Determinants of Insurance Distress Recovery

Working Paper

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Abstract

This paper investigates the determinants of distress recovery of insurance companies. I develop three complementary distress definitions capturing market-based signals. To address model uncertainty and heterogeneity across firms and states of the world, I apply a mixture-of-experts framework to these definitions. In the second part, the paper analyzes the determinants of distress recovery. The results show that firm characteristics, capitalization, asset allocation, and macro-economic conditions explain variation in recovery outcomes. Macroeconomic variables matter more for US insurers, whereas European insurers depend more on firm-specific variables. I benchmark competing empirical approaches to assess robustness and predictive performance. The results indicate that generalized linear models provide more accurate rank estimates of the order in which firms recover, while Cox proportional hazard models offer the most precise point estimate of distress duration.

Keywords: Insurance; Financial Stability; Distress Resilience

JEL Classification: G01, G17, G22, G23

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1 Introduction

In biology, persistence is one of the three dimensions of resilience. It describes an ecosystem's ability to return to its original state following an adverse event. In the context of the finance sector, this concept is particularly relevant when analyzing the impact of financial crises. A large body of literature discusses the prediction of financial distress or failure. Regarding financial firms, this strand of research has focused particularly on banks, especially in the aftermath of the Global Financial Crisis.[1] However, to the best of my knowledge there is limited research on the determinants of recovery, especially for insurance companies.

Following the market crash caused by the Covid-19 pandemic in early 2020, insurance firms' stock prices needed varying amounts of time to recover to pre-crisis levels. Thus, the impact of the pandemic on stock prices was not uniform across the insurance landscape. For instance, mandatory business closures affected business continuity insurance in the property and casualty (P&C) sector, while health insurers faced uncertainty about the effect of the pandemic on healthcare costs. Figure 1 shows the distribution of 37 European insurance firms, grouped by business line. The time to recovery on the x-axis measures the time that insurance firms' stock prices were below their 200-day moving average after the market crash. The figure shows that the pace of recovery varied widely, even within business lines. This variation provides reason to further examine the underlying factors that influence the speed of recovery.

I chose to focus on insurance companies because of their long-term investment horizons, which make their role during financial crises ambiguous. On the one hand, insurance firms might stabilize prices of riskier assets through asset insulation[2] or counter-cyclical investments.[3] On the other hand, they can also contribute to systemic stress through a flight to safety, which increases the demand for safer assets and puts riskier assets under further stress,[4] or through regulatory-driven fire sales, which increase the supply of riskier assets to the market.[5] Thus, insurance firms play a key role for financial stability, which motivates to understand the characteristics of resilient insurance firms.

Additionally, US insurance firms provide granular securities transactions data, that enables

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[1] see, for example, Andreou et al. (2021); Chen et al. (2015); Gogas et al. (2018); Habib et al. (2017); Lasfer et al. (2003)

[2] Chodorow-Reich et al. (2020), Coppola (2025)

[3] Timmer (2018)

[4] Becker and Ivashina (2015); Kirti (2024)

[5] Ellul et al. (2022)

me to include trading behavior in the analysis. The volume of trading activity before distress periods can play a crucial role in strengthening or weakening financial positions. Examining the factors that contribute to the resilience of the insurance sector improves the identification of insurers with price-stabilizing capacities, as well as the formation of expectations regarding the latter. Furthermore, it improves regulators' ability to respond effectively to future crises.

This paper addresses which ex-ante characteristics of firms or macroeconomic conditions contribute to faster recovery periods following individual and market stress. To address this question, I construct a flexible measure to define firm-specific distress periods with cross-sectional variation in distress durations. Using the cross-section of distress durations, I select variables from a large set of possible explanatory factors. Additionally, I test the out-of-sample predictive power of the selected variables. Lastly, the sample design allows me to compare the distress durations of European and US insurers.

In the variable selection, I find that asset composition, especially the share of cash and equivalents, interest and dividend income, and stock market conditions mostly determine distress durations of European firms. The US sample shows identifies the slope of the term structure, industrial production, and stock market conditions as relevant variables. In comparison, macroeconomic conditions more strongly determine the expected distress durations of US firms, whereas European insurance firms depend more on firm-specific variables. Interestingly, various models commonly select real estate investments in both samples as a signal for shorter distress durations.

In the prediction analysis, I aim to answer the question whether individual stress periods are informative about the recovery time during market crises. I show that models trained to predict distress durations during Covid-19 and thereafter, with data ranging from 2010 until 2019, produce an average prediction error[6] of 107 days in the best specification, and a cross-sectional rank correlation of 79% on the order of distress recovery. When comparing different distributional assumptions, I find that stratified Cox proportional hazard models better predict distress durations than pooled maximum likelihood optimizations. In contrast, pooled generalized linear models yield better rank estimates on the order of distress recovery. Overdispersion does matter both in the selection and prediction.[7]

My paper adds to the field of regime detection in financial time series. Bry and Boschan

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[6] Defines as mean absolute error (MAE).

[7] Overdispersion in this context refers to a sample whose variance is larger than its mean, violating the Poisson distribution property of identical mean and variance.

(1971) provide early advances in the field of defining turning points in macroeconomic time series. The authors base their methodology on various moving average measures that is still applied, for example, when determining bear market episodes.[8] Alonso (2025) provides an overview on recent rolling-window-based methods for regime detection in financial time series beyond their first moment. In contrast to the rolling-window-based approach by Bry and Boschan (1971), my distress-defining algorithm incorporates in-sample methods that detect structural regime changes through the optimization of statistical break-detection criteria. This improvement ensures that the distress periods depend on changes in underlying regimes based on volatility or auto-correlation, rather than identifying local extreme values. In a related study, Andreou et al. (2021) create a stock price crash-risk indicator based on abnormal returns. In contrast, my approach relies on raw stock returns. Raw returns better suit my application because they capture a firm's total value change, including market-wide and firm-specific effects that matter during periods of financial stress. Furthermore, raw returns avoid the friction of estimating a market expectation for each stock.

In addition to defining periods of distress, my paper contributes to the literature on the determinants of distress. Perez-Quiros and Timmermann (2000) find that smaller firms display greater differences in sensitivity to credit risk during recessions and expansions compared to larger firms. Lasfer et al. (2003) inspect market indices and provide early insights that overreaction alone cannot explain stock price behavior during periods of market stress. Campbell et al. (2008) and Wang et al. (2009) shift the focus from index-level data to individual firms, showing that firm characteristics help to explain crisis performance and stock price recovery. Giesecke et al. (2011) use regime models to describe the macroeconomic determinants of corporate bond default risk. Cenesizoglu (2015) assesses the effect of news on stock prices during good and bad times. His findings are consistent with my findings on news. Acharya et al. (2024) inspect why bank stock returns reacted more strongly to the Covid-19 crisis than those of other financial firms. The authors find that banks with larger capital buffers were less affected and recovered faster than firms whose with less flexibility in regulatory capital. Inspecting the insurance industry in particular, Becker and Ivashina (2015) document that the asset structure of insurance companies has a significant impact on their crisis performance, and Ma and Ren (2020) find that the ownership structure of insurance companies can affect their volatility during crisis periods. Beyond the ownership structure of listed insurers, the distress recovery implications of listed insurers might differ systematically from those of mutual insurers. However, I cannot address

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[8] For example in International Monetary Fund (2026).

potential differences, as my distress measure relies on stock prices.

My findings align with previous literature with respect to the importance of macroeconomic factors, such as industrial production, inflation and the structure of interest rates. Additionally, I find that firm-specific variables on asset allocation that proxy asset flexibility, such as cash and equivalents or securities held for sale, are associated with faster recovery from distress states, which is consistent to the capital buffer effect observed on banks by Acharya et al. (2024).

