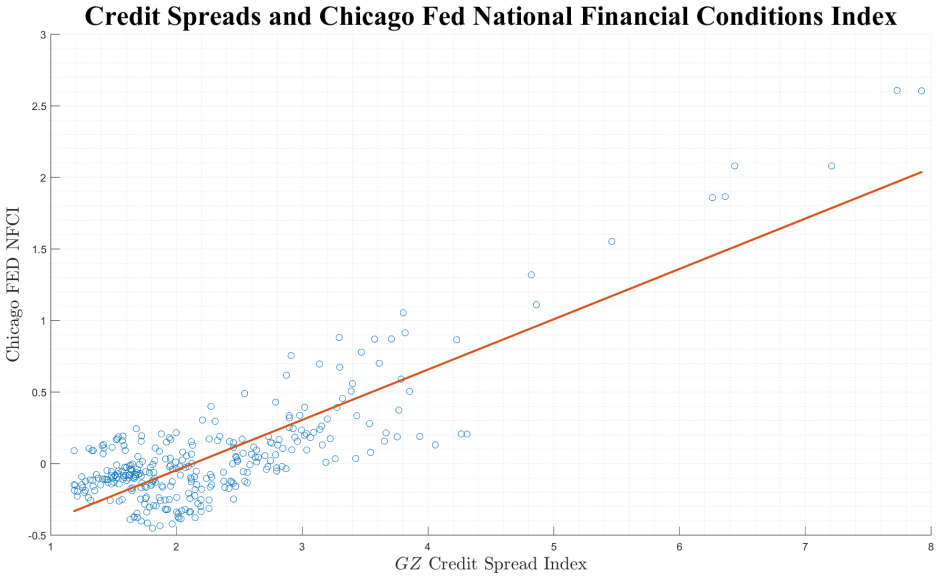
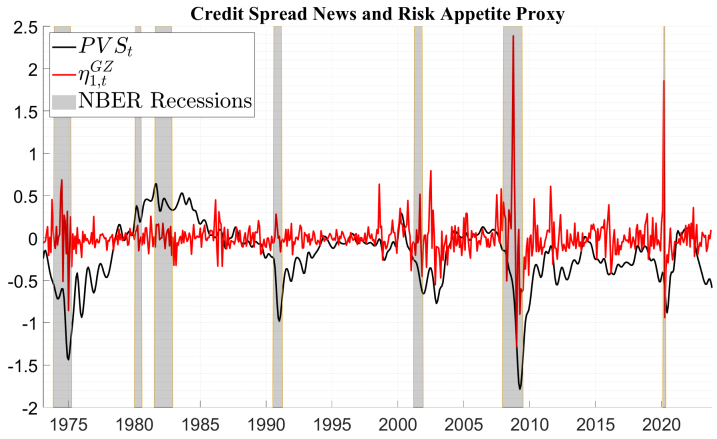
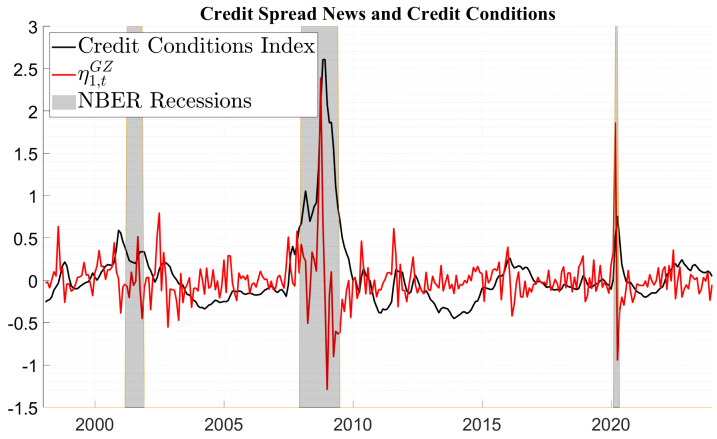


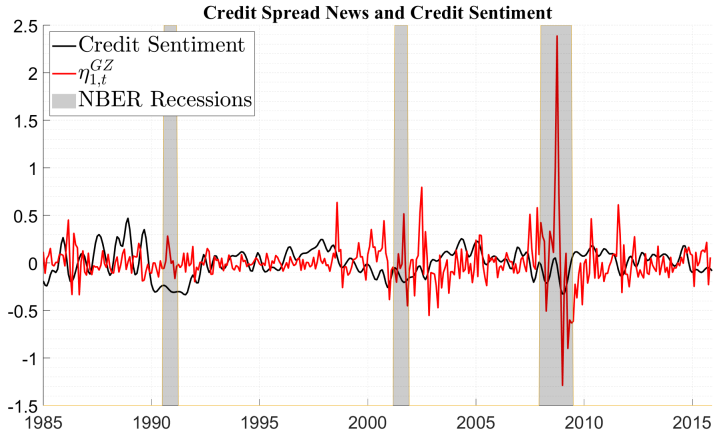
Figure 6: Credit Spreads and Financial Conditions Index. This figure plots the Gilchrist and Zakrajšek (2012) credit spread index and the Chicago Fed National Financial Conditions Index, along with the fitted linear relationship. The data are monthly and span January 1985 to December 2023. Positive values of the credit conditions index indicate tighter-than-usual credit conditions.



