Which Factors Drive Downside Risk in the U.S. Economy?

Christian Brownlees[†,⋆,*] Carlo Pavanello[†] Andre B.M. Souza[‡]

March 23, 2026

Abstract

We study which common factors drive downside risk across a large panel of U.S. macroeconomic variables. We consider a broad set of candidate predictors, comprising both observed factors constructed from macroeconomic, financial, and text data, as well as unobserved factors associated with the panel. The relevance of the factors is assessed by how much they improve out-of-sample downside risk prediction accuracy. Factors are mapped into forecasts via quantile regression and location-scale regression. Results point to a single factor associated with macroeconomic volatility, most closely proxied by the macroeconomic uncertainty index (Jurado et al., 2015).

Keywords: downside risk, quantile regression, location-scale regression, downside risk forecasting

JEL: C22, C23, C52, C53, C58

[⋆] Department of Economics and Finance, LUISS Guido Carli;
[†] Department of Economics and Business, Universitat Pompeu Fabra and Barcelona SE;
[‡] Department of Economics and Business Economics, ESADE;
e-mail addresses: `christian.brownlees@upf.edu`, `carlo.pavanello@upf.edu`, `andre.souza@esade.edu`.
[*] Corresponding author.
We have benefited from discussions with Davide De Bortoli, Efrem Castelnuovo, Pietro Dallari, Jordi Galí. Christian Brownlees acknowledges support from the Spanish Ministry of Science and Technology (Grant MTM2012-37195); the Ayudas Fundación BBVA Proyectos de Investigación Cientìfica en Matemáticas 2021; the Spanish Ministry of Economy and Competitiveness through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2011-0075).

1 Introduction

Macroeconomic downside risk modeling has recently emerged as a prominent field of research in economics (Adrian et al., 2019; Chavleishvili et al., 2021; Forni et al., 2024; Carriero et al., 2024; Korobilis and Schröder, 2025). The growing interest in this topic has been in part driven by the increased emphasis policymakers have placed on downside risk when determining economic policy (Powell, 2021, 2024). One of the seminal contributions that sparked much of the interest in this area is Adrian et al. (2019), which showed that downside risk to U.S. economic growth increases when financial conditions tighten. Since then, the literature has extended the study of downside risk to a broad collection of macroeconomic variables. This collection includes, to name a few, inflation, unemployment, business conditions, housing, and investment (Ghysels et al., 2018; Prasad et al., 2019; Lopez-Salido and Loria, 2020; Deghi et al., 2020; Banerjee et al., 2020; Lang and Forletta, 2020; Adams et al., 2021; Kiley, 2022; Adrian et al., 2022; Lenza et al., 2023; Amburgey and McCracken, 2023; Keijsers and van Dijk, 2024).

Most contributions in the literature analyze downside risk for individual macroeconomic variables in isolation. In this paper, we adopt a multivariate perspective and study downside risk across a large panel of U.S. macroeconomic variables. Our primary objective is to assess which factors (if any) capture the dynamics of downside risk across the entire panel. It is well established in empirical macroeconomics that a small number of factors can effectively track the location dynamics of a broad set of macroeconomic variables (Stock and Watson, 2016). We investigate whether analogous evidence holds for downside risk. Understanding which factors drive downside risk for a large number of macroeconomic variables is essential for effective risk monitoring, as these factors predict the occurrence of joint extreme adverse events in the economy.

We are interested in predicting downside risk for a large panel of (stationary) macroeconomic variables. We assume that an extreme negative realization of any variable in the panel signals an adverse economic outcome. We define downside risk for a macroeconomic variable over a given horizon as the p-th quantile of the conditional distribution of the forward-average of that variable. We link factors to downside risk through two model classes: quantile regression and location-scale regression. Quantile regression is a standard methodology in the downside risk literature (Adrian et al., 2019) and consists of modeling the conditional quantile of the forward-average of each variable as a linear function of the factors. Location-scale regression extends direct regression models widely used for macroeconomic forecasting (Stock and Watson, 2002; Kim and Swanson, 2014) and consists of modeling the conditional mean and variance of the forward-average of each variable as a function of the factors, from which the conditional quantiles follow in closed form. Location-scale regression is inspired by and closely related to Component GARCH and MIDAS-GARCH models, which have a rich literature in econometrics (Ding and Granger, 1996; Amado and Teräsvirta, 2013; Engle et al., 2013; Conrad and Engle, 2025).

We apply this framework to study downside risk for a large panel of U.S. macroeconomic variables using a broad set of candidate downside risk factors. The panel is constructed using a subset of the variables in the FRED-MD database (McCracken and Ng, 2016) over the period January 1959 to July 2025, after being appropriately transformed to ensure stationarity. We restrict the panel to variables whose extreme realizations signal adverse economic outcomes, excluding variables driven by policy decisions such as interest rates and monetary aggregates. We rotate the variables so that extreme negative realizations signal adverse economic conditions. We group the candidate factors into four categories. The financial, macroeconomic, and text-based categories consist of factors constructed from financial data (e.g., the NFCI; Adrian et al., 2019), macroeconomic data (e.g., the macroeconomic uncertainty index; Jurado et al., 2015), and text data (e.g., the geopolitical risk index; Caldara and Iacoviello, 2022), respectively, and designed to capture conditions harmful to macroeconomic and financial stability. The statistical category consists of PCA-based factors (Stock and Watson, 1998) and quantile factors (Chen et al., 2021) extracted from the macroeconomic panel, as well as the first principal component of the full set of financial, macroeconomic and text-based predictors.

Our empirical study consists of both in-sample and out-of-sample analyses, with primary emphasis on the latter.

The in-sample analysis yields several findings. First, the panel of macroeconomic variables exhibits substantial lower tail dependence. The joint occurrence of adverse economic outcomes follows a heavy-tailed distribution consistent with a power law, highlighting a strong cross-sectional clustering of extreme events. Second, a factor screening exercise identifies the macroeconomic uncertainty index of Jurado et al. (2015) as the most prominent downside risk factor in the panel, although financial and statistical factors also exhibit strong performance. Third, location-scale regression provides more accurate estimates of downside risk at short and medium horizons, whereas quantile regression proves most effective at longer horizons. Finally, a quantile impulse response function analysis based on both quantile regression and location-scale regression shows that the impact of downside risk factors on macroeconomic variables varies across quantiles, corroborating the findings in Adrian et al. (2019).

The out-of-sample analysis provides the primary evidence on which factors most effectively predict downside risk. Relying on an out-of-sample analysis is natural in this context as it mitigates overfitting concerns when identifying the factors that provide the most informative signals of macroeconomic distress. We forecast downside risk across multiple horizons from January 1990 through July 2025. We construct forecasts using a comprehensive collection of one-, two-, and three-factor models. Predictions are based on both quantile regression and location-scale regression, and are evaluated by their forecast accuracy and the adequacy of the corresponding prediction intervals. We apply the model confidence set (Hansen et al., 2011) to identify the set of models that are statistically indistinguishable from the best-performing model. Our results point to a one-factor structure: the macroeconomic uncertainty index consistently delivers the strongest forecasting performance across the panel, its sub-categories, and key policy-relevant variables. Forecasts based on the macroeconomic uncertainty index achieve gains of up to 25% over the historical quantile and sizable improvements over univariate benchmarks, especially at longer horizons. Several other financial and statistical indicators, such as the NFCI and quantile factors, achieve predictive accuracies that rival the macroeconomic uncertainty index. Location-scale regression performs best at short and medium horizons, whereas quantile regressions dominate at longer horizons.

Our results indicate that, as with location dynamics, a small number of factors effectively track downside risk across a broad range of macroeconomic variables. The key difference is that downside risk appears to be driven predominantly by a single factor, broadly associated with macroeconomic volatility, best proxied empirically by the macroeconomic uncertainty index of Jurado et al. (2015). Text-based factors are notably absent from the group of top-performing indicators as they generally fail to deliver strong predictive performance. Our findings suggest that downside risk in the U.S. economy is largely a volatility phenomenon, effectively captured by a parsimonious factor structure.

This paper contributes to two strands of the literature. The first is the literature on macroeconomic downside risk modeling (Delle Monache et al., 2024; Gächter et al., 2025; Carriero et al., 2025), which has largely focused on individual variables. We complement this work by adopting a panel perspective and systematically comparing the predictive content of a broad set of factors. The second is the literature on macroeconometric forecasting with factor models (Stock and Watson, 2002; Kim and Swanson, 2014, 2018; Medeiros et al., 2021; Goulet Coulombe et al., 2022). We contribute to this literature by showing that, unlike location dynamics, downside risk across the panel is driven by a single factor broadly associated with macroeconomic volatility.

The rest of the paper is organized as follows. Section 2 introduces the downside risk framework and the quantile regression and location-scale regression models. Section 3 describes the macroeconomic panel and the candidate factors. Section 4 presents the empirical results. Section 5 concludes.

2 Downside Risk Modeling and Forecasting

In this section we introduce the downside risk definition employed in our analysis and describe our strategies to forecast downside risk in a large panel of macroeconomic variables using common factors.

2.1 Downside Risk Definition

We consider a balanced panel of n stationary variables observed over T time periods. We denote by $Y_{i\,t}$ the measurement of the i-th variable at time t, for $i = 1, \ldots, n$ and $t = 1, \ldots, T$. We assume that a large negative realization represents an adverse economic outcome for each variable in the panel. We measure downside risk at horizon h for the i-th variable as the p-th conditional quantile of the forward-average of that variable over h future periods (Adrian et al., 2019). Formally, let $\overline{Y}^{(h)}_{i\,t+1} = \frac{1}{h}\sum_{l=1}^{h} Y_{i\,t+l}$ for $h \geq 1$ denote the forward-average of the i-th variable from $t+1$ to $t+h$. Then the p-th conditional quantile of $\overline{Y}^{(h)}_{i\,t+1}$ is denoted as $Q^{(h)}_{i\,t+1}(p)$ and is defined as

$$\mathbb{P}\left(\overline{Y}^{(h)}_{i\,t+1} \leq Q^{(h)}_{i\,t+1}(p) \middle| \mathcal{F}_t \right) = p \ ,$$

where $\mathcal{F}_t$ denotes the information set available at time t. We assume throughout that the conditional distribution function of each variable is invertible, which guarantees the uniqueness of the conditional quantiles.

2.2 Downside Risk Modeling and Forecasting

Our primary objective is to assess which factors (if any) capture the dynamics of downside risks in the panel. We therefore focus on the predictive content of factors. We forecast downside risks on the basis of two model classes that allow us to explore alternative functional forms linking the factors to downside risk measures. The first is quantile regression, in which the factors affect the conditional quantiles of the forward-average of the macroeconomic variables. The second is a class of models that we refer to as location-scale regression, in which the factors affect both the conditional mean and the conditional variance of the forward-average of the variables.

Quantile regression (QR) has become a standard tool for modeling downside risk (Adrian et al., 2019). Let $\boldsymbol{F}_t = (F_{1\,t}, \ldots, F_{r\,t})'$ denote the set of candidate factors to be used for downside risk prediction. QR specifies that the p-th conditional quantile of the forward-average at horizon h of the i-th macroeconomic variable be modeled as

$$Q^{(h)}_{i\,t+1}(p) = \alpha_{(p)\,i} + \boldsymbol{\beta}'_{(p)\,i}\boldsymbol{F}_t + \gamma_{(p)\,i}Y_{i\,t}\ . \tag{1}$$

In the QR framework, downside risk is directly modeled as a function of the factors and forecasts can be readily obtained on the basis of (1). If the impact of the factors is constrained to be zero, the QR specification is analogous to a (direct) quantile autoregression (QAR(1)), which we include as a benchmark in the empirical study. We remark that the parameters $\alpha_{(p)\,i}$, $\boldsymbol{\beta}_{(p)\,i}$ and $\gamma_{(p)\,i}$, depend on the horizon h, but we keep the dependence on this quantity implicit to avoid burdening notation. All parameters are estimated by minimizing the tick loss. Details on estimation and inference for this class of models is standard and can be found, for example, in Koenker and Basset (1978).

In order to summarise the impact of factors on downside risk implied by QR we rely on reduced form quantile impulse response functions (QIRFs). A highlight of QIRFs in the context of our analysis is that also they facilitate comparisons across different modeling approaches. For simplicity and in-line with the analysis of (Adrian et al., 2019) we introduce our notion of QIRF when the specification in (1) contains only one factor that we denote as F_t. Then, the QIRF measuring the impact of the factor on the p-th conditional quantile of the forward-average at horizon h of the i-th variable is defined as

$$\mathrm{QIRF}^{(h)}_{i\,j}(p) = \mathbb{E}\left(Q^{(h)}_{i\,t+1}(p) \middle| \, F_t = M_F + \delta, Y_{i\,t} = M_{Y_i} \right) - \mathbb{E}\left(Q^{(h)}_{i\,t+1}(p) \middle| \, F_t = M_F, Y_{i\,t} = M_{Y_i} \right)\ , \tag{2}$$

where M_F and M_{Y_i} denote respectively the median of the factor and the median of the i-th variable and δ is the "intervention" on the factor. In words, the QIRF measures the change in the downside risk forecast when the factor F increases from its median value M_F to the "intervened" value $M_F + \delta$. It is immediate to see that for QR the QIRF simplifies to

$$\text{QIRF}_{i\,j}^{(h)}(p) = \beta_{(p)\,i}\delta \ .$$

We remark that our QIRF definition is closely related to the definition of the ΔCoVaR (Adrian and Brunnermeier, 2016), which is a standard systemic risk measure in the literature.