I, further, add to the literature on insurance investment behavior during crisis times. Timmer (2018) and Beyer (2025) report that insurers invest more during periods of negative market performance. Becker and Ivashina (2015) observe less risk-taking by insurance companies during periods of market stress and Kirti (2024) documents that insurers more affected by the global financial crisis re-balance their portfolios stronger towards safer assets. Abbassi et al. (2016) find that banks with higher trading expertise invested more than their peers during the Global Financial Crisis. Previous literature documents varying investment styles during crises, so I include US insurers' security transactions in the analysis but observe no significant effect on recovery speed.

The remainder of this article is structured as follows: Section 2 discusses the definition of firm-specific distress periods. Estimation methodology, distributional concerns and the variable selection specifications are presented in 3.1 Section 4 discusses the data and sample properties. The results are presented in section 5. Section 6 concludes.

2 Distress Definition

Defining time- and firm-specific distress periods requires a flexible measure that is not tied to firm-invariant factors, such as market conditions or macroeconomic factors. To make the measure universally applicable, I also refrain from using firm-specific regulatory labels as their availability differs across regions and over time. To address the shortcomings of existing crisis or distress flags, I link the identification problem to the extensive literature on regime detection in biological and medical time series.

Alonso (2025) presents a multitude of entropy-based methods to obtain information from financial time series, including regime detection. These methods enable out-of-sample regime detection using rolling estimation windows. However, out-of-sample detection comes at the cost of losing information from the entire time series because the estimation window is usually much smaller than the available observations. Additionally, rolling estimation may result in a delayed response in the outcome variable.

To address the shortcomings of rolling estimations, one can revert to models that treat the available observations holistically. By construction, these models can only estimate regimes in-sample. Scott and Knott (1974) present the binary segmentation method for searching clusters within data.[9] While the binary segmentation method is fast, it is not optimal. The sequential segmentation might fail to identify global optima, a problem addressed by Jackson et al. (2005). Killick et al. (2012) extend this framework by presenting the pruned exact linear time (PELT) changepoint algorithm, which yields optimal results while maintaining linear computational time. The advantage of such changepoint models is that the model determines the number of changepoints endogenously. Yet, this also means that there is no upper limit on identified changepoints, which can lead to a high number of regimes requiring interpretation.

The properties of the changepoint detection algorithm are complemented by the features of regime-switching models. Hamilton (1989) first presented regime-switching models, which can account for various features of financial time series, such as fat-tails, volatility periods, and time-varying auto-correlations.[10] Contrary to changepoint models, regime-switching models rely on a predefined number of states, which allows researchers to test specific hypotheses about distinct structural dynamics within the data.

Depending on the context, the properties of each of the three methods — rolling estimation, changepoint detection, and regime switching — can be beneficial or require caution. To increase the robustness of the distress definition and mitigate the problem of possible misclassification, I use a mixture-of-experts approach. I compute the distress state for each of the three presented methods and define the final distress state based on an equally weighted majority decision. All of the methods are built solely on time-series data of stock returns. Each method emphasizes a different aspect of the time series, helping to identify the system's state by examining different moments of its distribution. The rolling window approach is mean-based, while the changepoint and regime-switching models utilize the variance and auto-correlation, respectively. The distress definitions are thus built on different models and distress characteristics and serve as complements to each other. Table 1 provides an overview of the methods and distress definitions.

First, I calculate the rolling 200-day average cumulative returns. I define the firm-specific distress state, $D_{i,t}^{MA}$, as one whenever the stock's compounded return falls below its past 200-day

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[9] See Aggarwal et al. (1999) for an application to financial data.

[10] see Ang and Timmermann (2012) for a detailed discussion and review of regime-switching models, especially for economic applications.

moving average.

$$D_{i,t}^{MA} = \begin{cases} 1 & \text{if } R_{i,t} < \text{MA}_{i,t}(200) \\ 0 & \text{otherwise} \end{cases}$$

For firm i on day t with compounded return $R_{i,t}$ and 200 day moving average $MA_{i,t}(200)$. This distress definition has several convenient properties. First, it is easy to interpret due to the daily availability of stock prices and the intuitive interpretation of the moving average. Second, the well defined-threshold provides a clear transition cut-off between distress and non-distress. Third, the measure is applicable out-of-sample. Using a moving average instead of an average over a fixed period allows the training data to adapt to changing trends. The length of the moving average window is a trade-off between misspecification of distress periods and incorporating outdated information.

Second, I apply a changepoint detection algorithm based on the variance of stock returns. I choose to apply the PELT algorithm, the exact algorithm is described in Killick et al. (2012). For the cost function of the detection, I use twice the negative log-likelihood under normality with a fixed mean and an estimated variance. For the penalty term, I use the Bayesian Information Criterion (BIC), both as proposed by Killick et al. (2012). The minimization of

$$\sum_{i=1}^{m+1} \left[C(r_{(\tau_{i-1}+1):\tau_i}) + \beta \right]$$

with cost function $C(\cdot)$, penalty term β, and return r with respect to τ_i, will yield the set of changepoints τ.

A given period between changepoints will then be identified as distressed, according to

$$D_{i,t}^{CP} = \begin{cases} 1 & \text{if } VAR(r_{i,cp} > 1.5 \cdot VAR(r_i) \\ 0 & \text{otherwise} \end{cases}$$

The variance of returns in changepoint *cp* must exceed 1.5 times the sample variance for firm i. Distress periods characteristically exhibit higher volatility in daily stock returns, which forms the basis of this definition. In theory, this measure also captures positive jumps in stock prices. However, the mixture-of-experts approach mitigates this problem because both the moving average and the regime-switching model definitions require negative average returns.

Third, the regime-switching model. The idea behind the model specification is that during distress periods and recovery phases, auto-correlations of returns may temporarily be positive. To estimate regime-dependent auto-correlations, I use a homogeneous, 3-state Markov model, with an underlying AR(1) process. The model allows for 3 states to capture not only low and high regimes, but also an intermediate regime. This specification offers greater flexibility than a two-state model and captures more nuanced dynamics in the underlying process. While the model requires within-firm transition probabilities to be homogeneous, they may differ in the cross-section.

The regression formula is described by

$$r_{i,t} = \mu_{i,k} + \rho_{i,k} r_{i,t-1} + \varepsilon_{i,t}, \qquad \text{for } S_{i,t} = k,\ k \in \{1,2,3\}.$$

for return r of firm i at time t with coefficients depending on state S. The distress definition then becomes

$$D_{i,t}^{RS} = \begin{cases} 1 & \text{if } t \in k \quad \& \quad \hat{\mu}_{i,k} < 0 \quad \& \quad \hat{\rho}_{i,k} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Finally, the mixture of experts approach collapses all three individual distress states into a single binary variable:

$$D_{i,t}^{MIX} = \begin{cases} 1 & \text{if } D_{i,t}^{MA} + D_{i,t}^{CP} + D_{i,t}^{RS} \geq 2 \\ 0 & \text{otherwise} \end{cases}$$

Figure A.1 and Figure A.2 in the Appendix show D^{MIX} for all firms in the European sample and the US sample, respectively.

Figure 2 presents the number of firms in a distressed state by date for the European and US samples. The figure shows that the distress definition method produces clustered results, which is consistent with the theory behind market crises. The methodology particularly well captures the European sovereign debt crisis of 2011 and 2012, as well as the 2020 market crash caused by the Covid-19 pandemic. The figure also shows that the method generates sufficient distress observations for predictive analyses. For this analysis, I divided the regional samples into a training set (defined as all observations up to 2019, just before the market crash caused by the pandemic) and a testing dataset thereafter. The dashed red line depicts the separation threshold between the two datasets.