(a) Credit Spread Innovations and Risk Appetite. This figure plots the time series of the credit spread innovations, $\eta_{1,t}^{GZ}$, and the PVS_t variable of Pflueger et al. (2020). The data is at monthly frequency and span from January 1973 to December 2023.

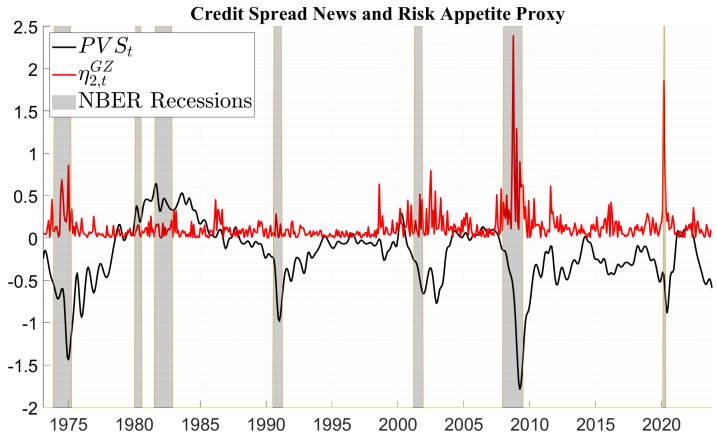


(b) Credit Spread Innovations and Credit Conditions. This figure plots the time series of the credit spread innovations, $\eta_{1,t}^{GZ}$, and the Chicago FED NFCI. The data is at monthly frequency and span from January 1998 to December 2023.

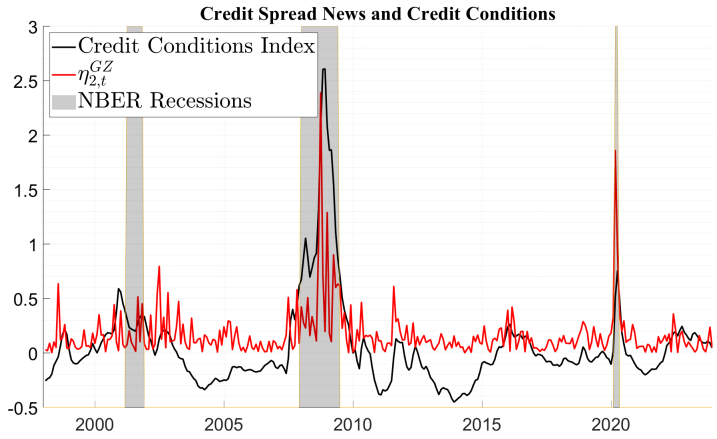


(c) Credit Spread Innovations and Credit Sentiment. This figure plots the time series of the credit spread innovations, $\eta_{1,t}^{GZ}$, and the high-yield share measure of credit market sentiment from Greenwood and Hanson (2013). The data is at monthly frequency and span from January 1985 to December 2015.

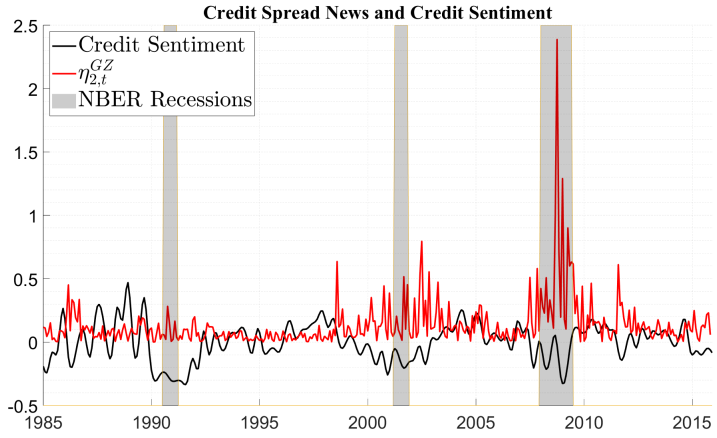
Figure 4: Credit Spread Innovations and Economic Mechanisms.