Location-scale regression (LSR) is an extension to the standard specifications used for prediction in macroeconomic applications (Kim and Swanson, 2014). It is customary in the macroeconometrics literature to employ a direct regression to model the location of a macroeconomic variable of interest using some appropriate set of predictors, typically factors recovered via PCA. Here we consider an extension of this modeling approach that consists in allowing the factors to impact both the location and the scale of the forward-average of the target variable of interest. That is, LSR specifies that the forward-average at horizon h of the i-th macroeconomic variable be modeled as

$$\overline{Y}_{i\,t+1}^{(h)} = \alpha_{(\mu)\,i} + \boldsymbol{\beta}'_{(\mu)\,i}\boldsymbol{F}_t + \gamma_{(\mu)\,i}Y_{i\,t} + \exp\left(\alpha_{(\sigma^2)\,i} + \boldsymbol{\beta}'_{(\sigma^2)\,i}\boldsymbol{F}_t\right)\epsilon_{i\,t+1}^{(h)} \ , \tag{3}$$

where $\epsilon_{i\,t+1}^{(h)}$ is a mean-zero unit-variance innovation term. Empirically, the specification in (3) is often unable to adequately capture the time-varying heteroscedasticity present in the data, which, in turn, may deteriorate the performance of quantile forecasts. To this extent, we explicitly model the heteroscedasticity dynamics of $\epsilon_{t+1}^{(h)}$. We specify that

$$\epsilon_{t+1}^{(h)} = \sqrt{v_{i\,t+1}^{(h)}}\,Z_{i\,t+1}^{(h)} \ , \tag{4}$$

where $Z_{i\,t+1}^{(h)}$ is a mean-zero unit variance innovation term with distribution $F_{Z_i^{(h)}}$ and $v_{i\,t+1}^{(h)}$ is a variance process assumed to be unit-mean and predictable given the information set in period t. The distribution $F_{Z_i^{(h)}}$ is assumed to belong to a location-scale family of distributions. We model $\{v_{i\,t}^{(h)}\}$ as a GARCH-type process defined as

$$v_{i\,t+1}^{(h)} = (1 - \delta_{1\,i} - \delta_{2\,i}) + \delta_{1\,i}(\epsilon_{t-h+1}^{(h)})^2 + \delta_{2\,i} v_{i\,t}^{(h)} \ , \tag{5}$$

where $\delta_{1\,1} > 0$, $\delta_{2\,1} \geq 0$, $\delta_{1\,1} + \delta_{2\,1} < 1$ and $v_{i\,1}^{(h)} = 1$. In the LSR framework, downside risk is indirectly modeled as a function of the factors through their impact on the conditional mean and conditional variance, and the downside risk forecast implied by the model specified in (3)–(5) is given by

$$Q_{i\,t+1}^{(h)}(p) = \alpha_{(\mu)\,i} + \boldsymbol{\beta}'_{(\mu)\,i}\boldsymbol{F}_t + \gamma_{(\mu)\,i} Y_{i\,t} + \exp\left(\alpha_{(\sigma^2)\,i} + \boldsymbol{\beta}'_{(\sigma^2)\,i}\boldsymbol{F}_t\right)\sqrt{v_{i\,t+1}^{(h)}}\, F^{-1}_{Z_i^{(h)}}(p) \ . \tag{6}$$

If the impact of the factors is constrained to be zero, the LSR specification is analogous to a (direct) AR(1)-GARCH(1,1), which we include as a benchmark in the empirical study. The parameters $\alpha_{(\mu)\,i}$, $\boldsymbol{\beta}_{(\mu)\,i}$, $\gamma_{(\mu)\,i}$, $\alpha_{(\sigma^2)\,i}$, $\boldsymbol{\beta}_{(\sigma^2)\,i}$, $\delta_{1\,i}$ and $\delta_{2\,i}$ depend on the horizon h but we keep the dependence on this quantity implicit for simplicity. We estimate the specification (3)–(5) using a quasi-maximum likelihood approach.[1] The location-scale regression parameters are estimated by maximising the Gaussian quasi-likelihood of the model and the standardized innovation distribution $F_{Z_i^{(h)}}$ is estimated nonparametrically as the empirical distribution function of the standardized residuals.

We summarise the impact of factors on downside risk implied by LSR using the same setup of (2). Importantly, we present QIRFs for the LSR under the restriction that the variance process $\{v_{i\,t}^{(h)}\}$ is constant and equal to one.[2] Under this restriction the QIRF for

[1]That is we maximise

$$\mathcal{L}_T(\boldsymbol{\theta}) = \sum_{t=1}^{T-H-1} \left(-\frac{1}{2}\log(2\pi\sigma_{t+1}^2) - \frac{(Y_{t+1}^{(h)} - \mu_{t+1})^2}{2\sigma_{t+1}^2} \right) \ ,$$

where μ_{t+1} and σ_{t+1} are the conditional mean and variance implied by the equations (3)–(5).

[2]This assumption can be relaxed at the expense of having to estimate the conditional expectation of the

LSR is given by

$$\mathrm{QIRF}_{ij}^{(h)}(p) = \beta_{(\mu)\,i}\delta + \left[\exp\left(\alpha_{(\sigma^2)\,i} + \beta_{(\sigma^2)\,i}(M_{F_j} + \delta)\right) - \exp\left(\alpha_{(\sigma^2)\,i} + \beta_{(\sigma^2)\,i}M_{F_j}\right)\right]\, F^{-1}_{Z_i^{(h)}}(p)\ .$$

We remark that the QIRF of the LSR model class varies across quantiles only if $\beta_{(\sigma^2)\,i}$ is nonzero, and its behavior is determined by the quantile function of the innovations $Z_i^{(h)}$. In particular, the QIRF will be asymmetric if the distribution of $Z_i^{(h)}$ is asymmetric.

A number of features of the LSR specification are worth emphasizing. First, the volatility specification of the model can be interpreted as a component volatility model. There is a large literature on component volatility models in econometrics (Ding and Granger, 1996; Amado and Teräsvirta, 2013; Engle et al., 2013; Conrad and Engle, 2025). This modeling approach allows for a flexible characterization of volatility dynamics, for example, by disentangling persistent and transitory volatility components. Second, we note that the LSR specification makes it possible to construct direct multi-step-ahead quantile forecasts by computing direct multi-step-ahead forecasts of the mean and the variance (Marcellino et al., 2006). This stands in contrast to more standard specifications, which construct multi-step-ahead quantile forecasts based on an iterated approach relying on simulation-based procedures (Brownlees and Engle, 2017). In the current setup, a direct forecasting approach is more appealing, as it does not require to specify the dynamics of the factors.[3]

3 Data

In this section we describe the panel of macroeconomic variables and the set of candidate downside risk factors considered in our analysis.

process $v_{i\,t}^{(h)}$, which can be carried out using nonparametric methods.

[3]We have considered an alternative specification of the LSR model with an iterated forecasting procedure to construct multi-step-ahead quantile forecasts based on simulations.The performance of such forecasts was to that of the direct forecasts.

3.1 Macroecomic Panel

We study a large panel of macroeconomic variables constructed on the basis of the August 2025 release of the FRED-MD database, which spans the period January 1959 to July 2025 (McCracken and Ng, 2016).

TABLE 1 ABOUT HERE

We outline our panel construction below. First, we exclude from the analysis four variables of FRED-MD that do not have observations prior to February 1968.[4] Second, we follow the standard guidelines of McCracken and Ng (2016) to identify outliers and transform variables to ensure stationarity. Observations identified as outliers are then replaced with the previous available value. Third, we restrict the panel to include only variables whose extreme realizations indicate adverse economic outcomes and that are not directly driven by policy decisions. This leads us to exclude interest rate (seventeen variables) and monetary base variables (six variables). Fourth, we adjust the remaining variables so that an extreme negative realization signals an adverse economic outcome, in line with our methodological framework. For variables where low realizations already indicate adverse outcomes, no adjustment is needed. This is the case for sixty-eight variables in the panel. For variables where high realizations indicate adverse outcomes, we multiply the series by minus one. This applies to ten variables: eight measures of unemployment, the USD/GBP exchange rate, and the CBOE Volatility Index. For variables where both extreme high and low realizations indicate adverse outcomes, we include the series in the panel twice, with opposite signs. This applies to twenty-one variables, which are all price index measures. Table 1 provides the economic interpretation associated with our definition of adverse outcomes. The procedure yields a panel of 120 variables.

[4]The FRED-MD codes of the excluded variables are ACOGNO, ANDENO, TWEXAFEGSMTH, and UMCSENT.

3.2 Downside Risk Factors

We consider a comprehensive collection of downside risk factors, grouped into four classes: financial, macro, text-based, and statistical. The financial, macro and text-based categories consist of measures whose large realizations capture conditions that are particularly harmful for macroeconomic and financial stability, such as increases in uncertainty, financial distress, or risk perceptions, as well as declines in housing prices, or excessive credit buildups. The statistical category includes estimates of latent factors associated with the macroeconomic panel as well as latent factors constructed from the set of financial, macro and text-based downside risk factors.

The class of financial factors consists of the national financial conditions index (Adrian et al., 2019, NFCI), financial uncertainty[5] (Ludvigson et al., 2021; Andreasen et al., 2024, FUNC), the CBOE volatility index (Bloom, 2009, VIX), the composite indicator of systemic stress[6] (Hollo et al., 2012, CISS), and the excess bond premium (Gilchrist and Zakrajšek, 2012; Favara et al., 2016, EBP).

The class of macroecomic factors consists of the macroeconomic uncertainty index[7] (Jurado et al., 2015; Jovanovic and Ma, 2022, MUNC), the housing price index[8] (Leamer, 2007; Claessens et al., 2009, HPI), and the credit-to-GDP gap (Borio et al., 2002, CTG).

The class of text-based downside risk factors consists of the economic policy uncertainty[9] (Baker et al., 2016; Hengge, 2019, EPU), the world uncertainty index[10] (Ahir et al., 2022, WUI), the geopolitical risk index[11] (Caldara and Iacoviello, 2022, GPR), and firm-level risk

[5] We use the 1-step-ahead uncertainty measure.

[6] We use the "NEW CISS – Composite Indicator of Systemic Stress., United States, Daily".

[7] We use the 1-step-ahead uncertainty measure.

[8] The monthly version of the index (CSUSHPINSA) is available from January 1987, we integrate it with the quarterly version (USSTHPI) which is available from January 1975. Both series are normalized to 100 in January 1987. We transform the resulting series using the log difference, dividing it by three in the period January 1975 – January 1987, where the frequency of the data is quarterly.

[9] We use the "News Based Policy Uncertainty Index" at monthly frequency.

[10] We use the US three-quarter weighted moving average of the world uncertainty index because the authors write that "This smoothed version of the index is our preferred measure for country-level data."

[11] We use the historical version, available from January 1900, because the standard GPR is available only from January 1985 and the correlation between the two series, in the overlapping period, is grater than 0.95.

measures[12] (Hassan et al., 2019, RISK, PRISK, NPRISK).

The class of statistical factors includes the first linear factor estimated via PCA (Stock and Watson, 2002, PC1) and the first 5% quantile factor (Chen et al., 2021, QF1) associated with the macroeconomic panel. Additionally, we also consider the first linear factor associated with the downside risk factors in the financial, macroeconomic and text categories (Keijsers and van Dijk, 2024, PCF1). We remark that the quantile factor estimation strategy used in this work differs from that employed in Chen et al. (2021) in their analysis of the FRED-QD database. Chen et al. (2021) do not adjust the variables in the panel so that an extreme negative realization of a variable signals an adverse economic outcome. As a result, the lower quantile factors they estimate may not have a straighforward interpretation as downside risk factors.

TABLE 2 ABOUT HERE

Table 2 provides summary information on the downside risk factors. It is important to emphasize that not all downside risk factors are constructed using exclusively backward-looking data, which clearly introduces look-ahead bias into the analysis. The column *Real Time* indicates whether the factors used in our analysis would have been available in real-time. Overall, the pool of candidate downside risk factors contains 20 predictors.

4 Empirical Analysis

Our empirical investigation combines both in-sample and out-of-sample analyses, with the primary emphasis placed on the out-of-sample results.