3 Methodology

3.1 Distribution Concerns

The logit model is a natural choice for analyzing binary variables. The logit model captures the probability of being in a state of distress given certain factors. While the partial effects of this model help identify the drivers of the distress state, two problems arise. First, the distress state is inherently autocorrelated. Thus, past distress is likely the best predictor of current distress. Second, the inclusion of duration as a regressor imposes a common functional relationship between duration and transition probabilities across both time and cross-sectional units, which can limit flexibility in capturing heterogeneous transition dynamics. Therefore, duration- or hazard-based approaches better analyze the duration dependence in recovery than the logit model.

To apply duration and hazard models that estimate the duration of each (non-)distress period, I transform the longitudinal panel dataset into a cross-sectional dataset. This transformation defines periods based on sequences of states and summarizes the data according to the periods' lengths. I set the minimum sequence length to 15 trading days. Thus, whenever a distress indicator equals zero for at least 15 consecutive days, those days form a non-distress period until a sequence of 15 consecutive distress days begins a new distressed period.

The cross-sectional dataset consists of alternating periods of non-distress and distress, as well as the duration of each period for all sample firms. The period durations serve as the dependent variable, which enables me to interact a variety of variables with the binary distress state variable to investigate potential effects on recovery times. Transforming the data from panel to cross-sectional entails losing the time-series dimension of the covariates. To preserve some time series information, I transformed the time series of the covariates into changes in the previous one quarter or the previous four quarters. A one-quarter change captures the difference between a covariate's value one quarter before the period changed and its value at the start of the current period, and similarly for four quarters.[11]

Because the data are discrete and strictly non-negative, the normality assumption of the conditional distribution of ordinary least squares (OLS) does not appear to be appropriate. The Poisson distribution generally suits countable, non-negative outcomes. However, the data show

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[11] Depending on the type of covariate, transformations other than differencing may be applied; for example, returns are compounded rather than differenced.

signs of over-dispersion; that is, the variance exceeds the mean. This property contrasts with the Poisson distribution, where the mean equals the variance. This observation applies to both the sample and estimated conditional properties. Therefore, the Poisson distribution might not accurately capture the conditional variance of the data. In the presence of overdispersion, the negative binomial distribution is a more appropriate choice because it introduces a dispersion parameter that models the variance-mean relationship more flexibly.

The negative binomial distribution (NB) is estimated via a generalized linear model. When linking with a log function, the dependent variable then has the conditional mean

$$E[Y \mid X] = \mu = exp(X\beta), \text{ with } Y \sim \text{NB}(\mu, \theta) \tag{1}$$

With θ being the dispersion parameter. The conditional variance can then be described as

$$\text{Var}(Y \mid X) = \mu + \frac{\mu^2}{\theta} \tag{2}$$

However, achieving a more precise variance estimation comes at the cost of computational stability, when maximizing the log-likelihood function.

Lastly, another natural approach to modeling the data is to use the Cox proportional hazards (CoxPH) model for survival analysis estimation. This model directly estimates the amount of time a firm spends in its current state and the time-dependent likelihood of transitioning out of it. Formally, the model specifies the hazard rate as

$$h(t \mid X) = h_0(t) \exp\bigl(\beta^\top X\bigr) \tag{3}$$

where $h_0(t)$ is the unspecified baseline hazard function, that is the probability of exiting the current state at time t, and $\exp(\beta^\top X)$ scales it according to covariates X. This semiparametric structure is powerful, as it does not make restrictive assumptions about the shape of $h_0(t)$, yet still yields consistent estimates of β via partial likelihood. Crucially, because the dependent variable is the duration of the modeled state, the Cox model naturally addresses both shortcomings of the logit model. The time dimension embeds the auto-correlation of the distress state directly into the hazard process. The process also models the duration instead of a time-invariant, transition probability. Covariates that accelerate or decelerate the hazard of recovery can thus be identified and quantified in this unified framework.

The shortcoming of this approach lies in the fact that it cannot model the length of two independent periods at the same time. This limitation forces the CoxPH model application to stratify the data into non-distress and distress observations and treat the exit of the respective state as the event. On the one hand, this approach clearly distinguishes the different influential factors during non-distress and distress periods. On the other hand, those results are less robust as the stratification effectively halves the sample size.

I also tested the application of repeated event approaches. I found no evidence to support the assumption of the PWP approach, as described in Prentice et al. (1981), that the order of events is informative. For example, this means that the length of the fifth financial distress period does not systematically differ from any previous periods.

I generate my results using the Poisson model, the negative binomial model, and the PH model and benchmark their performance with an out-of sample test.

3.2 Variable Selection

To identify the determinants of insurance distress recovery, I regress the duration of each period, measured in days, on a set of potential explanatory variables. To control for the influence of macroeconomic interdependencies, I apply a set of macroeconomic control variables. Furthermore, I include firm-specific variables to account for the influence of each insurer's business mix on its asset price, as well as size, income, and liquidity considerations. This approach yields the following regression model for the pooled specifications with underlying Poisson and negative binomial distributions:

$$Length = \alpha + \mathbf{X}\beta_1 + (\mathbf{X} \odot D)\beta_2 + \epsilon \tag{4}$$

I estimate the equation via maximum likelihood. The dependent variable *Length* is a vector of firm-specific period lengths measured in days. D is a binary vector that contains the distress state (either 1 for distress or 0 for non-distress) of each period multiplied element-wise with the covariate matrix $\mathbf{X}$. $\mathbf{X}$ contains all the independent variables for the model.[12] α is the intercept and ϵ the residual. Thus, equation (4) allows the effects of the determinants of period lengths to vary between non-distress and distress periods, thereby capturing state-dependent heterogeneity across regimes.

The covariates categorize into macroeconomic variables, stock market variables, and firm specific variables. The macroeconomic variables include daily interest rates, daily government bond yields, monthly consumer price index levels, monthly industrial production, and daily

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[12] See subsection 3.1 for an explanation of the transformation and definition of the period change variables.

exchange rates. The stock market variables include daily returns of the leading index for each region, its respective volatility index, and an indicator reflecting whether the stock market itself is in a distress period. The firm-specific covariates contain information on income and asset allocation scaled by total assets, news coverage and sentiment scores, the natural logarithm of total assets, and binary variables that indicate whether each firm belongs to the top or bottom decile of the cross-section in terms of cash and cash equivalents. On the one hand, the EU sample exclusively features information on Solvency Capital Ratios and premium income from index- and unit-linked products and guarantee products. The US sample, on the other hand, has unique information on trading volumes.

While previous empirical evidence[13] suggests that most of the covariates influence stock market performance, and thus indirectly influence the distress state, applying them all at once could lead to severe multicollinearity, singularities, or over-fitting of the data. The application of the best sample selection algorithm is not possible, as the runtime of the algorithm scales with $O(2^p)$, with p being the number of covariates. Since best sample selection is not possible, I use the backward sample selection algorithm as a baseline scenario. This algorithm starts with the full sample and then drops the one observation that contributes the least to the explained variation of the overall model. The process is repeated until the total explained variation of the overall model no longer increases. While this procedure helps to mitigate multicollinearity and reduces the model size, the approach focuses more on minimizing bias than variance, which leads to poor out-of-sample performance. Additionally, the backward sample selection likely does not produce an optimal final sample, given the number of covariates.

Regularization addresses the shortcomings of sample selection algorithms mentioned above. Regularization techniques, such as ridge or lasso regression, penalize the size of the regression coefficients. Ridge regression uses a quadratic penalty term that shrinks the coefficients but keeps them non-zero. I chose to use lasso regression with its absolute penalty term. Lasso regression can reduce coefficients with little explanatory power to zero, making it a reliable option for variable selection.

The lasso regression optimizes

$$\beta_{\text{lasso}} = \arg\min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - X_i\beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{5}$$

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[13] See literature overview in Section 1.

Where λ is the penalty coefficient, $(y_i - X_i\beta)^2$ are the squared regression residual, and β_j are the initial regression coefficients. λ is estimated via cross validation of the sample and can therefore fluctuate depending on the which parts of the population are sampled. To obtain a more robust framework, I generate bootstrap samples matching the number of input observations by resampling with replacement. I repeat the full estimation procedure for each resample, resulting in a distribution of selected variables.