(a) Credit Spread Magnitudes and Risk Appetite. This figure plots the time series of the credit spread magnitudes, $\eta_{2,t}^{GZ}$, and the PVS_t variable of Pflueger et al. (2020) at monthly frequency and span from January 1973 to December 2023.



(b) Credit Spread Magnitudes and Credit Conditions. This figure plots the time series of the credit spread magnitudes, $\eta_{2,t}^{GZ}$, and the Chicago FED NFCI. The data is at monthly frequency and span from January 1998 to December 2023.



(c) Credit Spread Magnitudes and Credit Sentiment. This figure plots the time series of the credit spread magnitudes, $\eta_{2,t}^{GZ}$, and the high-yield share measure of credit market sentiment from Greenwood and Hanson (2013). The data is at monthly frequency and span from January 1985 to December 2015.

Figure 5: Credit Spread Magnitudes and Economic Mechanisms.

APPENDIX

A Motivating Framework

In this appendix, I provide formal derivations that establish the main forecasting relationship analyzed in the paper within an intermediary-based asset pricing framework.

Nozawa (2017) (equation (3) pp. 2048) derives the following expression for the excess log return on a generic corporate bond:

$$r^e_{i,t+1} = c_0 - \rho ps_{i,t+1} + ps_{i,t} + l_{i,t+1}, \tag{15}$$

where $ps_{i,t}$ is the price spread of the corporate bond i on the matched Treasury bond (i.e., $ps_{i,t} \equiv \log(P^f_{i,t}/P_{i,t})$), $l_{i,t+1}$ is the loss given default, and ρ and c_0 are log-linearization terms.

For short time intervals, such as one month, the price spread is closely approximated by a linear transformation of the yield spread

$$ps_{i,t+1} \approx \kappa_1 ys_{i,t+1},$$

where κ_1 depends on the duration. Thus, I can re-write the expression for the excess log return on corporate bond i as:

$$r^e_{i,t+1} = k_0 - \rho\kappa_1 ys_{i,t+1} + \kappa_1 ys_{i,t} + l_{i,t+1}, \tag{16}$$

where the approximation error is in k_0.

Consider a well-diversified portfolio obtained by equally weighting the corporate bonds available at time t, and denote the return on this portfolio by $r^e_{M,t+1}$:

$$r^e_{M,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} r^e_{i,t+1}. \tag{17}$$

Using (16) in (17), I can re-write

$$\begin{aligned} r^e_{M,t+1} &= \frac{1}{N_t}\sum_{i=1}^{N_t} r^e_{i,t+1} \\ &= \frac{1}{N_t}\sum_{i=1}^{N_t}(\kappa_0 - \rho\kappa_1 ys_{i,t+1} + \kappa_1 ys_{i,t} + l_{i,t+1}) \end{aligned}$$

$$= k_0 - \rho\kappa_1 \left(\frac{1}{N_t} \sum_{i=1}^{N_t} ys_{i,t+1} \right) + \kappa_1 \left(\frac{1}{N_t} \sum_{i=1}^{N_t} ys_{i,t} \right) + \left(\frac{1}{N_t} \sum_{i=1}^{N_t} l_{i,t+1} \right). \quad (18)$$

The quantity $\frac{1}{N_t} \sum_{i=1}^{N_t} ys_{i,t}$ defines a credit spread index, i.e., $CS_t := \frac{1}{N_t} \sum_{i=1}^{N_t} ys_{i,t+1}$. Under mild conditions on the distribution of the losses given default,[46] the last term in equation (18) vanishes as N_t grows. Putting these together, I can express (18) as

$$r^e_{M,t+1} = k_0 - \rho\kappa_1 CS_{t+1} + \kappa_1 CS_t. \quad (19)$$

Given that $\rho \approx 1$, and the credit spread index can be re-written as $CS_{t+1} = CS_t + \eta^{CS}_{t+1}$, where $\eta^{CS}_{t+1} := CS_{t+1} - CS_t$ is the credit spread news. Thus,

$$r^e_{M,t+1} \approx k_0 + \kappa_1 \eta^{CS}_{t+1}. \quad (20)$$

The intermediary-based literature (see, for example, equation (1) pp. 1993 of Adrian et al. (2019)) shows that intermediary excess returns can be expressed as nonlinear functions of the amount of financial risk in the economy, i.e.,

$$E^I_t[r^e_{M,t+1}] = \varphi_0 + E^I_t[\varphi_1(V_{t+1})], \quad (21)$$

where V_{t+1} denotes financial market risk and $E^I_t[\cdot]$ denotes the expectations taken with respect to the intermediary-based measure.