4.1 In-sample Analysis

The in-sample analysis comprises four components. First, we conduct a screening exercise to identify which factors predict downside risk across the panel. Second, we assess whether

[12] We aggregate the firm-level data taking the cross-sectional average at each point in time.

which modeling approach is better suited for downside risk modeling. Third, we carry out a quantile impulse response analysis to assess the impact of downside risk factors on the distribution of macroeconomic variables. We conclude this section by examining the relationship between downside risk factors and macroeconomic volatility.

4.1.1 Downside Risk Factor Screening

We conduct a screening exercise to identify which downside risk factors most effectively predict downside risk across the panel. For each variable, we estimate the downside risk at horizons 1, 3, 6, and 12 for $p = 0.05$ using QR with one candidate risk factor at a time. We then compute the fraction of macroeconomic variables for which the coefficient on the factor is statistically significant at the 5% level. We remark that this procedure is close in spirit to (linear) bivariate Granger causality test used to assess the relevance of predictors.

TABLE 3 ABOUT HERE

Table 3 reports summary results. The table reports for each predictor the percentage of macroeconomic variables for which the $\beta_{(0.05)\,i}$ coefficient is significant at the 5% significance level over different forecasting horizons. The predictors are sorted in descending order by the average percentage of significant coefficients across horizons. A number of findings emerge. First, MUNC is statistically significant for the largest proportion of variables in the panel, ranging from 80% at horizon 1 to 70% at horizon 12. This performance is notable, as all other downside risk predictors are significant for up to 72% of the variables at horizon 1 and 50% at horizon 12. Second, with the exception of MUNC, the most relevant downside risk factors are either financial or statistical factors. The NFCI, arguably the most popular downside risk indicator, is ranked fourth in the table and relevant for about half of the series in the panel across all horizons. QF1 is ranked fifth, performs well at shorter horizons, and outperforms its location counterpart, PC1. These results are consistent with the view that indicators of financial distress and latent factors extracted from the panel are relevant downside risk predictors, at least in-sample. Third, text-based factors have limited predictive power and contribute modestly to capturing downside risk dynamics in the panel. Overall, the screening exercise indicates that a large fraction of the downside risk predictors considered convincingly capture downside risk across the panel, with MUNC exhibiting the strongest performance, and text-based factors the weakest.

4.1.2 Downside Risk Model Screening

We conduct out a screening exercise to examine which modeling approach best captures downside risk. For each variable, we estimate the downside risk at horizons 1, 3, 6, and 12 for $p = 0.05$ using QR and LSR with one candidate risk factor at a time. We estimate three variants of the LSR: (i) a model where the risk factor impacts only the location of the variables (i.e. $\beta_{(\sigma^2)\,i} = 0$), (ii) a model where the risk factor impacts only the scale of the variables (i.e. $\beta_{(\mu)\,i} = 0$), and (iii) a model where the risk factor impacts both the location and scale of the variables (i.e. no restrictions are imposed on the parameters). All LSR models feature time-varying volatility dynamics, as described in equation (4).

The goodness-of-fit of the models is benchmarked against the historical quantile. In addition to the historical quantile benchmark, we also consider models that rely solely on past values of the target series: a QAR(1) (for QR models) and an AR(1)-GARCH(1,1) (for LSR models). We assess the goodness-of-fit of each model by the average of the relative tick loss associated with the 5% quantile across all series. Define the tick loss associated with the p-th quantile for the i-th series as

$$\mathrm{TL}_{p\,i}^{(h)} = \frac{1}{T-h} \sum_{t=1}^{T-h} \rho_p\Big(\overline{Y}_{i\,t+1}^{(h)} - \widehat{Q}_{i\,t+1}^{(h)}(p)\Big)\,,$$

where $\rho_p(e) = (p - \mathbb{1}_{\{e<0\}})e$ and $\widehat{Q}_{i\,t+1}^{(h)}(p)$ denotes the forecasts of the p-th quantile for the

i-th series. We then define the average tick loss gain as

$$\overline{\mathrm{TLG}}_p^{(h)} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{\mathrm{TL}_{p\,i}^{(h)}}{\mathrm{TL}_{p\,i}^{(h),\mathrm{Bench}}} \right) \right] \times 100 \ , \tag{7}$$

where $\mathrm{TL}_{p\,i}^{(h),\mathrm{Bench}}$ is the p-quantile for the i-th variable of the benchmark model, which in this study is the historical quantile. As it is well known, the tick loss is a proper scoring rule for eliciting quantile forecasts (Giacomini and Komunjer, 2005) and is our primary criterion to assess goodness-of-fit. We note that the goodness-of-fit measure employed is not necessarily monotonic with respect to the number of restrictions imposed in the LSR model, and constrained models can, at least in principle, perform better than unconstrained models.

TABLE 4 ABOUT HERE

Table 4 presents summary results on the model screening analysis. The table reports the average tick loss gain for each downside risk factor and forecast horizon considered. At horizons 1 and 3 the unrestricted LSR model achieves the best fit, whereas at horizons 6 and 12 QR performs best. Comparing the performance of the three LSR specifications, factors in the scale component typically lead to better predictive performance than factors in the location component, which highlights the importance of accounting for volatility dynamics in downside risk forecasting. Reassuringly, the ranking of the downside risk predictors is fairly stable across different models. We note that the AR(1)–GARCH(1,1) specification, which does not rely on downside risk factors, performs on par with the best-performing models at short horizons. However, as the forecast horizon increases, the performance gap relative to factor-augmented models widens, reflecting the increasing value of downside risk factors.

4.1.3 Quantile Impulse Response Analysis

We carry out a (reduced form) QIRF analysis to study how changes in the downside risk factors affect the distribution of the macroeconomic variables in the panel, in the spirit of Adrian et al. (2019, Figure 4). In particular, we estimate the QIRF of the twelve-month forward-average of four policy-relevant variables (Kim and Swanson, 2014): Real Personal Income (RPI), Industrial Production (INDPRO), Unemployment Rate (UNRATE) and Consumer Price Index (CPI) to a change in MUNC from its median value to its 95% quantile. The QIRFs are estimated for nine equally spaced quantiles of the macroeconomic variables from the 10% to the 90% quantile. Estimates are obtained on the basis of both the QR and the LSR specifications over the full sample. For reference, we also include the QIRF implied by a LSR specification in whichh the downside risk factor affects only the location component (i.e. $\beta_{(\sigma^2)\,i} = 0$), implying a constant effect across all quantiles.

FIGURE 1 ABOUT HERE

Figure 1 displays the QIRFs for the selected variables, along with 95% confidence bands for the location only QIRF. There is strong evidence of heterogeneity in the impact of changes in MUNC across quantiles: the null hypothesis of a constant QIRF is consistently rejected at conventional significance levels. In general, an increase in MUNC has a negative effect on the location (as measured by the increase in the median) and a positive effect on the scale (as measured by the increase in the interquartile range), with the exception of CPI, for which the impact on location is negligible. The evidence for asymmetric effects of MUNC varies across target variables and modeling approaches. For RPI and INDPRO, the QR-based QIRFs exhibit substantial asymmetry in response to an intervention to MUNC, which is in line with the findings of Adrian et al. (2019, Figure 4). This result is consistent with the view that increases in macroeconomic uncertainty substantially worsen downside risk scenarios but have a limited effect on upside potential. By contrast, for UNRATE and CPI, the responses are more symmetric. The LSR-based QIRFs display largely symmetric effects for all variables. We stress that the LSR estimation approach adopted in this study does not impose symmetry. Rather, symmetry emerges as an empirical outcome of the estimation results.

4.1.4 Downside Risk Factors and Macroeconomic Volatility

We examine the relationship between the best-performing downside risk factors (as identified in the screening exercise) and macroeconomic volatility. It is important to point out that in this paper the term macroeconomic volatility refers to the square root of the cross-sectional average of the conditional variance of the macroeconomic variables in the panel. We acknowledge that there is an ongoing debate in macroeconomics regarding the distinction between uncertainty and volatility. This distinction is not central to our analysis and we largely abstract from it in the present discussion. Our objective is to provide insights on how to interpret the downside risk factors and what type of economic signals they capture.

FIGURE 2 ABOUT HERE

The top panel of Figure 2 displays the percentage of series in the panel with realizations below their historical 5% quantiles over time. Spikes in this percentage are associated with adverse economic conditions and, often, with recessions.[13] These spikes are also indicative of a factor structure: downside risks seem to increase simultaneously for a large fraction of the panel.

The middle panel of Figure 2 plots three candidate downside risk factors: the NFCI, QF1, and MUNC. Although originating from three distinct methodologies and datasets, these factors share similar time series dynamics, suggesting that they broadly capture the same underlying information rather than provide independent signals.

The bottom panel of the figure summarizes the dynamics of conditional volatility for the macroeconomic variables included in the panel. For each variable, we estimate a predictive regression that includes four lagged principal components extracted from the full macroeconomic panel, along with one lag of the variable itself.[14] We then fit a GARCH(1,1) model to the residuals of this regression and compute the model-implied conditional variance for each series. We remark that this procedure is close in spirit to one of the empirical illustrations

[13] We use the NBER-based recession indicators.

[14] For this exercise, all macroeconomic variables are standardized to have zero mean and unit variance.

of Jurado et al. (2015). The figure reports the square root of the cross-sectional average of these conditional variances, together with the cross-sectional first and third quartiles of the conditional volatilities. The time-series dynamics of macroeconomic volatility closely mirrors those of the downside risk factors shown in the middle panel. The strong association between macroeconomic volatility and MUNC is not surprising, as MUNC can be interpreted as a nonparametric estimator of the square root of the average conditional variance in the panel. Consistent with this interpretation, the first canonical correlation between the set of downside risk factors and the model-implied conditional volatilities of the macroeconomic variables exceeds 90%. Taken together, our results suggest that the most successful downside risk factors capture, to a large extent, macroeconomic volatility.

4.2 Out-of-sample Analysis

We present the main empirical evidence of our study through an out-of-sample forecasting analysis that evaluates which factors effectively predict downside risk across the entire panel.

The forecasting exercise is designed as follows. We construct out-of-sample downside risk ($p = 0.05$) forecasts at horizons 1, 3, 6 and 12 starting from January 1990 until July 2025. Starting the forecasting exercise from January 1990 implies that our out-of-sample analysis is based on, roughly, 55% of the sample. Forecasts are constructed on the basis of both QR and LSR. We consider all possible single-factor models that can be constructed from the entire set of factors[15] as well as all possible two- and three-factor models that can be constructed from the nine best-performing factors from the factor-screening exercise of Section 4.1.1, excluding PCF1. PCF1 is omitted from these multi-factor specifications because it represents an average of existing factors rather than a distinct source of information. This procedure yields 28 single-factor models, 78 two-factor models, and 184 three-factor models, for a total of 280 specifications. The predictive performance of the factor-based forecasts is evaluated relative to three benchmarks: the historical quantile, a QAR(1) model, and an AR(1)-

[15] In the out-of-sample analysis, we exclude from the set of downside risk factors the variables RISK, PRISK, and NPRISK, as these are only available starting from 2002.

GARCH(1,1) model. All forecasting models are recursively estimated each month.

Forecast accuracy is evaluated using standard metrics from the risk management literature. We rely on the average tick loss gain as defined in Section 4.1.2, as our primary performance measure. We then evaluate the quality of the forecasts by examining whether the corresponding prediction intervals attain adequate coverage properties. To this end, we rely on the dynamic quantile test (Engle and Manganelli, 2004) which assesses the accuracy of prediction intervals by studying the properties of the so-called hit variable. The hit variable at horizon h for the i-th macroeconomic variable is defined as $H^{(h)}_{i\,t+1} = \mathbb{1}_{\{\overline{Y}^{(h)}_{i\,t+1} \leq \widehat{Q}^{(h)}_{i\,t+1}(p)\}}$, that is the indicator variable taking the value one when the realized value of $\overline{Y}^{(h)}_{i\,t+1}$ is not included in the one-sided forecast interval $(\widehat{Q}^{(h)}_{i\,t+1}(p), \infty)$. It can be shown (Christoffersen, 1998) that when $\widehat{Q}^{(h)}_{i\,t+1}(p)$ is the p-th conditional quantile of $\overline{Y}^{(h)}_{i\,t+1}$ then the corresponding hit variable is unpredictable given the information set available at t. This fact motivates (Engle and Manganelli, 2004) to propose the dynamic quantile test. Let $W_{1\,t}, \ldots, W_{K\,t}$ denote a set of auxiliary regressors, and consider the regression

$$H^{(h)}_{i\,t+1} - p = c_0 + \sum_{k=1}^{K} c_k W_{k\,t} + u^{(h)}_{i\,t+1}, \tag{8}$$

where $u^{(h)}_{i\,t+1}$ is an error term. The dynamic quantile test thus consists of testing the null hypothesis $\mathrm{H}_0 : c_0 = \cdots = c_K = 0$ against the alternative $\mathrm{H}_1 : c_k \neq 0$ for some $k = 0, \ldots, K$. Failure to reject the null hypothesis implies that the forecasts exhibit correct coverage conditional on the information set associated with the auxiliary predictors. We consider two variants of this test. The first is based on no auxiliary predictors (we label this DQU). This tests whether downside forecasts have correct unconditional coverage. The second is based on setting the auxiliary predictors to four lags of the hit sequence (we label this DQC). This tests whether downside forecasts have correct coverage conditional on the information set generated by the hit sequence itself. Additionally, we employ the Model Confidence Set (MCS) procedure of Hansen et al. (2011) to assess the relative predictive performance of competing models. The MCS is a procedure that detects the set of models that are not significantly inferior to the best-performing model. In particular, we run the MCS procedure for the four horizons, one at a time, using a weighted average[16] of tick loss as a measure of forecast accuracy. Starting from an initial collection of candidate models, the procedure sequentially eliminates models that exhibit significantly worse performance until a set remains for which the null hypothesis of equal predictive ability cannot be rejected at a given confidence level. The resulting model confidence set thus contains the best model among the candidates with a given confidence.