(4) presents the regression formula for the backward sample selection and the lasso when assuming a Poisson or negative binomial distribution. I use the specification with interaction terms over the estimation without interaction terms, because of the implications on sample selection. Without interaction terms, the model would fit the period durations regardless of their characterization as (non-)distress and would select the optimal sample accordingly, ignoring their state. The interaction specification uses individual effects for non-distress and distress periods of all variables, implying that all variables might affect non-distress and distress periods differently. This comes with the caveat that individual effects might be removed while the distress interaction remains, or vice versa, which needs to be reflected when interpreting coefficients. For the PH model, interaction terms are not present, as the data are stratified. In these cases, (3) applies.

4 Data

I retrieve daily stock prices and index values from January 1, 2009 until December 31, 2023 from LSEG. The cross-section of the European sample consists of 43 insurance firms from 18 countries. Of these firms, 26 are domiciled in EU member states, with the remainder split between 12 firms domiciled in the UK, and 5 firms in Switzerland. The US sample features 110 publicly traded firms.

I adjust the dataset for non-trading days and stale price observations. In the time series, I exclude all trading days on which at least 25% of firms were not traded. In the cross-section, I exclude firms for which the price did not change on subsequent days in at least 25% of the observations. The process removes 10 individual firm observations from the European sample and 34 firm observations from the US sample. By the end of 2020, the European sample represents a total of 37 percent of the market share of the European insurance sector[14].

S&P Global Market Intelligence provides company-specific financial information, such as balance sheet and income statement items, for EU and US insurers. The S&P Global Market Intelligence database contains data from semi-annual and annual regulatory filings, as well as

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[14] Measured in gross written premiums; market size includes non-listed firms

quarterly earnings updates. I collect this data for all issue dates throughout my sample period. For European insurers, I further obtain information on premium income and capital requirements from Solvency Financial Condition Reports via S&P Global Market Intelligence. For US insurers, I additionally collect quarterly reported transactions of individual securities as part of the National Association of Insurance Commissioners (NAIC) reporting. I obtain this information from Schedule D of the reports via S&P Global Market Intelligence. The transactions include acquisitions and disposals, along with their respective par values and transaction dates.

Bloomberg provides data on the VSTOXX volatility index, which I use to account for stock market volatility in Europe. For the US sample, I obtain S&P 500 index data and S&P 500 volatility index (VIX) data from Yahoo Finance.

I obtain News data from the WRDS RavenPack database. The dataset contains individual news, newsflash, and report sentiment data from 2009 to 2024. I exclude all stock price-related news, including news on real-time stock market updates, because such news would introduce endogeneity to the models, given that distress states depend on stock prices. I summarize the news data to obtain the number of articles and the average sentiment score for each firm and day.

Finally, the ECB Data Warehouse and the Federal Reserve Bank Economic Database provide macroeconomic variables for European and US insurers, respectively. These variables include the monthly percentage change in the consumer price index, euro and dollar exchange rates, treasury rates, industrial production, and government bond yields with varying maturities.

Table 2 presents the descriptive statistics for European data, and Table 3 presents the descriptive statistics for US data. Panels A and B of the respective tables show summary statistics for distressed and non-distressed stock performance periods, respectively. The number of observations shows that the subsamples do not maintain panel structure because the distress periods of multiple firms do not necessarily overlap, and some firms may never experience distress.

In the European sample distressed firms are on average larger than non-distressed firms, which is consistent with the US sample. Table 2 further shows no significant difference in net income between distressed and non-distressed firms. In contrast, Table 3 shows that the average net income of firms during distress periods is less than half that of the non-distressed period.

On average, US firms receive more news coverage, with more than six articles per firm during non-distress periods, compared to European firms, which receive roughly two articles.

During distress periods, coverage of both samples rises by about 50%. Interestingly, the average sentiment remains neutral, with minimal leaning towards positive news.[15]

Table 2 shows that the majority of European insurers are multi-line insurers with 62.7%, 29.5% are life insurers and only 8% operate exclusively in P&C. These business line shares match those in the non-distress subsample, indicating that business line may not be a characterizing factor for a distressed state. The US data in Table 3 exhibits, on average, a tendency for a weaker presence of P&C insurers in the distress sample.

Consistently for both subsamples, the average daily return during the distress and the non-distress subsamples is approximately zero, though the standard deviation is higher in the distress state. The fact that daily returns average zero during distress periods hints towards the fact that my distress definition is able to capture both the initial impact and the recovery of distress periods on stock prices.

Table 2 shows that the quarterly cash and equivalents share in total assets are comparable across distress state subsets. The US sample exhibits that firms in distress states hold less cash on average. Table 2 further presents that the solvency ratio is on average seven percentage points lower during the crisis, indicating either an increase in capital requirements or a decrease in eligible own funds.

Interestingly, the average weekly absolute transaction volume (that is acquisitions plus disposals) exceeds that of non-distressed periods for all relevant bond types during distressed periods. This observation suggests that distress periods can catalyze capital reallocations, which is consistent with the trading behavior of US insurers during crises.[16]

5 Results

5.1 Stepwise Selection

Panel A of Table 4 reports the results of backward stepwise sample selection under the assumption of a Poisson distribution for the errors. For each region, I present two specifications of the input data, depending on the variable with the largest number of missing observations. The longer specification allows for fewer missing observations per variable, resulting in more observations on fewer variables. To include more variables, I introduce a wider specification, which increases the number of variables at the expense of some observations. The wider specification

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[15] The sentiment measure is designed to represent positive sentiment by values greater than 0 and negative sentiment by values smaller than zero.

[16] See Becker and Ivashina (2015), Ellul et al. (2022), Kirti (2024), and Beyer (2025).

includes trend variables, containing time-series information and produce missing values during the generation process.[17]

Panel A shows that the backward stepwise algorithm does not eliminate many variables. It deems 50 variables important in the longer specification for both regions, resulting in very large AICs. Additional variables in the wider specification reduce the AICs, yet the algorithm still barely excludes any variables, with 19 exclusions in the European sample and 31 in the US sample. The large number of included variables suggests overfitting. For Panels B and C of Table 4, I divide the sample into training and testing datasets to assess the predictive power of the selected variables in the 'selection' column compared to a specification with all the variables in the 'all_vars' column.[18] The table shows that almost all models perform poorly in explaining new data, even after sample selection. Only the first specification with US data produces reasonable errors, though it still yields a mean absolute error of 386 days when predicting period lengths. This suggests that the stepwise models are not selective enough, drastically overfitting the training data and leading to significant errors when applied to new data. As anticipated, the results of the stepwise selection method indicate that it fails to select the relevant variables.

5.2 Regularized Selection

Tables 5 through 8 present the aggregated results on lasso regularization with bootstrapped samples.[19] Each table presents the ten most commonly selected variables for longer and wider specifications, similar to Table 4. The columns within each specification show the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values.[20] The tables alternate between European and US samples and impose different distributional assumptions on the errors, as discussed in subsection 3.1.

The lower part of the tables reports the average regularization parameter and the number of observations in the original sample. The number of bootstrap samples equals the number of observations in the original sample. I select the regularization parameter that minimizes cross-validated error, which usually results in less parsimonious models. The results remain robust

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[17] See Table A.1 for an overview of the variables relevant for the results.

[18] Due to the large number of variables in the US sample, I had to be more restrictive with the number of included variables in the wider specification, leading to an NA count of 75 in Panels B and C, compared to 123 in Panel A.

[19] For brevity, the results based on the Poisson distribution are discussed in the Appendix, in subsection A.2.