As shown by Adrian et al. (2019), $\varphi_1(\cdot)$ is a nonlinear function of financial risk. Using a a first-order Taylor approximation, I log-linearize $\varphi_1(V_{t+1})$ around V and obtain

$$\varphi_1(V_{t+1}) = \varphi_1(V) + \varphi^*_1(V_{t+1} - V) + o(|V_{t+1} - V|),$$

which gives me

$$E^I_t[r^e_{M,t+1}] = \varphi^*_0 + \varphi^*_1 E^I_t[V_{t+1}], \quad (22)$$

where $\varphi^*_0 \equiv \varphi_0 + \varphi_1(V) + \varphi^*_1(V) + o(|V_{t+1} - V|)$.

Taking the intermediary-based expectation of equation (20) and equating it to (22), I obtain

$$\varphi^*_0 + \varphi^*_1 E^I_t[V_{t+1}] \simeq k_0 + \kappa_1 E^I_t[\eta^{CS}_{t+1}]. \quad (23)$$

Re-adjusting the terms in (23), I obtain

$$E^I_t[V_{t+1}] = \mu + \gamma \; E^I_t[\eta^{CS}_{t+1}]. \quad (24)$$

[46] Mathematically, assuming that $\sum_{i,j} Cov(l_{i,t+1}, l_{j,t+1}) = o(N_t^2)$.

Finally, taking $E_t^I[\eta_{t+1}^{CS}] = \eta_t^{CS}$, yields the main forecasting regression of the paper:

$$V_{t+1} = \mu + \gamma \ \ \eta_t^{CS} + \varepsilon_{t+1}.$$

B Data

B.1 Data Sources and Data Construction

B.1.1 Credit Market Data

***GZ* Credit Spread Index.** The primary credit spread measure used in this paper is the index proposed by Gilchrist and Zakrajšek (2012) (*GZ* index). I here give additional details on the specifics of this index and its construction. The *GZ* index is computed using a broad cross-section of bond spreads issued by nonfinancial firms, matched in duration to a corresponding risk-free security. These are matched by discounting the cash-flow sequence of the corresponding corporate bonds using continuously compounded zero-coupon Treasury yields from Gürkaynak et al. (2007). The resulting index is therefore free from "duration mismatch" issues. The value of the index at time t is computed as the cross-sectional average of all the individual spreads available at the time. In the original sample of Gilchrist and Zakrajšek (2012), there are a total of 5,982 bonds linked to 1,112 firms. The bonds range from short-term (1-year) to long-term (30-year) maturities, with an average length of 13 years. The default risk of these bonds spans credit classes from 'AAA' to 'D' (Credit ratings of S&P Global). I obtain the updated series of the *GZ* index from the FED's website, where it has been made available by Favara et al. (2016) at the following link: https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html

Credit Conditions. To proxy for credit market tightness and funding conditions I use the Chicago Fed National Financial Conditions Index (CFNFCI). Description of the methodology used to construct the index and can be found on the Chicago FED website at the following link: https://www.chicagofed.org/research/data/nfci/current-data, while the index is sourced from FRED at: https://fred.stlouisfed.org/graph/?g=k5Pf

B.1.2 Financial Market Risk Measures

Realized Volatility. Let $r_{j,t}$ denote the log return on the S&P 500 index on day j of month t. Realized volatility of month t is computed as

$$RV_t = \sum_{j=1}^{m(t)} r_{j,t}^2. \tag{25}$$

VIX. Let VIX_t^{12} be the monthly annualized VIX measure available from the CBOE at https://fred.stlouisfed.org/series/VIXCLS. I obtain the monthly VIX measure used in my study as

$$VIX_t = \frac{[VIX_t^{12}]^2}{12}. \tag{26}$$

GARCH-based Volatility. I construct the GARCH-based volatility measure by first estimating a GARCH(1,1) using the monthly log returns on the S&P 500:

$$\begin{aligned} r_t &= \mu + \epsilon_t, \\ \epsilon_t &= \sqrt{\sigma_{t-1}^2} u_t, \\ \sigma_t^2 &= \omega + \beta \sigma_{t-1}^2 + \alpha \epsilon_{t-1}^2. \end{aligned}$$

I use the obtained coefficients' estimates $\widehat{\omega}, \widehat{\beta}, \widehat{\alpha}$, to produce the series of filtered conditional volatility:

$$GARCH_t = \widehat{\omega} + \widehat{\beta}\ GARCH_{t-1} + \widehat{\alpha}\ (r_{t-1} - \widehat{\mu})^2. \tag{27}$$

Summary Statistics. Table 18 reports the descriptive statistics of the volatility measures.