TABLE 5 ABOUT HERE

Table 5 summarizes the MCS for each forecast horizon. The top rows of the table report, for each specification subgroup, the share of models included in the MCS and the highest average tick loss gain for that subgroup. The first row considers the full set of models, while the next two decompose it by model type and number of factors. The bottom rows of the table report, for individual models, whether they are elements in the model confidence set, as well as the corresponding average tick loss gain. A number of findings emerge. First, the MCS procedure is fairly conservative in the sense that the fraction of models included in the set of best performing models is large across all horizons. Second, the share of LSR models in the MCS is large across all horizons and this set always includes (at least) the model that achieves the highest average tick loss gain. QR models on the contrary are rarely included in the MCS at horizons 1 and 3, whereas roughly half of them are included MCS for horizons 6 and 12. Third, a large fraction of one-factor models is included in the MCS across all horizons. Moreover, the best performing model at horizon 6 and 12 is a one-factor model. This suggests that richer multi-factor specifications do not lead to superior forecast accuracy than simple one-factor models. Fourth, it is interesting to note that the AR(1)-GARCH(1,1) is always included in the MCS, implying that factor models do not significantly outperform models that rely exclusively on univariate time-series models. That being said,

[16] Each tick loss series is scaled by the in-sample standard deviation of the target variable. why?

the gap between the forecasting performance of the best-performing factor model and the time series specifications tends to widen with the forecasting horizon.

TABLE 6 ABOUT HERE

Table 6 summarizes the performance of one-factor models across the entire panel and for each forecast horizon. The table reports for each model the average tick loss gain, the number of times this model is the best one-factor model, the grand average of the hit variable, and the fraction of series for which we do not reject the null of correct forecasts for the DQU and DQC tests. Results are shown separately for QR and LSR. A number of findings emerge. First, overall the specifications based on MUNC achieve the best performance. In particular, at horizons 1 and 3 the LSR one-factor based on MUNC has the highest average tick loss gain and achieves the minimum tick loss more frequently for individual series. At horizons 6 and 12 the QR one-factor model with MUNC is also the specification that achieves the minimum tick loss most often for individual series, whereas the LSR one-factor model based on FUNC achieves the highest average tick loss gain. Factors in the financial category tend to perform best on average across all horizons. PCF1 has a good performance, which is close to MUNC. QF1 and PC1 also perform satisfactorily. Interestingly, QF1 always has a better average tick loss gain than PC1. The DQ tests show that LSR prediction intervals have substantially better coverage properties than their QR counterparts across nearly all factors and horizons.

TABLE 7 ABOUT HERE

Table 7 reports the summary performance of multiple-factor models across the entire panel and for each forecast horizon. The table reports for each multi-factor model the average number hits, the average tick loss gain and the fraction of series that do not reject the null of correct forecasts for the DQU and DQC tests. We report results for a selection of multi-factor specifications that complement the top-performing one-factor models identified above.

TABLE 8 ABOUT HERE

Table 8 reports the summary performance of the one-factor models across the subcategories of the panel for each forecast horizon. This table reports for each forecast horizon the average tick loss gain relative computed with respect to each FRED–MD category.

Results are shown separately for QR and LSR. The evidence in the table is consistent with the previous results. In particular, MUNC frequently emerges as the factor that produces the most accurate downside risk forecasts. At horizons 1 and 6, LSR-based forecasts generally achieve the highest accuracy, whereas at horizons 9 and 12, both QR and LSR contribute to top-performing forecasts. In some instances indices in the financial category, such as FUNC, also demonstrate strong predictive performance.

TABLE 9 ABOUT HERE

Table 9 reports the performance of the one-factor models for the policy-relevant variables of the panel for each forecast horizon. This table reports for the tick loss gain for the policy-relavant variables of the FRED-MD. Results are shown separately for QR and LSR. Again, the table presents results that are broadly consistent with our previous findings. Notably, MUNC frequently stands out as the factor delivering the most accurate downside risk forecasts. At horizons 1 and 3 forecasts based on LSR tend to perform best, while at horizons 6 and 12, both QR and LSR contribute to the strongest predictive results.

In conclusion, a one-factor model based on MUNC demonstrates moderate effectiveness across individual FRED–MD categories. While alternative indicators occasionally show strong predictive performance, none consistently outperform MUNC in any specific category.

5 Conclusions

This paper studies which common factors drive downside risk across a large panel of U.S. macroeconomic variables. We consider a rich pool of candidate factors, drawn from financial, macroeconomic, statistical, and text-based sources. We evaluate the relevance of each factor through a comprehensive out-of-sample forecasting exercise, where we construct downside risk forecasts using quantile regression and location-scale regression. By comparing a broad set of competing specifications across horizons and predictors, our goal is to identify which factors provide the most reliable signals of adverse macroeconomic scenarios across the entire panel. Overall, the out-of-sample evidence highlights that across horizons, variables, and model specifications, the factors that best predict downside risk are those that track macroeconomic volatility. In particular, forecasts based on the macroeconomic uncertainty index of Jurado et al. (2015) repeatedly emerge among the top performers, and a pure volatility model with no other factors performs at par with the best performing models. Our findings highlight that monitoring the overall level of volatility in the economy provides a practical, informative and direct approach for tracking downside risks across a broad set of macroeconomic variables.

References

Adams, P. A., Adrian, T., Boyarchenko, N., and Giannone, D. (2021). Forecasting macroeconomic risks. *International Journal of Forecasting*, 37(3):1173–1191.

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4):1263–89.

Adrian, T. and Brunnermeier, M. K. (2016). Covar. *American Economic Review*, 106(7):1705–1741.

Adrian, T., Grinberg, F., Liang, N., Malik, S., and Yu, J. (2022). The term structure of growth-at-risk. *American Economic Journal: Macroeconomics*, 14(3):283–323.

Ahir, H., Bloom, N., and Furceri, D. (2022). The world uncertainty index. Technical report, National bureau of economic research.

Amado, C. and Teräsvirta, T. (2013). Modelling volatility by variance decomposition. *Journal of Econometrics*, 175(2):142–153.

Amburgey, A. and McCracken, M. W. (2023). *Growth-at-risk is Investment-at-risk*. Federal Reserve Bank of St. Louis, Research Division.

Andreasen, M. M., Caggiano, G., Castelnuovo, E., and Pellegrino, G. (2024). Does risk matter more in recessions than in expansions? implications for monetary policy. *Journal of Monetary Economics*, 143:103533.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Banerjee, R. N., Mehrotra, A., and Zampolli, F. (2020). Inflation at risk from covid-19. Technical report, Bank for International Settlements.

Bank for International Settlements (2025). Credit-to-gdp gaps, bis ws_credit_gap 1.0. `https://data.bis.org/topics/CREDIT_GAPS/data?filter=FREQ%3DQ%255ETC_LENDERS%3DA%255EBORROWERS_CTY_TXT%3DUnited%2520States%255ETC_BORROWERS%3DP%255ECG_DTYPE%3DC%255ETIMESPAN%3D1949-01-01_2025-09-25&selected_ts=BIS%2CWS_CREDIT_GAP%2C1.0%255EQ.US.P.A.C`. [Data set] Accessed on 25 September 2025.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, 77(3):623–685.

Borio, C., Lowe, P., et al. (2002). Assessing the risk of banking crises. *BIS Quarterly Review*, 7(1):43–54.

Brownlees, C. and Engle, R. F. (2017). Srisk: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, 30(1):48–79.

Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4):1194–1225. Data available here.

Carriero, A., Clark, T. E., and Marcellino, M. (2024). Capturing macro-economic tail risks with bayesian vector autoregressions. *Journal of Money, Credit and Banking*, 56(5):1099–1127.

Carriero, A., Clark, T. E., and Marcellino, M. (2025). Specification choices in quantile regression for empirical macroeconomics. *Journal of Applied Econometrics*, 40(1):57–73.

Chavleishvili, S., Engle, R. F., Fahr, S., Kremer, M., Manganelli, S., and Schwaab, B. (2021). The risk management approach to macro-prudential policy. Working Paper Series 2565, European Central Bank.

Chen, L., Dolado, J. J., and Gonzalo, J. (2021). Quantile factor models. *Econometrica*, 89(2):875–910.

Chicago Board Options Exchange (2025). Cboe volatility index: Vix [vixcls]. `https://www.stlouisfed.org/research/economists/mccracken/fred-databases`. Retrieved from the FRED-MD, Federal Reserve Bank of St. Louis on September 25, 2025.

Christoffersen, P. (1998). Evaluating interval forecasts. *International Economic Review*, 39(4):841–862.

Claessens, S., Kose, M. A., and Terrones, M. E. (2009). What happens during recessions, crunches and busts? *Economic Policy*, 24(60):653–700.

Conrad, C. and Engle, R. F. (2025). Modelling volatility cycles: The mf2-garch model. *Journal of Applied Econometrics*, 40(4):438–454.

Deghi, A., Katagiri, M., Shahid, M. S., and Valckx, N. (2020). *Predicting downside risks to house prices and macro-financial stability*. International Monetary Fund.

Delle Monache, D., De Polis, A., and Petrella, I. (2024). Modeling and forecasting macroeconomic downside risk. *Journal of Business & Economic Statistics*, 42(3):1010–1025.

Ding, Z. and Granger, C. W. (1996). Modeling volatility persistence of speculative returns: A new approach. *Journal of Econometrics*, 73(1):185–215.

Engle, R. F., Ghysels, E., and Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *The Review of Economics and Statistics*, 95(3):776–797.

Engle, R. F. and Manganelli, S. (2004). Caviar: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economics Statistics*, 22(4):367–381.

Favara, G., Gilchrist, S., Lewis, K. F., and Zakrajšek, E. (2016). Updating the recession risk and the excess bond premium. FEDS Notes. Washington: Board of Governors of the Federal Reserve System, October 6, 2016.

Federal Reserve Bank of Chicago (2025). National financial conditions index (nfci). `https://www.chicagofed.org/nfci`. [Data set].

Federal Reserve Bank of New York (2016). Excess bond premium (ebp). `https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html`. [Data set].

Forni, M., Gambetti, L., Maffei-Faccioli, N., and Sala, L. (2024). The effects of monetary policy on macroeconomic risk. *European Economic Review*, 167:104789.

Gächter, M., Hasler, E., and Huber, F. (2025). A tale of two tails: 130 years of growth at risk. *Macroeconomic Dynamics*, 29:46.

Ghysels, E., Iania, L., and Striaukas, J. (2018). Quantile-based inflation risk models. Technical report, NBB Working Paper.

Giacomini, R. and Komunjer, I. (2005). Evaluation and combination of conditional quantile forecasts. *Journal of Business & Economics Statistics*, 23(4):416–431.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720.

Goulet Coulombe, P., Leroux, M., Stevanovic, D., and Surprenant, S. (2022). How is machine learning useful for macroeconomic forecasting? *Journal of Applied Econometrics*, 37(5):920–964.

Hansen, P. R., Lunde, A., and Nason, J. M. (2011). The model confidence set. *Econometrica*, 79(2):453–497.

Hassan, T. A., Hollander, S., Van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202. Data available here.

Hengge, M. (2019). Uncertainty as a predictor of economic activity.

Hollo, D., Kremer, M., and Lo Duca, M. (2012). Ciss-a composite indicator of systemic stress in the financial system.

Joe, H. (1997). *Multivariate models and dependence concepts*. Monographs on statistics and applied probability 73. Chapman & Hall, London.

Jovanovic, B. and Ma, S. (2022). Uncertainty and growth disasters. *Review of Economic Dynamics*, 44:33–64.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Keijsers, B. and van Dijk, D. (2024). Does economic uncertainty predict real activity in real time? *International Journal of Forecasting*.

Kiley, M. T. (2022). Unemployment risk. *Journal of Money, Credit and Banking*, 54(5):1407–1424.

Kim, H. H. and Swanson, N. R. (2014). Forecasting financial and macroeconomic variables using data reduction methods: New empirical evidence. *Journal of Econometrics*, 178:352–367.