[20] Median coefficients are not reported because the analysis prioritized predictive performance over interpretation of individual coefficients, with bootstrap results used primarily for uncertainty assessment. Interpretation of individual coefficients is further limited because predictors were standardized and coefficients are expressed on the link scale rather than the response scale.

when I use the more conservative choice based on the one-standard-error rule, which selects the largest regularization parameter whose cross-validated error is within one standard error of the minimum.

The data are curated not to induce a look-ahead bias in the analysis, meaning that the distress duration and the independent variables are not measured contemporaneously. Thus, all variables reflect the information at the beginning of each period, the duration of which is unknown. This important implication arises from transforming time-series data into cross-sectional data, as presented in subsection 3.1.

Table 5 presents the selection results of error terms assuming a negative binomial distribution for the European sample. The selection rate thresholds for the top ten are 79% for the longer specification and 60% for the wider specification. There are 286 and 221 observations for the longer and wider specification, respectively. As expected, the model regularization parameters are lower on average in the longer specification than in the wider specification due to the combination of fewer observations and more variables.

In the longer specification, the interaction of cash and equivalents and distress state is among the most commonly selected variables. Other influential parameters on the length of the distress period include interest and dividend income, with almost 99%, separate account assets, with 93%, and lowest decile of absolute cash holdings (liq_low_bin), with 93% selection rate. The selection of interest and dividend income and the lowest decile of absolute cash holdings as reducing distress duration is consistent to the wider specification results under Poisson distribution in Table A.2. The observation that equity investments and higher interest and dividend income decrease the length of distress periods might seem counter-intuitive because equity investments and investments with higher interest income should be associated with higher risk. One possible explanation is that equity investments are pro-cyclical and subject to short-term fluctuations, resulting in more frequent but shorter periods of distress for firms with higher investments in these assets. Alternatively, higher regulatory capital requirements for riskier assets may mean that these variables proxy capitalization.

Separate account assets are the only effect in the longer specification that does not appear in the wider specification.

Aside from the distress effects present in the longer specification, the wider specification selects equity investments in 95% of cases, firm size growth, in 86% of cases, the average market crisis state over the previous four quarters, in 81% of cases, and the level of CPI in 60% of cases. The observation on size indicates that firms growing in size before entering a distress state are more likely to exit it early, while shrinking firms tend to struggle for longer. Average market crisis conditions over the prior four quarters and higher CPI levels seem to shorten periods of distress. One plausible explanation is that, when inflation is high and/or markets are under sustained stress, policymakers usually already adopt a supportive stance. Furthermore, conditional on the environment, firms that enter distress later than the market may be more resilient, which helps explain why their subsequent recoveries are faster.

Table 6 shows the results of the negative binomial model on the US sample. Regarding distress state effects, the level of the term structure appears in both the longer and wider specifications. The longer specification further features interaction terms on property and casualty insurers, available for sale securities, which is consistent to the Poisson distribution model.[21] The longer specification also includes interaction terms for property and casualty insurers, operating expenses and available-for-sale securities. Of these effects, only the slope of the term structure appears in the wider specification, indicating that, for the US sample, distress periods are shorter during times with a steeper yield curve. The wider specification further includes investments in real estate and trend variables based on the average market crisis state over the previous four quarters, the maximum drawdown change of individual stocks over one quarter before the distress state, total asset development over the previous four quarters and the average daily number of negative news over the previous quarter. It seems puzzling that firms with more negative news coverage and firms with increasing drawdowns before entering distress subsequently recover faster.[22] Both effects follow the same intuition, where firms that already experience a slow but steady decline in equity value eventually enter shorter periods of rapid price movements. Additional information leading to higher news coverage increases trading activity and amplifies volatility, which can result in sharp price corrections.

Controlling for over-dispersion by assuming a negative binomial distribution leads to more consistent selection rates and a greater emphasis on distress interactions across both specifications than under the Poisson distribution.[23] Yet, the negative binomial model still treats duration in reduced-form. Table 7 and Table 8 present the results of the variable selection using the Cox proportional hazard model with stratified samples. Note that the interpretation of the coefficients reverts as positive coefficients raise the hazard function, meaning that a conversion to the other state becomes more likely and estimated period durations become shorter. Due to

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[21] See subsection A.2.

[22] Counter-cyclical effects of news on stock returns are not a new phenomenon, see Cenesizoglu (2015).

[23] See Table A.2 and Table A.3 in subsection A.2.

the stratification, the tables display the results for non-distress observations at the top and the results for distress observations at the bottom. Overall, the selection rates are lower compared to the pooled models, mainly due to the reduction in observations.[24]

Table 7 presents the results using European data under the Cox proportional hazard model. For non-distress periods, the longer specification of the model selects primarily firm-specific variables. The share of cash and equivalents remains dominant, while other factors such as liquidity, asset allocation, size and investment income favor longer non-distress periods. Relevant macroeconomic variables include inflation, market volatility, and the slope of the term structure. The latter indicates that a steeper term structure leads to shorter non-distress periods. The selection of these firm-specific variables is consistent to the pooled models. The wider specification adds selects trend variables but with substantially lower selection rates. Even the most commonly selected variable appears in only half of the iterations. This result shows the problem of the stratification, where the division of the sample and the resulting reduction of observations hinder model training. The model selects only firm-specific variables related to asset allocation in at least 40 percent of the cases. Consistent with pooled models, the level of liquidity and increasing equity investments over the previous four quarters are associated with a lower transition probability to the distress state.

Regarding the distress state observations, selection rates are higher overall than for the non-distress sub-sample. The longer specification selects the firm-specific variables, cash and equivalents in 91% of cases, interest and dividend income in 88% of cases, and size in 66 % of cases. In the wider specification, increasing factors associated with faster recovery are firm growth one quarter prior to the crisis, the share of equity investments and liquid assets in total asset, interest and dividend income, and general news coverage prior to the distress state. While growing stock prices on both individual insurers and the general insurance market, and the level of three month interest rates reduce the recovery probability.

Table 8 shows the results using US data under the Cox proportional hazard model. In the non-distress subsample, both specifications frequently select industrial production as a variable, that shortens non-distress periods. Furthermore, the algorithm frequently selects 10-year government bond yields. The positive coefficients indicate that rising long-term rates are associated with an increased event hazard during non-distress periods. While this seems counterintuitive, it also indicates the role of insurance as a counter-cyclical industry. A higher share of securities available for sale, property and casualty insurers, and operating income are associated with

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[24] Pooled models are presented in tables A.2, A.3, 5, and 6

longer non-distress phases. Conversely, firms with higher investments or interest and dividend income enter distress faster, which is consistent with the hypothesis of riskier assets. The wider specification emphasizes trend variables on industrial production, size, interest and dividend income and news. In line with pooled models, firms with negative sentiment remain in non-distress periods longer.

Regarding the distress sub-sample, the longer specification shows that operating income, real estate investments, and investment income indicate a faster recovery from distress, while other variables are not significantly different from zero. The wider specification retains real estate investments and inflation. The specification further adds trend variables on the term structure, stock market and individual stock performance, investment, interest and dividend income, and the number of negative news articles. The negative coefficient on negative news indicates that firms with more negative news coverage before entering a non-distress state are less likely to enter a distress state. This result is consistent with the pooled models.

Furthermore, the model selects the market crisis indicator and the industrial production selection rates in almost all iterations, with different effect signs. This finding provides further evidence that insurers recover faster from a distress period if it occurs during a market crisis.

A comparison of the selection results for the European and US samples under negative binomial distribution in tables 5 and 6 shows that selection rates are higher for the US sample. This indicates that the selection approach suggests larger models for US data. For the European sample in Table 5, the longer specification selects more firm-specific variables with crisis interaction. For the US sample, the term structure remains the most influential factor on distress duration. Yet, the model for the US sample also includes business lines, asset composition, and expenses. In the wider specification, macroeconomic variables continue to drive distress duration in the US sample, and the model selects term structure and stock market crisis state as the most influential parameters. Negative news before the distress state also emerges as relevant. Macroeconomic variables also appear for the European sample, but the model selects them less frequently than it does firm-specific variables.