Summary Statistics			
	RV	VIX	GARCH
Mean	25.582	36.724	20.801
Median	13.805	26.255	17.905
Std. Dev.	54.064	35.623	13.463
Skew	9.503	4.288	2.220
AR(1)	0.387	0.791	0.909

Table 18: Summary Statistics of Financial Risk Measures. This table presents the summary statistics of the series used to measure financial risk. The sample is monthly and covers January 1973 to December 2023 for the realized volatility and the GARCH-based measures, and January 1990 to December 2023 for the VIX.

B.2 Further Empirical Properties

B.2.1 Relationship with the Excess Bond Premium

This appendix compares the measures of credit spread news I propose with the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012). I start by displaying the time series of credit spread news and the EBP in Figure 7. The figure shows that the two series exhibit distinct behavior. While credit spread news fluctuate around zero and exhibit no systematic trend, the EBP displays a pronounced persistent component. This is also reflected in its first-order autocorrelation, which is roughly 0.90

To formally investigate the relationship between credit spread news and the excess bond premium, I report in Table 19 a lead-lag correlation analysis. The left panel of the table reports the correlations between lagged credit spread news and the lead excess bond premium, from contemporaneous values up to a lead–lag horizon of 36 months. As the table shows, the two measures of credit spread news are only weakly correlated with the excess bond premium. Moreover, the correlations decay rapidly, vanishing after about 12 months. The results hold symmetrically when the correlations are computed using the lagged excess bond premium and leading credit spread news. Overall, these findings suggest that credit spread news capture a component of information contained in credit spreads that is distinct from that captured by the excess bond premium.

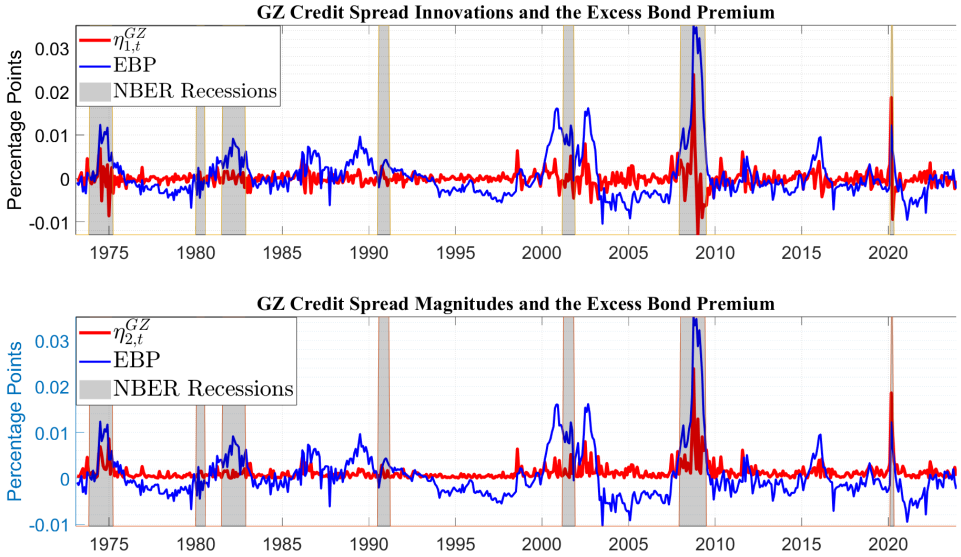


Figure 7: Credit Spread News and Excess Bond Premium. This figure plots the time series of the credit spread innovations and the credit spread magnitudes and the excess bond premium of Gilchrist and Zakrajšek (2012). The innovations are constructed as $\eta_{1,t}^{GZ} = \Delta GZ_t$, while the magnitudes as $\eta_{2,t}^{GZ} = |\Delta GZ_t|$. The GZ index and the EBP are from from Favara et al. (2016) The data is at monthly frequency, and the sample goes from January 1973 to December 2023. Shaded areas denote NBER-declared recession dates.

Credit Spread News and the Excess Bond Premium

	EBP_{t+l}		EBP_t	
	$\eta_{1,t}$	$\eta_{2,t}$	$\eta_{1,t+l}$	$\eta_{2,t+l}$
lag				
0	0.193	0.491	0.193	0.491
1	0.242	0.495	-0.097	0.424
3	0.261	0.382	-0.170	0.336
6	0.238	0.254	-0.210	0.279
12	0.109	0.030	-0.137	0.078
36	0.020	-0.073	-0.057	-0.064

Table 19: Correlations between Credit Spread News and the Excess Bond Premium. This table reports the lead-lag correlations between the credit spread news and the excess bond premium of Gilchrist and Zakrajšek (2012). The data is at monthly frequency and span the period January 1973 to December 2023 and are from the FED, see Favara et al. (2016).