Kim, H. H. and Swanson, N. R. (2018). Mining big data using parsimonious factor, machine learning, variable selection and shrinkage methods. *International Journal of Forecasting*, 34(2):339–354.

Koenker, R. W. and Basset, Jr., G. (1978). Regression quantiles. *Econometrica*, 46(1):33–50.

Korobilis, D. and Schröder, M. (2025). Monitoring multi-country macroeconomic risk: A quantile factor-augmented vector autoregressive (qfavar) approach. *Journal of Econometrics*, 249:105730.

Lang, J. H. and Forletta, M. (2020). Cyclical systemic risk and downside risks to bank profitability.

Leamer, E. E. (2007). Housing is the business cycle.

Lenza, M., Moutachaker, I., and Paredes, J. (2023). Density forecasts of inflation: a quantile regression forest approach.

Lopez-Salido, D. and Loria, F. (2020). Inflation at risk.

Ludvigson, S. C., Ma, S., and Ng, S. (2021). Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, 13(4):369–410.

Marcellino, M., Stock, J. H., and Watson, M. W. (2006). A comparison of direct and iterated multistep ar methods for forecasting macroeconomic time series. *Journal of Econometrics*, 135(1-2):499–526.

McCracken, M. W. and Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4):574–589.

Medeiros, M. C., Vasconcelos, G. F. R., Álvaro Veiga, and Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. *Journal of Business & Economic Statistics*, 39(1):98–119.

Powell, J. H. (2021). Monetary Policy in the Time of COVID. "Macroeconomic Policy in an Uneven Economy", an economic policy symposium sponsored by the Federal Reserve Bank of Kansas City.

Powell, J. H. (2024). Transcript of Chair Powell's Press Conference. FOMC Press Conference.

Prasad, M. A., Elekdag, S., Jeasakul, M. P., Lafarguette, R., Alter, M. A., Feng, A. X., and Wang, C. (2019). *Growth at risk: Concept and application in IMF country surveillance*. International Monetary Fund.

S&P Dow Jones Indices LLC (2025). S&p corelogic case–shiller u.s. national home price index [csushpinsa]. `https://fred.stlouisfed.org/series/CSUSHPINSA`. Retrieved from FRED, Federal Reserve Bank of St. Louis on September 26, 2025.

Stock, J. and Watson, M. (2016). Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In Taylor, J. B. and Uhlig, H., editors, *Handbook of Macroeconomics*, volume 2 of *Handbook of Macroeconomics*, chapter 0, pages 415–525. Elsevier.

Stock, J. H. and Watson, M. W. (1998). Diffusion indexes.

Stock, J. H. and Watson, M. W. (2002). Macroeconomic Forecasting Using Diffusion Indexes. *Journal of Business & Economic Statistics*, 20(2):147–162.

Table 1: Downside Risk Interpretation by Category

Category	Adverse Economic Outcome
Output and Income	Decreasing output
Labor Market	Rising unemployment, decreasing employment or worked hours
Housing	Low starts and permits
Orders & Inventories	Decreasing sales, consumption, unfilled orders, and inventories
Credit	Decreasing growth rate in loans
Exchange rates	Weakening US dollar
Prices	Falling and soaring inflation
Stock Market	Falling S&P and spiking VIX

This table reports the definition of adverse economic outcomes across the FRED–MD categories. For each category, the table indicates the type of realization that signals a deterioration in economic conditions and is therefore interpreted as downside risk in the analysis.

Table 2: Downside Risk Factors

Class	Name	Mnemonic	Reference	Real Time
Financial	National Financial Condition Index	NFCI	Federal Reserve Bank of Chicago, 2025	No
	Excess Bond Premium	EBP	Federal Reserve Bank of New York, 2016	No
	Financial Uncertainty	FUNC	Ludvigson et al., 2021	No
	CBOE Volatility Index	VIX	Chicago Board Options Exchange, 2025	Yes
	Composite Indicator of Systemic Stress	CISS	Hollo et al., 2012	No
Macroeconomic	Macroeconomic Uncertainty	MUNC	Jurado et al., 2015	No
	U.S. National Home Price Index	HPI	S&P Dow Jones Indices LLC, 2025	No
	Credit-to-GDP	CTG	Bank for International Settlements, 2025	No
Statistical	Principal Component	PC	Stock and Watson, 1998	No
	Quantile Factor	QF	Chen et al., 2021	No
Text	World Uncertainty Index - US	WUIUS	Ahir et al., 2022	Yes*
	Geopolitical Risk Index	GPR	Caldara and Iacoviello, 2022	No
	Economic Policy Uncertainty Index	EPU	Baker et al., 2016	No
	Firm-Level Political Risk	PRISK	Hassan et al., 2019	Yes*
	Firm-Level Non Political Risk	NPRISK	Hassan et al., 2019	Yes*
	Firm-Level Risk	RISK	Hassan et al., 2019	Yes*

This table reports summary information on the downside risk factors considered in the analysis. The factors are grouped into four classes—financial, macroeconomic, statistical, and text—and for each factor the table lists its name, mnemonic, reference, and whether the series is constructed using exclusively backward-looking data. An asterisk (*) in the last column denotes factors constructed using data through the latest quarter that are not subject to subsequent revision.

Table 3: Downside Risk Factor Screening

		Horizon			
		1	3	6	12
MUNC	Macro	80.0	81.7	79.2	70.0
PCF1	Stat	71.7	66.7	57.5	46.7
FUNC	Fin	62.5	66.7	63.3	49.2
NFCI	Fin	40.8	50.0	50.8	46.7
QF1	Stat	68.3	53.3	41.7	24.2
VIX	Fin	58.3	52.5	45.0	31.7
PC1	Stat	50.8	59.2	45.8	31.7
CISS	Fin	52.5	50.0	44.2	20.0
EBP	Fin	37.5	43.3	38.3	36.7
EPU	Text	35.0	32.5	24.2	13.3
CTG	Macro	28.3	19.2	21.7	27.5
HPI	Macro	10.0	22.5	17.5	11.7
RISK	Text	17.5	19.2	10.8	10.0
PRISK	Text	15.0	14.2	9.2	16.7
NPRISK	Text	15.0	15.8	10.8	8.3
WUI	Text	16.7	16.7	10.0	5.8
GPR	Text	4.2	1.7	5.0	10.0

This table reports the results of the downside risk factor screening exercise. For each predictor, the table lists the percentage of macroeconomic variables for which the coefficient on the predictor is statistically significant at the 5% level. The percentages are obtained from quantile regression, with $p = 0.05$, at horizons of 1, 3, 6, and 12 months. Predictors are sorted in descending order according to the average percentage of significant coefficients across horizons.

Table 4: Downside Risk Model Screening

	FRED-MD		$\overline{TLG}$			
h	Class	Model	QR	LR	SR	LSR
1	Bench	HIST	0.0	0.0	0.0	0.0
		AR	14.6	22.6	22.6	22.6
	Fin	NFCI	16.9	22.6	23.0	23.1
		EBP	16.3	22.4	22.6	22.7
		FUNC	18.2	23.3	24.2	24.2
		VIX	17.2	22.9	23.2	23.2
		CISS	19.1	23.7	24.2	24.2
	Macro	MUNC	20.9	23.1	25.2	**25.4**
		HPI	15.8	23.1	22.9	23.0
		CTG	15.6	22.6	22.7	22.7
	Stat	PC1	17.3	23.5	23.1	23.9
		QF1	19.1	23.1	23.7	23.9
		PCF1	20.6	23.7	25.0	25.0
	Text	WUI	15.5	22.6	22.7	22.7
		GPR	14.8	22.6	22.6	22.7
		EPU	16.7	22.7	23.1	23.1
3	Bench	HIST	0.0	0.0	0.0	0.0
		AR	16.2	22.1	22.1	22.1
	Fin	NFCI	20.7	22.7	23.1	24.0
		EBP	18.9	21.7	21.5	22.2
		FUNC	23.2	24.2	26.3	27.2
		VIX	20.7	23.2	23.7	24.0
		CISS	21.6	24.0	23.9	24.6
	Macro	MUNC	26.1	23.5	26.8	**27.6**
		HPI	18.2	22.9	22.7	23.1
		CTG	17.6	22.2	22.3	22.4
	Stat	PC1	20.5	24.1	23.4	25.0
		QF1	22.3	23.1	24.5	24.8
		PCF1	24.5	24.3	25.3	25.9
	Text	WUI	17.9	22.3	22.9	23.0
		GPR	16.6	22.2	22.1	22.3
		EPU	19.0	22.3	22.7	22.8
6	Bench	HIST	0.0	0.0	0.0	0.0
		AR	15.3	19.2	19.2	19.2
	Fin	NFCI	21.8	21.3	22.0	23.7
		EBP	19.5	20.0	20.2	21.7
		FUNC	24.0	22.4	24.9	25.9
		VIX	20.2	20.7	21.4	21.9
		CISS	22.0	22.2	22.0	23.0
	Macro	MUNC	**26.4**	21.3	24.2	25.1
		HPI	19.0	21.4	21.0	21.6
		CTG	17.6	19.5	20.0	20.2
	Stat	PC1	19.8	21.6	21.5	23.3
		QF1	20.6	20.3	21.5	21.9
		PCF1	25.6	23.1	24.6	25.3
	Text	WUI	17.2	19.4	19.7	20.2
		GPR	15.7	19.2	19.2	19.4
		EPU	18.0	19.5	19.2	19.4
12	Bench	HIST	0.0	0.0	0.0	0.0
		AR	11.1	14.7	14.7	14.7
	Fin	NFCI	16.0	15.8	15.5	17.2
		EBP	14.7	16.4	15.7	17.6
		FUNC	18.3	17.7	17.9	20.4
		VIX	15.2	16.0	16.4	16.8
		CISS	17.4	18.0	18.6	19.1
	Macro	MUNC	**21.6**	16.6	17.1	19.2
		HPI	14.9	17.7	17.1	18.4
		CTG	15.1	15.9	16.8	17.6
	Stat	PC1	14.3	16.3	16.0	17.4
		QF1	14.5	15.3	15.5	15.8
		PCF1	21.2	19.1	19.5	21.0
	Text	WUI	13.4	15.3	15.3	16.1
		GPR	11.9	14.8	15.2	15.4
		EPU	14.1	15.2	14.9	14.9

This table reports the results of the downside risk model screening exercise. For each downside risk factor and forecast horizon, the table lists the average tick loss gain associated with quantile regression, with $p = 0.05$, and the three variants of the location-scale regression at horizons of 1, 3, 6, and 12 months. The gains are computed relative to the historical quantile benchmark.

Table 5: Model Confidence Set

	Horizon							
	1		3		6		12	
	%	TLG	%	TLG	%	TLG	%	TLG
All	38.5	26.9	49.1	29.0	71.0	27.9	60.4	19.4
QR	0.0	22.1	0.7	24.5	47.5	24.9	42.6	17.6
LSR	77.3	26.9	97.9	29.0	95.0	27.9	78.7	19.4
1 Factor	42.9	26.6	50.0	28.7	71.4	27.9	78.6	19.4
2 Factors	43.6	26.9	51.3	29.0	79.5	27.1	70.5	18.3
3 Factors	35.6	26.9	48.3	29.0	67.2	27.0	52.9	17.2
QR NFCI	×	16.8	×	19.5	✓	18.4	✓	9.1
LSR NFCI	✓	25	✓	25.4	✓	23.5	✓	14.3
QAR(1)	×	14	×	15.9	✓	15.6	✓	11.1
AR(1)-GARCH(1,1)	✓	24.1	✓	23.9	✓	20.3	✓	15.3

This table reports the results of the Model Confidence Set procedure for the downside risk forecasts at horizons 1, 3, 6, and 12. For each forecast horizon, the table lists the share of models included in the MCS and the highest average tick loss gain within each specification subgroup. The first row refers to the full set of models, while the following rows decompose the results by model type and by number of factors. The bottom rows report, for selected individual models, whether the specification is included in the MCS together with the corresponding average tick loss gain.