In the Cox models (Tables 7 and 8), both regions show that macroeconomic indicators such as industrial production, interest rates and inflation, consistently serve as important predictors across subsamples and specifications. Trends in stock market performance appear commonly in the wider specifications across regions. The longer specification shows that European hazard dynamics are more sensitive to firm-specific, liquidity-related variables, whereas US dynamics are more sensitive to operating income and business lines.

5.3 Distress Duration Prediction

This section presents the quasi out-of-sample prediction results for the selected variables. The results are quasi out-of-sample because I performed the variable selection procedure on the full sample but constrained the parameter estimation to include only data up to the end of 2019. I select the 2019 cutoff to include all information prior to the Covid-19 market crash, deliberately leaving it inside the testing window. Figure 2 shows the distribution of distressed firm observations per day over the observation period. The red dashed line depicts the separation between the training window on the left and the test window on the right. I estimate the duration of each distress period for every model and specification over multiple selection thresholds in the test window using the training window parameters. Figure 3 depicts the selection thresholds on its x-axis, the y-axis reports the logarithmic value of the predictions' mean absolute errors. Each panel contains the results for a specific model, the colored paths represent the specifications. The Poisson model produces the highest errors, albeit lower than under the stepwise method. The NB model produces lower absolute errors, especially for selection thresholds between 50% and 70%. Stratifying the sample into distress and non-distress subsamples, yields the lowest errors on crisis observations in the Cox proportional hazard model for distress, even though the sample sizes are smallest. The non-distress proportional hazard model produces stable errors across all selection thresholds and specifications.

The wider specifications for the European sample and the longer specification for the US sample perform best, across all models that include distress observations. The CoxPH distress model achieves a minimal logarithmic mean absolute error (MAE) of 4.68, corresponding to an average error in predicting the correct distress duration of 107 days in the European sample under the wider specification. The longer specification on US data yields a logarithmic MAE of 5.05, which corresponds to an error of 148 days.

The results suggest that the CoxPH specification reasonably captures relative duration dynamics, even though exact calendar timing remains difficult to predict. The duration of distress depends on various factors, such as legal negotiations, creditor coordination, refinancing windows, government interventions, and managerial decisions that are unobservable at the prediction date. The long-tailed distribution of distress durations and the model's optimization in logarithmic space lead the model to act prudently, often overstating crisis duration, which is a convenient property for policy application. Lastly, in duration-based distress modeling, accurate risk ordering often provides more predictive usefulness than precise point forecasts of exit dates. Figure 4 presents the Spearman correlation for all specifications. The negative binomial model produces correlations between the estimated and actual ranks of recovery speed of over 70% across all specifications at a selection threshold of 70%. The stratified models produce better point estimates, but do not predict the order of recoveries well. This clear trade-off between calibration and discrimination shows that pooled models maintain robust cross-regional rankings of distress timing yet overestimate absolute durations. Conversely, stratified models improve pointwise accuracy at the expense of weaker global ordering.

6 Conclusion and Policy Implications

This paper investigates the determinants of recovery speed in the insurance sector following periods of firm-specific distress, as measured by stock prices. I construct a flexible measure of firm-specific distress periods to obtain cross-sectional variation in distress durations across US and European insurers. Using this measure, I create a cross-sectional sample of firm-specific distress periods and their respective durations.

To find relevant factors, I perform a regularization-based, bootstrapped sample selection. The results appear in Tables 5 to 8. The variable selection reveals distinct patterns across the two samples. Asset composition variables, such as the proportion of cash and equivalents, interest and dividend income, as well as stock market conditions primarily drive European insurers' distress durations. By contrast, US insurers exhibit stronger dependence on macroeconomic variables, particularly the slope of the term structure of interest rates and industrial production. These results suggest that the relative importance of firm-specific versus macroeconomic factors in shaping resilience differs systematically across regulatory and market environments.

This paper contributes to the literature on the determinants of financial resilience by broadening the scope of analysis to include recovery in addition to distress likelihood. The predictive analysis shows that models trained on pre-crisis data maintain significant out-of-sample predictive power. The best models produce an average absolute error of 107 days and a cross-sectional rank correlation of 79% for recoveries during and after the pandemic period of 2020–2022. This suggests that individual stress episodes provide valuable insights into firms' behavior during broader market crises. Among the distributional specifications, stratified Cox proportional hazard models produce superior predictions of distress duration, while pooled maximum likelihood optimizations yield more accurate rank orderings of recovery speed.

These results have practical implications for financial stability analysis: Regulators can use ex-ante firm characteristics and macroeconomic indicators to identify insurers with price-stabilizing capacities and anticipate recovery dynamics ahead of future crises. This further carries policy implications for the regulation and supervision of the insurance market. First, liquidity is a key factor in insurer resilience.

Second, larger insurers' stock prices show the tendency to be more stable. This observation supports the importance of high entry barriers to the insurance sector. Possible explanations include that larger firms may achieve more effective diversification, greater operational capacity, and enhanced risk absorption.

Third, the findings suggest that the composition of investment portfolios is a more important factor in share price resilience than income-related factors. However, this result should be interpreted with caution, as it may be subject to endogeneity. One possible explanation is that certain assets inherently absorb shocks better. However, it may also be the case that asset allocation proxies the skill of portfolio management. Another possibility is that current regulations with risk-based capital requirements already incentivize insurers toward prudent exposures, leading to firms with higher own funds having more risky assets on paper. Distinguishing between these channels is an important area for future research.

Finally, evidence suggests that real estate investments with lower exposure to traditional market cycles may positively impact share price resilience. This finding relates to the literature on returns on real estate investments[25] by providing evidence that long-term investors may accept lower returns in exchange for non-systematic risk exposure. This interpretation aligns with the finding of Giacoletti (2021) that the risk return trade-off of real estate investments is holding period dependent.

While real estate investments might be beneficial for insurance stability given the cyclical nature of insurance business models, regulators must consider the geographic concentration of these investments. For example, concentrated investment exposure to infrastructure or real estate assets in regions affected by catastrophic events could create "double-hit" scenarios, in which insurers simultaneously face elevated claims and deteriorating asset values. This could generate systemic vulnerabilities instead of fostering resilience.

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[25] See Jordà et al. (2019), Eichholtz et al. (2021), and Chambers et al. (2021).

7 Tables

Table 1: Summary of methods and definitions

This Table presents three methods and the applied crisis definitions that underlie the mixture-of-experts to define cross-sectional distress periods.

Method	**Method Info**	**Distress Definition**
MA200	200-day moving average	Compounded return below 200-day moving average
CP	Changepoint detection (PELT)	Variance of changepoint 1.5 times larger than sample variance
RS	AR(1) regime switching	Positive auto-correlation & negative average return

Table 2: European Sample Descriptive Statistics

This table presents selected descriptive statistics of the European sample. Panel A presents the subsample of distress periods. Panel B presents the non-distress periods. The columns show the variables, the number of observations, the average, standard deviation, minimum, and maximum values, respectively. For a complete overview of all applied variables and name coding, see Table A.1.