B.2.2 Empirical Properties of the GZ Index

In Table 20, I report summary statistics that describe the stochastic properties of the GZ index over the full sample (January 1973-December 2023) and a subsample following the split in Gilchrist and Zakrajšek (2012) (January 1985-December 2023). In both periods, the first-order autocorrelation of the GZ index is nearly unity ($\approx$ 0.97), making it close to a unit-root process. Moreover, a Dickey-Fuller test for the null of unit root versus the alternative of trend stationary cannot be rejected at any conventional significance level. Taken together, these results indicate that the GZ index exhibits behavior consistent with a unit root process.

Stochastic Behavior of the GZ Index

Sample	Jan 1973 - Dec 2023	Jan 1985 - Dec 2023
	Autocorrelation	
AR(1)	0.969	0.966
	Dickey-Fuller Test	
H_0	Not Rejected	Not Rejected
p-value	0.155	0.220

Table 20: Stochastic Properties of the *GZ* credit spread index. This table reports the stochastic properties of the Gilchrist and Zakrajšek (2012) credit spread index for two subsamples: January 1973-December 2023 and January 1985-December 2023. The upper panel reports the estimated first-order autocorrelation coefficient (AR(1)). The bottom panel reports the results of a Dickey-Fuller test (Dickey and Fuller (1979)), which tests the null of unit root versus an alternative of difference stationarity.

Figure 8 plots the time series of the GZ credit spread index. The figure shows that the level of the index fluctuates with high persistence over the sample period. The GZ index reaches an all-time high during the Global Financial Crisis and displays pronounced peaks during other episodes of financial and economic stress, such as the collapse of Long-Term Capital Management (LTCM) and the COVID-19 pandemic.

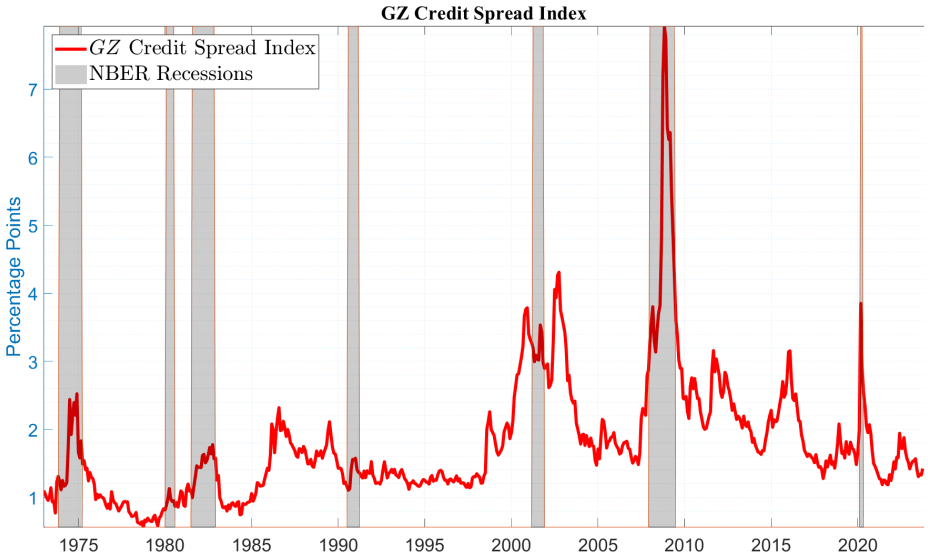


Figure 8: GZ **Credit Spread Index.** This figure plots the time series of the GZ credit spread index. The data is at monthly frequency and span the period January 1973 to December 2023 and is sourced from the FED (Favara et al. (2016)). Shaded areas denote NBER recession dates.

B.3 Final Remarks on the Credit Spread Index

The use of the Gilchrist and Zakrajšek (2012) credit spread index is motivated by the derivations in Appendix A. There, I show that the credit spread index used to construct the news must be well diversified in order to average away the loss given default components. The GZ index is well diversified both in terms of risk profile as well as in terms of duration, making it an ideal candidate. By contrast, a credit spread index such as the default spread, constructed as the spread between AAA and BAA bonds, is not well diversified. Therefore, equations (17)–(19) do not hold, invalidating its use as a baseline index for news construction.

C Further Robustness Checks and Results

In this section of the appendix, I report additional results and robustness checks.

Realized Volatility Regressions. I begin by considering the predictive regressions of the realized volatility augmented by the VIX:

$$RV_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + b \, VIX_t + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+1}^{RV}. \tag{28}$$

The results of these regressions are reported in Table 21. These results further corroborate the forecasting regression's main results. The t-statistics associated with credit spread news are all above 2, ensuring significance at the 5% level, regardless of the specification considered. Interestingly, when the VIX is added, most of the lagged values of RV_t do not have significant t-statistics, with credit spread news remaining the only significant predictor. These results robustify and reinforce the role of credit spread news for financial risk prediction.