Table 6: Downside Risk Prediction Using One Factor

	FRED-MD		QR						LSR					
h	Class	Model	$\overline{TLG}$	W	$\overline{H}$	DQU	DQC	MCS	$\overline{TLG}$	W	$\overline{H}$	DQU	DQC	MCS
1	Bench	HIST	0.0	1	6.4	47.5	26.7	×	0.0	1	6.4	47.5	26.7	×
		AR	14.0	0	6.2	47.5	36.7	×	24.1	1	5.4	75.8	80.0	✓
	Fin	NFCI	16.8	1	7.3	35.0	40.8	×	25.0	5	6.3	57.5	65.0	✓
		EBP	16.4	0	6.3	47.5	47.5	×	24.9	4	5.6	70.0	83.3	✓
		FUNC	17.4	2	6.1	49.2	48.3	×	25.5	7	5.3	71.7	81.7	✓
		VIX	16.2	0	6.1	47.5	50.8	×	24.1	1	5.4	74.2	79.2	✓
		CISS	18.4	2	6.9	44.2	49.2	×	25.1	9	6.1	68.3	74.2	✓
	Macro	MUNC	21.0	6	6.2	45.8	53.3	×	**26.6**	**41**	5.6	73.3	74.2	✓
		HPI	14.1	0	6.3	54.2	43.3	×	23.4	7	5.5	78.3	80.8	×
		CTG	13.5	0	7.0	50.8	39.2	×	23.7	2	5.8	72.5	75.0	✓
	Stat	PC1	15.1	0	5.8	47.5	50.0	×	23.9	3	5.3	70.0	81.7	✓
		QF1	18.5	4	5.8	50.8	54.2	×	24.8	5	5.3	75.8	80.8	✓
		PCF1	19.6	1	6.6	51.7	46.7	×	25.7	10	5.9	70.8	72.5	✓
	Text	WUI	14.1	0	5.8	55.0	38.3	×	23.7	1	5.2	78.3	82.5	✓
		GPR	13.1	0	6.4	48.3	35.8	×	23.8	2	5.5	74.2	80.0	✓
		EPU	14.3	0	5.4	55.8	47.5	×	23.0	5	4.9	71.7	84.2	×
3	Bench	HIST	0.0	0	6.7	67.5	38.3	×	0.0	0	6.7	67.5	38.3	×
		AR	15.9	0	6.1	65.0	63.3	×	23.9	2	5.6	84.2	79.2	✓
	Fin	NFCI	19.5	3	8.5	38.3	46.7	×	25.4	3	7.4	52.5	64.2	✓
		EBP	19.4	1	6.1	60.8	62.5	×	25.6	1	5.7	77.5	74.2	✓
		FUNC	22.1	2	6.5	60.0	62.5	×	28.4	21	5.8	74.2	76.7	✓
		VIX	18.7	1	6.2	54.2	64.2	×	24.8	2	5.6	80.0	80.8	✓
		CISS	21.1	1	6.9	66.7	64.2	×	25.9	3	6.3	75.8	81.7	✓
	Macro	MUNC	25.5	15	6.6	51.7	60.8	×	**28.7**	**25**	6.1	69.2	75.0	✓
		HPI	15.9	0	6.5	70.0	58.3	×	23.6	3	6.1	80.8	76.7	✓
		CTG	14.7	0	7.5	64.2	68.3	×	23.4	11	6.3	77.5	73.3	✓
	Stat	PC1	17.6	0	5.9	57.5	63.3	×	25.0	4	5.4	76.7	80.8	✓
		QF1	21.1	0	5.7	52.5	60.0	×	26.0	3	5.5	78.3	76.7	✓
		PCF1	23.4	3	7.0	64.2	62.5	×	26.6	8	6.4	69.2	76.7	✓
	Text	WUI	15.5	1	5.9	70.8	71.7	×	23.5	2	5.5	82.5	80.0	✓
		GPR	14.9	0	6.4	64.2	55.0	×	23.6	2	5.8	85.0	71.7	✓
		EPU	16.4	1	5.0	80.0	78.3	×	22.5	2	5.0	85.0	75.8	✓
6	Bench	HIST	0.0	1	6.9	70.8	50.0	×	0.0	1	6.9	70.8	50.0	×
		AR	15.6	0	6.3	64.2	60.8	✓	20.3	1	5.8	84.2	89.2	✓
	Fin	NFCI	18.4	0	9.4	40.8	55.0	✓	23.5	11	8.2	52.5	71.7	✓
		EBP	19.6	1	6.5	63.3	75.8	×	24.7	4	5.7	76.7	87.5	✓
		FUNC	22.4	4	7.0	59.2	63.3	✓	**27.9**	16	6.1	75.0	85.0	✓
		VIX	18.5	0	6.5	55.0	65.8	×	23.2	1	5.7	80.8	81.7	✓
		CISS	18.8	5	7.5	65.0	73.3	✓	23.4	6	6.9	81.7	83.3	✓
	Macro	MUNC	24.7	**24**	7.4	44.2	64.2	✓	25.9	8	6.5	61.7	73.3	✓
		HPI	14.4	0	7.2	69.2	69.2	×	21.4	3	6.5	85.8	79.2	✓
		CTG	13.8	1	8.3	60.0	69.2	×	20.2	5	6.9	74.2	80.8	✓
	Stat	PC1	17.4	3	6.2	65.8	65.0	×	23.6	7	5.8	81.7	80.8	✓
		QF1	20.8	2	5.9	60.0	62.5	×	24.0	1	5.5	79.2	82.5	✓
		PCF1	21.2	5	7.8	63.3	67.5	✓	24.6	2	6.8	76.7	84.2	✓
	Text	WUI	13.9	2	6.4	70.8	67.5	✓	18.9	0	6.0	87.5	75.8	✓
		GPR	13.9	0	6.7	65.8	56.7	✓	19.8	2	6.0	80.8	85.0	✓
		EPU	15.2	1	5.3	71.7	71.7	×	18.6	4	5.1	81.7	73.3	×
12	Bench	HIST	0.0	1	7.5	62.5	58.3	×	0.0	1	7.5	62.5	58.3	×
		AR	11.1	1	6.8	69.2	79.2	✓	15.3	3	6.2	81.7	84.2	✓
	Fin	NFCI	9.1	4	10.0	48.3	75.0	✓	14.3	8	9.3	56.7	79.2	✓
		EBP	13.1	10	6.8	70.8	77.5	✓	18.8	13	6.8	76.7	86.7	✓
		FUNC	13.9	1	8.0	65.8	73.3	✓	**19.4**	5	7.1	78.3	75.8	✓
		VIX	13.2	1	7.0	64.2	77.5	✓	17.5	1	6.4	75.0	87.5	✓
		CISS	9.4	1	8.4	71.7	80.0	✓	15.7	3	7.9	80.8	84.2	✓
	Macro	MUNC	17.6	**21**	8.4	52.5	72.5	✓	16.7	11	7.7	65.0	77.5	✓
		HPI	5.9	1	7.8	67.5	83.3	×	12.7	6	7.4	73.3	85.8	✓
		CTG	3.5	3	10.0	54.2	73.3	×	12.4	6	8.2	68.3	78.3	✓
	Stat	PC1	9.7	2	7.0	69.2	77.5	✓	16.6	5	6.6	75.8	81.7	✓
		QF1	12.9	1	6.8	70.0	78.3	✓	16.4	1	6.5	77.5	80.0	✓
		PCF1	11.5	0	9.3	60.8	78.3	✓	16.7	7	8.3	74.2	82.5	✓
	Text	WUI	7.6	0	7.3	70.8	79.2	×	12.8	2	6.9	79.2	86.7	✓
		GPR	9.4	0	7.1	68.3	82.5	×	14.7	0	6.6	77.5	85.8	✓
		EPU	8.4	1	6.0	79.2	82.5	×	12.2	1	5.8	81.7	82.5	×

This table reports backtesting statistics for the downside risk forecasts of one-factor specifications at horizons 1, 3, 6, and 12. For each forecast horizon and specification, the table lists the average tick loss gain, the number of pairwise wins against other one-factor models, the grand average of the hit variable, the fraction of series that do not reject the null of correct coverage in the dynamic quantile tests for unconditional and conditional coverage, and whether the specification is included in the model confidence set. Results are reported separately for quantile regression and location–scale regression specifications.

Table 7: Downside Risk Prediction Using Multiple Factors

FRED-MD			QR					LSR				
h	Class	Model	$\overline{TLG}$	$\overline{H}$	DQU	DQC	MCS	$\overline{TLG}$	$\overline{H}$	DQU	DQC	MCS
	Bench	HIST	0.0	6.4	47.5	26.7	×	0.0	6.4	47.5	26.7	×
	Macro	MUNC	21.0	6.2	45.8	53.3	×	26.6	5.6	73.3	74.2	✓
	Macro + Fin	MUNC + FUNC	20.7	6.3	51.7	54.2	×	26.8	5.6	70.0	71.7	✓
		MUNC + NFCI	22.1	6.6	45.0	49.2	×	**26.9**	6.0	61.7	70.8	✓
		MUNC + EBP	20.9	6.8	44.2	43.3	×	26.8	6.0	68.3	69.2	✓
		MUNC + FUNC + EBP	20.6	6.8	44.2	42.5	×	26.4	6.0	65.0	64.2	✓
	Macro + Text	MUNC + EPU	19.6	6.4	50.0	50.0	×	25.6	5.6	73.3	80.0	✓
	Macro + Stat	MUNC + PC1	20.6	6.1	52.5	50.8	×	26.1	5.4	67.5	72.5	✓
		MUNC + PC1 + QF1	20.4	6.2	55.8	52.5	×	25.2	5.5	70.8	75.8	✓
	Fin	FUNC + CISS	18.8	6.7	50.8	47.5	×	25.5	5.9	71.7	74.2	✓
1		FUNC + EBP	17.4	6.4	50.8	48.3	×	25.4	5.7	72.5	79.2	✓
		CISS + EBP	17.3	7.5	38.3	41.7	×	24.8	6.3	63.3	73.3	✓
	Fin + Text	FUNC + EPU	16.6	5.9	58.3	55.0	×	24.3	5.2	73.3	80.8	×
	Fin + Stat	NFCI + PC1	16.8	6.9	41.7	40.8	×	24.6	5.9	64.2	74.2	✓
	Fin + Stat + Text	FUNC + PC1 + EPU	16.5	5.9	56.7	55.8	×	23.5	5.3	68.3	77.5	×
		FUNC + QF1 + EPU	18.2	6.0	52.5	58.3	×	24.1	5.3	72.5	80.8	×
		NFCI + CISS + QF1	19.1	6.7	42.5	48.3	×	24.3	6.2	60.0	65.8	✓
		NFCI + EPU	17.6	6.8	45.0	40.0	×	24.6	6.1	62.5	65.8	✓
	Stat	QF1 + QF2 + QF3	18.5	6.1	53.3	56.7	×	24.6	5.3	75.8	80.8	✓
		PC1 + QF1	18.2	5.8	53.3	59.2	×	24.1	5.2	71.7	75.0	✓
	Stat + Text	PC1 + QF1 + EPU	17.5	5.6	58.3	65.8	×	22.4	5.2	78.3	83.3	×
	Bench	HIST	0.0	6.7	67.5	38.3	×	0.0	6.7	67.5	38.3	×
	Macro	MUNC	25.5	6.6	51.7	60.8	×	28.7	6.1	69.2	75.0	✓
	Macro + Fin	MUNC + FUNC	25.0	7.0	54.2	58.3	×	**29.0**	6.3	65.8	73.3	✓
		MUNC + NFCI	24.5	7.6	50.0	61.7	✓	27.2	7.1	55.0	65.0	✓
		MUNC + EBP	24.3	7.6	51.7	59.2	×	28.2	6.7	64.2	64.2	✓
		MUNC + FUNC + EBP	23.5	7.8	50.0	52.5	×	28.0	6.8	64.2	68.3	✓
	Macro + Text	MUNC + EPU	23.5	6.8	68.3	63.3	×	26.9	6.2	71.7	71.7	✓
	Macro + Stat	MUNC + PC1	25.3	6.5	52.5	62.5	×	28.2	5.9	65.8	71.7	✓
		MUNC + PC1 + QF1	25.2	6.6	54.2	65.0	×	28.3	6.0	66.7	68.3	✓
	Fin	FUNC + CISS	22.3	6.8	64.2	63.3	×	27.5	6.3	79.2	80.0	✓
3		FUNC + EBP	20.6	7.1	60.8	61.7	×	27.4	6.0	73.3	73.3	✓
		CISS + EBP	20.0	7.5	55.8	58.3	×	25.5	6.7	67.5	73.3	✓
	Fin + Text	FUNC + EPU	21.8	6.1	73.3	75.0	×	26.6	5.7	81.7	74.2	✓
	Fin + Stat	NFCI + PC1	19.7	7.9	45.8	51.7	×	25.4	6.9	57.5	64.2	✓
	Fin + Stat + Text	FUNC + PC1 + EPU	21.1	6.2	70.0	70.0	×	26.2	5.7	78.3	79.2	✓
		FUNC + QF1 + EPU	21.9	6.3	70.0	69.2	×	26.3	5.8	76.7	70.0	✓
		NFCI + CISS + QF1	20.8	7.7	55.0	56.7	×	24.4	7.0	60.0	74.2	✓
		NFCI + EPU	20.0	7.9	50.0	65.8	×	24.5	7.1	56.7	67.5	✓
	Stat	QF1 + QF2 + QF3	20.1	6.1	56.7	64.2	×	25.4	5.5	73.3	80.8	✓
		PC1 + QF1	20.2	5.7	51.7	63.3	×	24.7	5.5	74.2	80.0	✓
	Stat + Text	PC1 + QF1 + EPU	20.1	5.5	66.7	72.5	×	23.0	5.2	77.5	79.2	✓
	Bench	HIST	0.0	6.9	70.8	50.0	×	0.0	6.9	70.8	50.0	×
	Macro	MUNC	24.7	7.4	44.2	64.2	✓	25.9	6.5	61.7	73.3	✓
	Macro + Fin	MUNC + FUNC	23.8	8.0	48.3	55.0	✓	**27.0**	6.8	64.2	73.3	✓
		MUNC + NFCI	22.0	9.0	42.5	58.3	✓	22.7	8.2	50.8	65.8	✓
		MUNC + EBP	22.9	8.1	55.0	60.0	✓	23.8	7.0	65.0	75.8	✓
		MUNC + FUNC + EBP	21.4	8.8	50.8	61.7	✓	23.4	7.5	59.2	77.5	✓
	Macro + Text	MUNC + EPU	22.2	8.0	51.7	60.0	✓	23.7	6.7	72.5	68.3	✓
	Macro + Stat	MUNC + PC1	24.9	7.3	54.2	61.7	✓	24.9	6.4	67.5	77.5	✓
		MUNC + PC1 + QF1	24.6	7.4	56.7	61.7	✓	26.3	6.6	66.7	78.3	✓
	Fin	FUNC + CISS	21.4	7.6	65.0	65.8	✓	25.1	6.8	81.7	85.8	✓
6		FUNC + EBP	20.6	8.0	55.0	72.5	✓	25.2	6.5	74.2	79.2	✓
		CISS + EBP	18.2	8.3	51.7	75.8	×	22.8	7.3	75.8	80.0	✓
	Fin + Text	FUNC + EPU	21.3	6.8	70.8	75.8	✓	25.7	6.0	78.3	82.5	✓
	Fin + Stat	NFCI + PC1	18.1	9.1	46.7	57.5	✓	23.6	7.9	60.8	75.0	✓
	Fin + Stat + Text	FUNC + PC1 + EPU	20.6	7.0	66.7	65.0	✓	25.3	6.1	80.8	77.5	✓
		FUNC + QF1 + EPU	21.4	7.0	68.3	67.5	✓	25.2	6.1	77.5	80.8	✓
		NFCI + CISS + QF1	17.7	8.8	52.5	60.0	×	21.2	7.9	67.5	68.3	✓
		NFCI + EPU	18.0	9.3	44.2	65.0	✓	22.3	8.3	47.5	75.0	✓
	Stat	QF1 + QF2 + QF3	19.7	6.3	65.0	60.0	×	23.2	5.4	76.7	84.2	✓
		PC1 + QF1	19.2	6.0	60.0	60.0	×	23.7	5.8	81.7	78.3	✓
	Stat + Text	PC1 + QF1 + EPU	18.1	5.8	64.2	68.3	×	21.8	5.4	80.0	80.8	✓
	Bench	HIST	0.0	7.5	62.5	58.3	×	0.0	7.5	62.5	58.3	×
	Macro	MUNC	17.6	8.4	52.5	72.5	✓	16.7	7.7	65.0	77.5	✓
	Macro + Fin	MUNC + FUNC	14.1	9.2	53.3	68.3	✓	16.4	8.5	62.5	70.8	✓
		MUNC + NFCI	13.9	9.5	50.8	76.7	✓	12.4	9.3	50.8	74.2	✓
		MUNC + EBP	14.0	9.3	57.5	75.8	✓	14.2	8.5	60.8	77.5	✓
		MUNC + FUNC + EBP	10.6	10.2	55.8	75.8	×	12.6	9.0	60.8	80.8	✓
	Macro + Text	MUNC + EPU	14.1	9.4	50.8	72.5	×	14.1	8.3	65.8	77.5	✓
	Macro + Stat	MUNC + PC1	16.7	8.7	52.5	65.8	✓	15.9	8.0	63.3	77.5	✓
		MUNC + PC1 + QF1	16.5	8.9	49.2	70.8	✓	17.2	8.4	58.3	80.8	✓
	Fin	FUNC + CISS	9.1	9.0	63.3	85.8	×	13.7	8.7	71.7	80.8	✓
12		FUNC + EBP	9.7	8.9	56.7	72.5	×	**17.6**	7.4	73.3	85.0	✓
		CISS + EBP	10.5	9.5	55.8	70.0	×	15.5	8.9	70.0	82.5	✓
	Fin + Text	FUNC + EPU	10.8	7.9	72.5	75.0	×	15.8	7.0	80.0	78.3	×
	Fin + Stat	NFCI + PC1	7.7	10.3	45.8	79.2	✓	14.2	9.3	57.5	76.7	✓
	Fin + Stat + Text	FUNC + PC1 + EPU	8.4	8.5	62.5	72.5	×	15.0	7.4	72.5	75.8	×
		FUNC + QF1 + EPU	10.3	8.2	68.3	70.0	×	14.5	7.2	78.3	75.8	×
		NFCI + CISS + QF1	4.2	10.3	51.7	69.2	✓	10.1	9.7	56.7	77.5	✓
		NFCI + EPU	7.0	10.5	36.7	73.3	×	12.4	9.6	51.7	70.0	✓
	Stat	QF1 + QF2 + QF3	11.7	7.2	67.5	76.7	✓	15.3	6.5	72.5	83.3	✓
		PC1 + QF1	10.6	7.0	68.3	76.7	✓	16.2	6.7	75.8	81.7	✓
	Stat + Text	PC1 + QF1 + EPU	8.4	6.9	70.0	79.2	×	13.3	6.3	79.2	80.0	×