(a) Panel A: Distress European Data

Statistic	N	Mean	St. Dev.	Min	Max
return	12,006	−0.001	0.033	−0.256	0.432
net_inc	11,452	324,993	572,540	−1,068,186	3,001,000
total_assets	11,246	261,484,301	275,960,942	58,115	1,139,428,640
coverage	12,006	2.58	11.71	0	339
news_mcq_maj	12,006	0.049	0.341	−3	3
cash_equiv	11,246	0.030	0.025	0.001	0.138
solv_ratio	6,189	192.444	33.670	122.000	351.000
business_lah	11,597	0.295	0.456	0	1
business_multi	11,597	0.627	0.484	0	1
business_pac	11,597	0.079	0.270	0	1

(b) Panel B: Non-Distress European Data

Statistic	N	Mean	St. Dev.	Min	Max
return	98,759	0.001	0.015	−0.143	0.367
net_inc	90,290	318,043	469,232	−1,155,000	3,259,000
total_assets	90,301	188,948,804	242,513,409	23,113	1,139,428,640
coverage	98,759	1.86	10.41	0	656
news_mcq_maj	98,759	0.051	0.290	−3	4
cash_equiv	90,301	0.035	0.026	0.001	0.212
solv_ratio	52,162	199.838	35.567	122.000	405.000
business_lah	92,238	0.300	0.458	0	1
business_multi	92,238	0.597	0.490	0	1
business_pac	92,238	0.103	0.304	0	1

Table 3: US Sample Descriptive Statistics

This table presents selected descriptive statistics of the US sample. Panel A presents the subsample of distress periods. Panel B presents the non-distress periods. The columns show the variables, the number of observations, the average, standard deviation, minimum, and maximum values, respectively. For a complete overview of all applied variables and name coding, see Table A.1.

(a) Panel A: Distress US Data

Statistic	N	Mean	St. Dev.	Min	Max
return	20,043	−0.001	0.042	−0.641	0.818
net_inc	20,043	113,883	817,368	−7,766,000	4,401,000
total_assets	20,043	149,896,705	255,925,851	62,979	942,567,000
coverage	20,043	9.02	29.85	0	1,060
news_mcq_maj	20,043	0.070	0.497	−3	4
cash_equiv	20,043	0.037	0.047	0.001	0.427
lh_bin	20,043	0.394	0.489	0	1
pc_bin	20,043	0.430	0.495	0	1
vol.abs_industrial	15,141	40,972	325,329	0	28,707,911
vol.abs_us federal gov't	15,141	6,875	30,736	0	1,175,971
vol.abs_foreign gov't	15,141	2,273	71,260	0	8,659,786

(b) Panel B: Non-Distress US Data

Statistic	N	Mean	St. Dev.	Min	Max
return	205,677	0.001	0.018	−0.483	0.624
net_inc	205,615	294,929	767,803	−6,672,000	21,602,000
total_assets	205,613	77,067,990	158,152,873	53,320	952,904,000
coverage	205,677	6.64	20.06	0	1,032
news_mcq_maj	205,677	0.096	0.481	−3	4
cash_equiv	205,613	0.052	0.082	0.001	0.735
lh_bin	205,677	0.361	0.480	0	1
pc_bin	205,677	0.540	0.498	0	1
vol.abs_industrial	158,415	28,725	111,001	0	21,235,536
vol.abs_us federal gov't	158,415	5,167	26,037	0	1,552,030
vol.abs_foreign gov't	158,415	1,000	8,446	0	903,529

Table 4: Backward Stepwise Sample Selection and Prediction

This table shows the results of the stepwise sample selection algorithm and prediction. The results are presented for two specifications. The longer specification allows for fewer missing values per variable, resulting in more observations but fewer variables. The maximum number of missing values is reported in parentheses. Panel A shows the results of the stepwise sample selection algorithm for the European and US samples. Panels B and C present the prediction analysis results for the European and US samples, respectively. The panels compare two models: 'all_vars' includes all available variables, and 'selection' includes the variables that the stepwise algorithm selected. AIC stands for the Akaike information criterion., MAE stands for mean absolute error, RMSE stands for root mean squared error, and Rsq stands for the squared correlation.

(a) Panel A: Full Sample Backwards Stepwise Selection

	EU		US	
Specification (Maximum Missing Obs)	Long (31)	Wide (82)	Long (62)	Wide (123)
n_selected	50	210	50	224
n_vars_removed	7	19	5	31
AIC	51890	1900	104224	28526

(b) Panel B: Prediction with European Data

Region	EU			
Specification (Maximum Missing Obs)	Long (31)		Wide (82)	
Model	all_vars	selection	all_vars	selection
N	55	53	104	101
log(MAE)	14.62	14.60	293.71	285.24
log(RMSE)	16.52	16.50	296.05	287.61
Rsq	0.001	0.001	0.005	0.002

(c) Panel C: Prediction with US Data

Region	US			
Specification (Maximum Missing Obs)	Long (62)		Wide (75)	
Model	all_vars	selection	all_vars	selection
N	53	49	139	132
log(MAE)	5.96	5.95	20.76	20.80
log(RMSE)	6.57	6.57	23.45	23.48
Rsq	0.133	0.133	0.001	0.001

Table 5: European Data: Bootstrapped Lasso Selection Rates under Negative Binomial Distribution
This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original European subset data. The columns are grouped by the maximum number of allowed missing observations per variable. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. The bottom of the table shows the average regularization coefficients and the number of observations in the original dataset, which equals the total number of bootstrap samples created. The errors are assumed to be distributed according to a negative binomial distribution with a logarithmic link function. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 31)				Wider (Maximum Missing Obs: 82)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
cash_equiv × distress	100.00	-26.75	-7.25	cash_equiv × distress	95.93	-13.19	-0.75
int_div_inc × distress	98.95	-45.91	-2.90	int_div_inc × distress	94.57	-46.87	-3.40
cash_equiv	94.06	0.25	11.49	equity_invest × distress	94.57	-8.44	-0.43
sep_acct_assets × distress	93.36	-2.19	-0.13	liq_low_bin1 × distress	89.59	-0.72	-0.03
m_cpi_lvl	93.01	-0.11	-0.00	ln_assets_1q × distress	85.97	-10.08	-0.23
liq_low_bin1 × distress	93.01	-0.90	-0.02	return_1q	85.52	0.05	1.38
m_indprod_lvl	82.52	-0.07	0.01	market_crisis_4q × distress	81.00	-1.02	-0.02
liq_high_bin1	79.72	-0.55	0.03	d_y10_hpr_4q	76.47	0.21	3.56
m_y10_lvl	79.37	0.01	1.32	m_y10_lvl	69.23	0.01	0.16
sep_acct_assets	79.37	0.03	2.04	m_cpi_lvl × distress	60.18	-0.14	-0.00
Bootstrap Specs							
Average Regularization Parameter			0.01	Average Regularization Parameter			0.03
Sample Size — Bootstrap Samples			286	Sample Size — Bootstrap Samples			221

Table 6: US Data: Bootstrapped Lasso Selection Rates under Negative Binomial Distribution

This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original US subset data. The columns are grouped by the maximum number of allowed missing observations per variable. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. The bottom of the table shows the average regularization coefficients and the number of observations in the original dataset, which equals the total number of bootstrap samples created. The errors are assumed to be distributed according to a negative binomial distribution with a logarithmic link function. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 62)				Wider (Maximum Missing Obs: 123)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
indprod_lvl	98.83	-0.07	-0.00	indprod_lvl	99.53	-0.11	-0.01
fx_lvl	98.45	-0.04	-0.00	d_termst_slp × distress	98.60	-0.58	-0.14
market_crisis	96.70	0.04	0.43	indprod_lvl_1q	94.65	0.00	0.06
d_termst_slp × distress	92.82	-0.34	-0.02	market_crisis_4q × distress	94.65	-2.14	-0.10
pc_bin1 × distress	91.46	-0.98	-0.03	fx_lvl	94.42	-0.05	-0.00
afs_secs	90.49	0.05	1.02	market_crisis	91.40	0.02	0.53
afs_secs × distress	90.49	-1.56	-0.06	drawdown_ppts_1q × distress	90.47	-0.78	-0.03
invest_inc	89.90	-39.57	-0.31	invest_in_re × distress	87.44	-17.53	-0.46
invest_in_re	88.93	-9.52	0.40	ln_assets_4q × distress	85.12	-2.96	-0.10
total_oper_exp_cm × distress	85.24	-13.17	-0.37	bad_news_ess_1q × distress	82.79	-5.62	-0.21
Bootstrap Specs							
Average Regularization Parameter			0.01	Average Regularization Parameter			0.02
Sample Size — Bootstrap Samples			515	Sample Size — Bootstrap Samples			430