VIX Regressions. Similarly, I report the results of the predictive regressions for the VIX, augmenting them with realized volatility:

$$VIX_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + b \, RV_t + \sum_{j=1}^{l} \beta_j VIX_{t+1-j} + \epsilon_{t+1}^{VIX}. \tag{29}$$

I report the results in Table 22. The results lead to similar conclusions as those in Table 21 for realized volatility. Credit spread news remain significant at the 10% level in all specifications, and the only other significant predictor is the first lag of the VIX.

Volatility News Regressions. As largely argued by the literature on the variance risk premium,[47] the VIX is a forward looking risk measure, which reflects investors expectations under the risk-neutral probability measure, i.e., $VIX_t \approx E_t^Q[V_{t+1}]$. Realized volatility, instead, reflects the actual risk in any given period $RV_{t+1} \approx V_{t+1}$. The difference between RV_{t+1} and VIX_t can thus be interpreted as a volatility innovation:

$$e_{t+1}^V := RV_{t+1} - VIX_t \approx V_{t+1} - E_t^Q[V_{t+1}]. \tag{30}$$

I construct the series of the absolute volatility innovation, $V_{t+1}^N \equiv |e_{t+1}^V|$, which I

[47] See, e.g., Bollerslev et al. (2009).

term volatility news, and run the following predictive regressions

$$V_{t+1}^{N} = \mu + \gamma_i \ \eta_{i,t}^{GZ} + \sum_{j=1}^{l} \beta_j V_{t+1-j}^{N} + \epsilon_{t+1}^{V}. \tag{31}$$

I report the results of the volatility news regressions in Table 23.

Predictive Regressions for Monthly Realized Volatility

$RV_{t+1} = \mu + \gamma_i \ \eta_{i,t}^{GZ} + b \ VIX_t + \sum_{j=1}^{l} \beta_j RV_{t+1-j} + \epsilon_{t+1}^{RV}$

	η_1-Panel				η_2-Panel			
μ	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
t-stat	1.718	1.641	1.715	1.717	1.794	1.351	1.383	1.263
$\eta_{1,t}^{GZ}$	0.462	0.503	0.585	0.640				
t-stat	2.355	2.074	2.315	2.350				
$\eta_{2,t}^{GZ}$					0.540	0.558	0.549	0.568
t-stat					2.092	2.107	2.075	2.109
VIX_t	0.384	0.294	0.140	0.071	0.161	0.238	0.166	0.216
t-stat	1.251	0.907	0.374	0.168	0.615	0.750	0.453	0.550
RV_t	0.164	0.169	0.200	0.203	0.250	0.226	0.257	0.234
t-stat	0.522	0.544	0.638	0.657	0.924	0.767	0.818	0.717
RV_{t-1}		0.066	0.062	0.084		-0.046	-0.053	-0.063
t-stat		1.080	0.924	1.207		-1.029	-1.416	-1.577
RV_{t-2}			0.124	0.109			0.052	0.066
t-stat			2.156	2.480			1.272	1.699
RV_{t-3}				0.061				-0.042
t-stat				0.736				-1.283
Adj. R^2(%)	26.818	26.809	27.525	27.564	26.056	25.971	25.943	25.854

Table 21: RV Predictive Regressions. This table presents additional results from predictive regressions on the realized volatility, including a larger set of control variables. The sample spans January 1990 to December 2023. I refer to Tables 3-4 of the main section for additional explanation of the variables used. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection procedure of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Predictive Regressions for Monthly VIX

$$VIX_{t+1} = \mu + \gamma_i \, \eta_{i,t}^{GZ} + b \, RV_t + \sum_{j=1}^{l} \beta_j VIX_{t+1-j} + \epsilon_{t+1}^{VIX}$$

	η_1-Panel				η_2-Panel			
μ	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
t-stat	3.512	3.292	3.941	4.354	4.253	3.560	3.770	3.815
$\eta_{1,t}^{GZ}$	0.206	0.284	0.358	0.388				
t-stat	1.929	1.687	2.152	2.119				
$\eta_{2,t}^{GZ}$					0.313	0.319	0.283	0.283
t-stat					2.117	2.268	2.026	2.023
RV_t	-0.008	0.031	0.053	0.068	0.012	-0.026	0.006	0.008
t-stat	-0.041	0.155	0.279	0.347	0.077	-0.126	0.026	0.036
VIX_t	0.755	0.564	0.479	0.408	0.652	0.754	0.726	0.720
t-stat	4.145	1.811	1.539	1.155	4.305	2.422	2.466	2.325
VIX_{t-1}		0.153	0.037	0.091		-0.070	-0.172	-0.168
t-stat		0.975	0.229	0.519		-0.606	-2.405	-2.106
VIX_{t-2}			0.226	0.155			0.140	0.130
t-stat			2.443	3.170			2.598	3.789
VIX_{t-3}				0.087				0.011
t-stat				1.377				0.270
Adj. R^2(%)	64.147	64.356	66.044	66.208	64.353	64.358	64.964	64.891

Table 22: VIX Predictive Regressions. This table presents additional results from predictive regressions on the VIX, including a larger set of control variables. The sample spans January 1990 to December 2023. I refer to Tables 3-4 of the main section for additional explanation of the variables used. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection procedure of Newey and West (1994). The adjusted R^2 is reported in percentage points.