This table reports backtesting statistics for the downside risk forecasts of selected one-, two-, and three-

Table 8: Downside Risk Prediction for the FRED-MD Sub-Categories

h	Class	Model	Output	Labor	Hous	Ord Inv	Credit	Exch Rates	Prices Down	Prices Up	Stocks
1	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	5.1	17.7	72.2	8.7	4.4	7.9	2.9	3.3	19.3
		AR LS	14.6	26.4	74.4	21.3	15.4	12.5	15.0	18.2	28.1
	QR	NFCI	9.0	22.1	72.0	10.2	4.6	8.7	5.9	5.2	25.9
		EBP	6.7	21.1	72.0	13.3	4.1	6.0	6.3	6.5	21.7
		FUNC	10.7	22.1	72.5	15.6	4.6	7.3	6.9	4.3	28.2
		MUNC	16.0	25.0	72.4	20.1	5.3	7.2	11.5	10.8	25.6
		QF1	11.5	23.0	72.7	19.2	6.0	8.5	9.1	6.3	21.4
		PCF1	11.5	24.6	72.3	18.5	5.2	6.3	11.1	8.2	27.2
	LSR	NFCI	16.8	28.6	74.3	19.5	15.9	**12.8**	16.0	18.2	25.8
		EBP	14.4	28.6	74.4	22.2	15.4	12.4	16.2	18.1	29.0
		FUNC	17.3	28.2	74.6	23.2	15.0	11.2	17.2	18.0	**34.7**
		MUNC	**20.9**	29.6	74.4	**27.1**	14.6	8.5	17.8	**19.9**	27.9
		QF1	14.5	28.3	**74.8**	25.0	15.0	12.2	16.4	17.1	27.4
		PCF1	14.8	**30.0**	74.3	25.9	**15.9**	11.2	**17.8**	18.4	26.4
3	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	4.3	19.6	73.1	9.4	6.7	0.5	7.1	9.5	12.6
		AR LS	10.2	26.0	74.1	15.2	10.6	**7.6**	14.1	26.5	28.3
	QR	NFCI	12.3	24.7	73.3	15.0	6.7	0.1	8.8	12.2	18.1
		EBP	9.6	27.1	73.2	19.5	3.3	-5.2	7.7	12.2	17.4
		FUNC	18.4	29.6	74.4	23.7	7.3	-0.6	8.9	10.6	25.5
		MUNC	**24.0**	32.4	74.4	27.7	7.5	-0.2	13.4	16.6	20.0
		QF1	12.8	28.4	73.6	23.9	5.8	0.1	8.6	13.6	16.0
		PCF1	18.7	30.6	73.8	26.8	6.8	0.1	9.9	15.8	16.8
	LSR	NFCI	14.4	29.7	74.0	16.0	13.0	3.8	14.6	26.3	22.6
		EBP	13.9	31.6	75.1	19.7	11.3	2.9	14.5	24.6	24.1
		FUNC	20.1	32.6	**75.5**	23.5	12.9	7.2	17.3	**26.6**	**34.3**
		MUNC	22.1	**35.0**	75.0	**30.3**	12.9	6.1	**18.2**	23.0	22.9
		QF1	10.6	31.3	74.9	24.7	**13.0**	6.9	14.5	26.3	25.4
		PCF1	16.9	33.7	74.0	25.8	11.8	2.5	14.0	24.2	19.9
6	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	4.9	16.8	71.6	7.8	6.7	-1.0	9.1	11.7	8.3
		AR LS	5.1	20.1	73.0	11.5	5.5	3.7	12.5	23.8	**28.2**
	QR	NFCI	12.2	19.9	71.3	11.8	6.9	-4.9	11.1	13.2	16.4
		EBP	14.4	28.0	72.0	20.2	3.8	-8.7	7.6	10.0	13.8
		FUNC	17.8	29.9	73.3	24.4	8.6	-3.6	10.4	11.9	20.3
		MUNC	**21.9**	32.1	73.8	**27.4**	8.2	-5.4	12.5	16.6	17.6
		QF1	14.3	27.7	71.9	22.7	7.9	-1.8	9.4	12.5	11.2
		PCF1	15.2	29.2	73.1	20.8	6.3	-6.3	10.4	12.5	11.0
	LSR	NFCI	12.9	24.7	72.5	13.6	10.7	-1.4	14.7	27.2	22.2
		EBP	16.1	31.0	74.0	19.4	8.0	0.3	12.2	24.5	16.9
		FUNC	20.3	**33.5**	**75.5**	24.2	**11.0**	3.4	**14.9**	**27.3**	27.7
		MUNC	20.0	30.9	74.5	26.0	7.7	**4.2**	11.7	25.0	21.4
		QF1	12.6	28.6	73.3	19.7	9.1	2.9	12.0	25.2	21.1
		PCF1	13.7	31.0	73.1	20.6	10.2	1.2	12.8	25.5	9.5
12	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	1.5	11.4	66.6	2.2	7.5	0.2	3.5	6.1	6.0
		AR LS	1.7	12.2	67.7	-0.4	0.0	-1.1	12.8	20.7	13.9
	QR	NFCI	1.5	5.9	63.1	0.7	3.2	-11.5	5.2	5.3	13.9
		EBP	6.8	22.4	66.9	13.7	2.0	-9.4	0.7	-1.2	11.4
		FUNC	4.3	18.6	67.4	**14.1**	7.7	-7.3	3.5	5.0	15.4
		MUNC	**10.0**	21.4	68.7	12.9	**8.4**	-5.9	6.8	13.4	16.0
		QF1	4.5	18.0	65.9	11.7	7.3	-3.9	3.1	3.0	7.9
		PCF1	-1.5	16.9	66.0	7.5	7.9	-15.0	2.3	6.1	2.5
	LSR	NFCI	1.9	8.3	65.0	3.2	1.5	-12.2	13.2	21.6	15.3
		EBP	4.9	**23.7**	67.7	10.2	-0.9	-9.4	**14.9**	18.5	11.5
		FUNC	5.8	22.6	**69.4**	12.2	1.8	**1.5**	11.2	21.6	**16.2**
		MUNC	9.2	17.7	68.5	12.9	-5.7	0.5	5.0	21.1	7.4
		QF1	4.9	17.6	67.9	7.3	0.2	-0.7	11.4	17.5	5.4
		PCF1	0.3	18.5	65.8	9.2	1.5	-6.5	11.5	**23.0**	-0.2

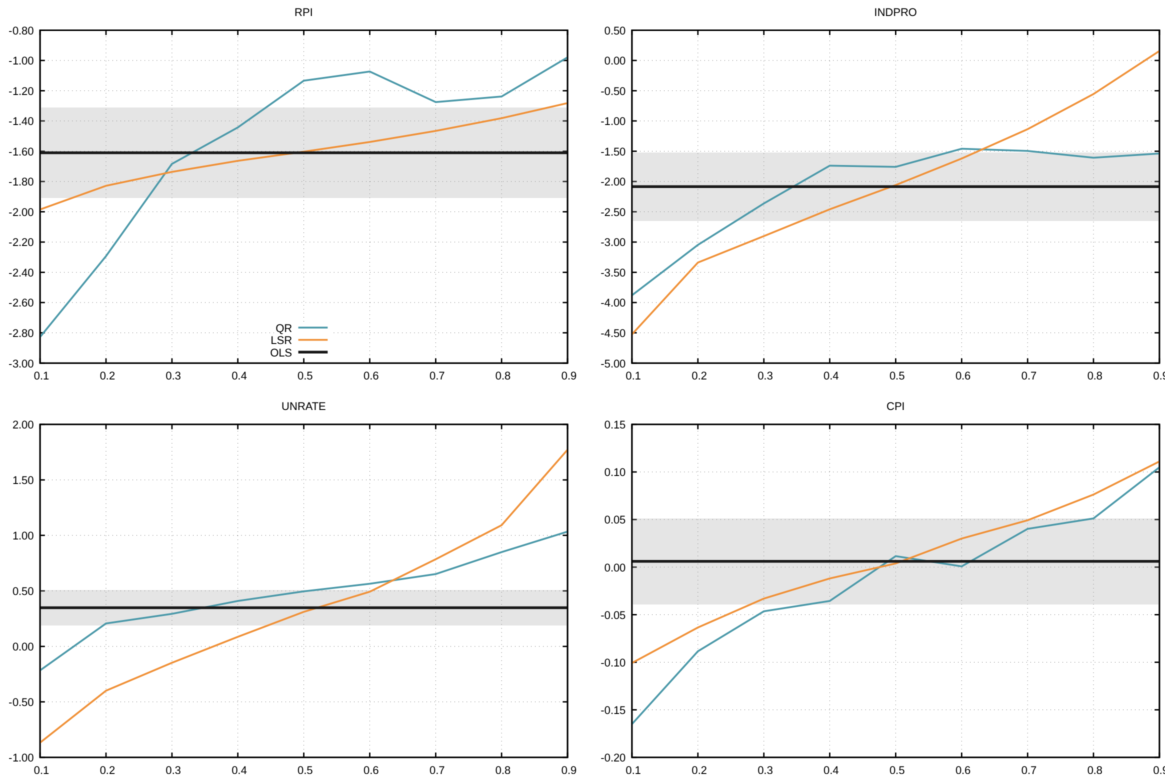
This table reports the out-of-sample predictive performance of selected one-factor downside risk models across the FRED–MD categories at horizons 1, 3, 6, and 12. For each forecast horizon, specification, and sub-category, the table lists the average tick loss gain relative to the historical quantile benchmark. Results are reported separately for quantile regression and location–scale regression specifications.

Table 9: Downside Risk Prediction for Policy-Relevant Variables

h	Class	Model	RPI	IP	UR	ALL EMP	HOU ST	PPI	PPI up	CPI	CPI up
1	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	-4.1	9.7	10.3	37.7	84.2	6.3	13.8	-0.0	-3.8
		AR LS	24.1	19.5	9.8	46.9	84.4	15.7	25.9	14.1	12.5
	QR	NFCI	-1.9	17.6	19.6	48.8	83.6	10.0	14.5	3.8	-2.9
		EBP	1.5	12.3	14.1	45.2	84.1	10.7	14.0	6.2	1.4
		FUNC	1.0	18.9	13.8	45.9	84.1	11.9	15.7	6.4	-2.0
		MUNC	5.6	**29.2**	20.4	50.5	84.5	18.7	22.6	14.3	10.8
		QF1	4.1	18.5	14.6	44.6	84.9	15.6	20.7	10.7	0.5
		PCF1	-5.0	21.9	16.6	**51.5**	83.4	15.2	18.3	13.1	2.1
	LSR	NFCI	27.1	22.0	17.8	50.5	84.1	16.2	26.3	14.1	11.5
		EBP	29.6	17.1	12.0	47.9	84.0	16.3	26.9	14.5	13.8
		FUNC	27.8	22.2	15.1	49.7	84.4	19.1	27.6	16.3	10.8
		MUNC	**30.8**	28.0	**22.1**	51.4	**85.3**	**19.4**	**31.9**	**18.6**	**15.6**
		QF1	26.2	15.8	15.1	48.0	85.2	16.2	31.1	16.7	8.2
		PCF1	15.5	19.9	17.9	49.5	84.4	19.2	28.3	15.6	12.6
3	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	-10.6	9.5	14.7	37.2	83.6	8.3	13.6	8.0	12.0
		AR LS	-0.7	20.5	19.9	38.0	83.7	9.3	33.8	12.2	31.3
	QR	NFCI	-1.0	22.7	32.0	44.1	83.7	8.8	14.6	8.1	13.4
		EBP	2.6	18.6	30.7	47.9	83.7	11.6	16.9	8.4	13.9
		FUNC	4.7	27.7	32.4	53.6	85.1	10.7	18.6	8.4	9.9
		MUNC	8.2	**39.6**	**35.0**	**57.5**	86.2	**15.9**	29.8	19.3	19.8
		QF1	9.7	22.0	25.4	48.0	84.3	12.0	20.4	8.0	18.0
		PCF1	4.6	30.6	32.8	51.6	84.5	9.3	19.6	9.4	18.9
	LSR	NFCI	-0.9	25.1	31.3	45.7	84.4	9.3	34.4	9.7	**31.7**
		EBP	11.1	21.1	26.1	50.9	85.2	10.5	32.5	12.9	28.3
		FUNC	4.5	29.3	30.1	53.8	85.9	12.6	**36.1**	13.0	31.2
		MUNC	**11.7**	34.7	34.1	55.1	**86.6**	12.9	34.0	**20.5**	26.6
		QF1	9.1	16.5	23.2	48.3	85.8	10.9	32.4	11.6	30.3
		PCF1	8.9	23.7	30.4	53.5	84.8	9.2	34.9	8.1	25.6
6	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	-6.9	8.7	15.9	25.7	81.0	11.9	28.8	9.4	13.2
		AR LS	-10.7	9.4	16.7	20.7	82.2	10.6	42.0	9.6	31.0
	QR	NFCI	-1.8	20.5	29.6	26.1	80.3	12.0	28.9	9.5	13.6
		EBP	12.4	21.0	36.2	47.0	82.2	11.0	29.4	4.2	5.8
		FUNC	16.6	27.4	34.2	49.4	83.1	11.7	29.9	9.4	11.5
		MUNC	16.1	**32.4**	**40.7**	**57.0**	86.2	12.0	38.1	**12.8**	19.2
		QF1	**18.0**	19.0	28.8	44.9	81.5	12.3	32.9	8.5	13.5
		PCF1	14.8	22.0	34.4	47.3	82.8	**12.5**	29.0	7.3	12.2
	LSR	NFCI	-1.8	20.1	27.2	36.8	80.2	11.8	39.3	9.6	**34.6**
		EBP	8.6	22.6	33.3	49.5	83.2	10.8	42.3	1.4	24.6
		FUNC	11.4	26.0	34.2	52.5	**86.4**	11.1	**45.3**	10.9	31.6
		MUNC	15.8	30.2	32.7	50.7	84.9	8.4	41.6	7.2	28.6
		QF1	13.7	18.1	26.3	43.8	83.2	10.6	43.1	4.9	27.3
		PCF1	11.9	16.4	31.9	48.3	83.0	11.3	43.7	4.4	22.4
12	Bench	HIST	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		AR QR	-1.9	4.2	12.7	12.1	73.9	-1.0	18.0	0.4	1.2
		AR LS	-4.9	4.5	9.6	19.8	73.5	4.4	41.0	8.6	20.9
	QR	NFCI	-1.8	6.2	19.7	-3.7	70.1	-0.5	14.2	-1.9	-2.2
		EBP	3.5	12.3	33.3	**41.0**	76.7	-0.9	16.5	-2.9	-7.9
		FUNC	6.2	11.0	22.2	25.0	74.9	-1.5	16.4	2.2	-2.9
		MUNC	17.3	**14.4**	**34.3**	35.3	**80.0**	1.6	32.6	5.2	12.1
		QF1	4.7	10.6	18.2	26.0	72.5	-0.1	17.5	2.1	0.1
		PCF1	2.3	-0.2	24.4	24.2	74.9	-0.2	16.2	1.4	-2.2
	LSR	NFCI	1.0	5.3	18.2	3.1	72.5	6.9	37.4	4.6	19.4
		EBP	10.2	7.6	30.8	29.8	74.8	**11.1**	37.4	11.7	17.9
		FUNC	3.8	3.3	15.8	36.7	79.9	3.1	**41.9**	8.7	**22.0**
		MUNC	**18.0**	12.9	17.4	28.3	77.2	-2.4	39.5	6.1	21.0
		QF1	10.0	9.5	16.5	28.0	75.9	3.1	38.0	10.1	8.9
		PCF1	2.5	3.2	28.0	24.9	75.4	5.9	39.7	**14.3**	17.3

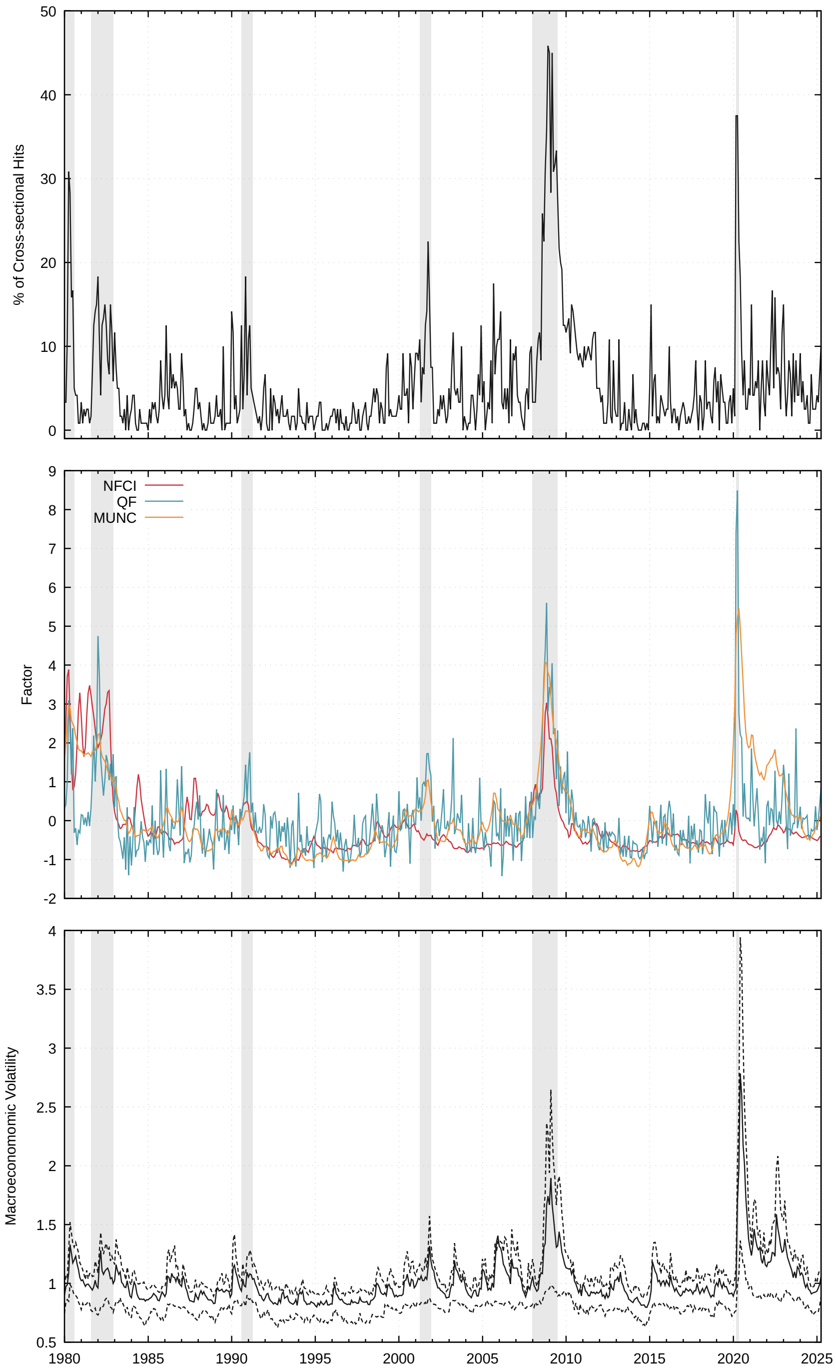
This table reports the out-of-sample predictive performance of one-factor downside risk models for selected policy-relevant variables at horizons 1, 3, 6, and 12. For each forecast horizon, specification, and variable, the table lists the average tick loss gain relative to the historical quantile benchmark. Results are reported separately for quantile regression and location–scale regression specifications.

Figure 1: Quantile Impulse Response Analysis



This figure displays the QIRFs of selected macroeconomic variables to an increase in MUNC from its median to its 95% quantile. The responses refer to the twelve-month forward average of Real Personal Income (RPI), Industrial Production (INDPRO), the Unemployment Rate (UNRATE), and the Consumer Price Index (CPI). The QIRFs are reported for nine equally-spaced quantiles from the 10% to the 90% of the distribution and are estimated using quantile regression and location–scale regression. The shaded area represents the 95% confidence band around the OLS estimate.

Figure 2: Downside Risk Factors and Macroeconomic Volatility



This figure displays the relationship between selected downside risk factors and macroeconomic volatility. The top panel reports the share of macroeconomic variables with realizations below their 5% empirical quantile. The middle panel reports the time series of the three leading downside risk factors: NFCI, QF, and MUNC. The bottom panel reports the cross-sectional average, along with the first and third quartiles, of the estimated macroeconomic volatility.