Predictive Regressions for Volatility News

$$V^N_{t+1} = \mu + \gamma_i \, \eta^{GZ}_{i,t} + \sum_{j=1}^{l} \beta_j V^N_{t+1-j} + \epsilon^V_{t+1}.$$

	η_1-Panel				η_2-Panel			
μ	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.001
t-stat	7.037	5.342	4.397	4.108	6.394	5.407	4.022	4.455
$\eta^{GZ}_{1,t}$	0.317	0.220	0.184	0.203				
t-stat	3.136	2.811	1.908	2.037				
$\eta^{GZ}_{2,t}$					0.398	0.226	0.243	0.469
t-stat					7.844	3.146	2.429	2.318
V^N_t		0.259	0.047	0.244		0.251	0.061	0.248
t-stat		3.545	0.903	3.466		3.383	1.802	3.580
V^N_{t-1}			0.249	0.031			0.246	0.066
t-stat			3.503	0.629			3.592	2.148
V^N_{t-2}				0.044				-0.135
t-stat				1.224				-1.725
Adj. $R^2(\%)$	2.722	8.922	8.858	8.799	2.992	8.488	9.161	9.666
Adj. $R^2(\%)$	2.72	8.92	8.86	8.80	2.99	8.49	8.30	8.08

Table 23: Volatility News Predictive Regressions. This table reports the results from the volatility news predictive regressions defined in equation (30). The sample spans January 1990 to December 2023. I refer to Tables 3-4 of the main section for additional explanation of the variables used. Reported t-statistics are HAC-robust, computed using a Bartlett kernel with the automatic lag-length selection procedure of Newey and West (1994). The adjusted R^2 is reported in percentage points.

D Measures of Out-of-Sample Performance

In this appendix, I provide additional details on the computation of the out-of-sample evaluation metrics.

D.1 Cumulative Sums Plots

I start from the cumulative sum of the loss-difference series illustrated in Section 3.3.6. Given a loss function of interest, $\mathcal{L}(\cdot)$, the cumulative sum of the loss error differences ($CuSLED$) at time τ is given by

$$CuSLED_{\tau} = \sum_{t_{OoS}=1}^{\tau} LED_{t_{OoS}}(bmk, \mathcal{M}),$$

where the loss error difference (LED) is defined as

$$LED_{t_{OoS}}(bmk, \mathcal{M}) := \mathcal{L}(\widehat{e}_{t_{OoS}}(bmk)) - \mathcal{L}(\widehat{e}_{t_{OoS}}(\mathcal{M})).$$

Given a proxy for financial market risk, denoted by σ, and a corresponding forecast, $\widehat{\sigma}$, the loss functions that I consider (based on Patton (2011)) are defined as follows:

$$\begin{aligned} \text{Absolute Error} &: \mathcal{L} = |\sigma - \widehat{\sigma}|, \\ \text{QLIKE} &: \mathcal{L} = \log(\widehat{\sigma}) + \frac{\sigma}{\widehat{\sigma}}. \end{aligned}$$

The cumulative sum of error differences are popular metrics to compare the forecasting performance of two competing models, see Smith and Timmermann (2021) and Farmer et al. (2023) for an extensive discussion related to return predictability.

D.2 R^2_{OoS}

The computation of the out-of-sample R^2 (R^2_{OoS}) follows Campbell and Thompson (2008). Consider the forecast errors from the benchmark, $\widehat{e}_{t_{OoS}}(bmk)$, and the forecast errors from a competing model $\widehat{e}_{t_{OoS}}(\mathcal{M})$. The recursive $R^2_{OoS,\tau}$ is given by

$$R^2_{OoS,\tau} = 1 - \frac{\sum_{t_{OoS}=1}^{\tau}(\widehat{e}_{t_{OoS}}(\mathcal{M}))^2}{\sum_{t_{OoS}=1}^{\tau}(\widehat{e}_{t_{OoS}}(bmk))^2}.$$

Positive values of $R^2_{OoS,\tau}$ denote superior performance of the competing model with respect to the benchmark in a squared loss sense.