Table 7: European Data: Bootstrapped Lasso Selection Rates under Cox Proportional Hazard Model

This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original European subset data. The columns are grouped by the maximum number of allowed missing observations per variable. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. Total number of bootstrap samples created equals the number of observations in the original dataset. The errors are assumed to be distributed according to a cox proportional hazard model. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 31)				Wider (Maximum Missing Obs: 82)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
Non-Distress Observations							
cash_equiv	98.72	-23.68	-2.31	equity_invest_4q	51.38	-26.34	-0.67
liq_high_bin	78.85	-0.76	-0.02	invest_in_re	47.71	-20.23	-0.49
invest_in_re	77.56	-12.96	-0.13	tot_inv_1q	44.04	-55.56	5.19
m_cpi_lvl	73.72	-0.18	-0.00	cash_equiv	43.12	-21.06	-1.49
sep_acct_assets	69.23	-2.14	-0.08	return_1q	39.45	-3.15	-0.07
vstoxx_lvl	62.82	-0.05	0.01	drawdown_ppts_1q	35.78	0.04	1.22
ln_assets	59.62	0.00	0.37	d_m3_lvl	34.86	-1.05	-0.00
d_termst_slp	52.56	0.01	1.05	liq_high_bin	30.28	-1.00	-0.02
tot_inv	52.56	-0.35	3.22	int_div_inc_4q	28.44	-22.89	-0.21
invest_inc	50.00	-55.64	4.95	tot_inv_1q	27.52	-18.85	19.14
Distress Observations							
vstoxx_lvl	90.77	0.00	0.06	ln_assets_1q	90.18	1.21	19.03
cash_equiv	90.77	0.76	25.83	estx.ins_4q	77.68	-4.71	-0.13
int_div_inc	87.69	3.48	54.39	equity_invest	76.79	0.45	11.00
m_indprod_lvl	80.77	0.01	0.16	cash_equiv	71.43	0.25	17.58
d_m3_lvl	80.00	-1.33	-0.03	m_y10_lvl_1q	67.86	0.06	1.73
ln_assets	65.38	-0.19	-0.01	int_div_inc	66.96	0.97	69.43
liq_low_bin	62.31	0.01	0.85	d_m3_lvl	61.61	-1.02	-0.02
market_crisis	59.23	-0.04	0.96	return_4q	57.14	-2.18	-0.04
sep_acct_assets	58.46	-0.02	1.88	liq_low_bin	56.25	0.02	0.91
m_cpi_lvl	56.15	-0.03	0.15	coverage_1q	52.68	0.00	0.07
Bootstrap Specs							
R			130.00	R			112.00

Table 8: US Data: Bootstrapped Lasso Selection Rates under Cox Proportional Hazard Model

This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original US subset data. The columns are grouped by the maximum number of allowed missing observations per variable. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. Total number of bootstrap samples created equals the number of observations in the original dataset. The errors are assumed to be distributed according to a cox proportional hazard model. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 62)				Wider (Maximum Missing Obs: 123)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
Non-Distress Observations							
d_y10_lvl	98.57	0.05	0.49	m_indprod_lvl	99.53	0.03	0.22
m_indprod_lvl	98.21	0.01	0.16	m_indprod_lvl_1q	82.79	-0.16	-0.00
afs_secs	97.85	-1.67	-0.22	afs_secs	77.67	-1.58	-0.02
pc_bin	89.61	-0.90	-0.03	ln_assets_1q	75.81	-11.14	-0.15
invest_in_re	86.38	0.15	15.62	ln_assets_4q	69.30	-2.93	-0.09
int_div_inc	84.95	2.72	152.53	int_div_inc_4q	65.58	4.49	146.72
total_oper_exp_cm	83.87	-23.94	-0.10	bad_news_mcq_1q	64.65	-7.26	-0.14
liq_high_bin1	83.15	0.05	1.18	fx_lvl	62.79	0.00	0.05
market_crisis	82.80	-0.53	0.05	pc_bin	61.40	-0.78	-0.01
invest_inc	77.78	0.64	52.75	trad_net_us_gov_1q	58.14	0.00	0.00
Distress observations							
total_oper_exp_cm	75.00	0.08	3.54	invest_in_re	82.33	0.52	24.32
invest_in_re	71.19	0.54	26.86	d_termst_slp_1q	80.47	0.02	1.00
m_indprod_lvl	67.37	-0.00	0.10	sp500_4q	79.53	-3.20	-0.08
vix_lvl	65.25	-0.03	0.01	drawdown_ppts_1q	78.60	0.04	1.08
cpi_lvl	60.59	-0.97	0.00	cpi_lvl	69.30	-1.31	-0.03
liq_high_bin1	53.39	-0.75	-0.02	invest_inc_1q	66.51	0.54	37.43
afs_secs	52.54	-0.22	1.40	prem_inc	65.12	0.04	3.04
pc_bin	49.58	-0.22	0.76	market_crisis_4q	64.65	0.06	1.54
invest_inc	48.73	0.74	98.65	int_div_inc_4q	62.33	-111.64	-0.51
lh_bin	45.76	-0.93	0.01	bad_news_mcq_4q	60.93	-6.99	-0.06
Bootstrap Specs							
R			236.00	R			215.00

8 Figures

Figure 1: Days to recovery during the Covid-19 market crash.
This figure shows the absolute frequencies of 37 European insurance firms, grouped by business line. The time to recovery on the x-axis measures the time that insurance firms' stock prices were below their 200-day moving average after the market crash during the Covid-19 pandemic.

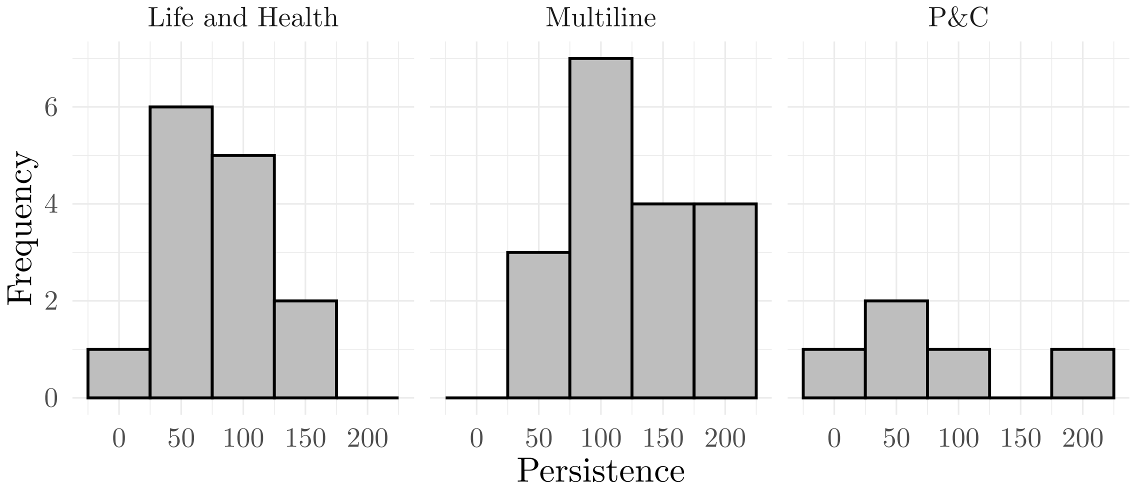


Figure 2: Distressed Firm Histogram

This figure presents the histogram of contemporaneously distressed firms under the distress definition $D_{i,t}^{MIX}$ over time from January 2010 until December 2023. The upper panel represents the European sample and the lower panel represents the US sample. The dashed red line resembles the 31 December 2019 and serves as the threshold for separating the training and testing data for all prediction analyses.

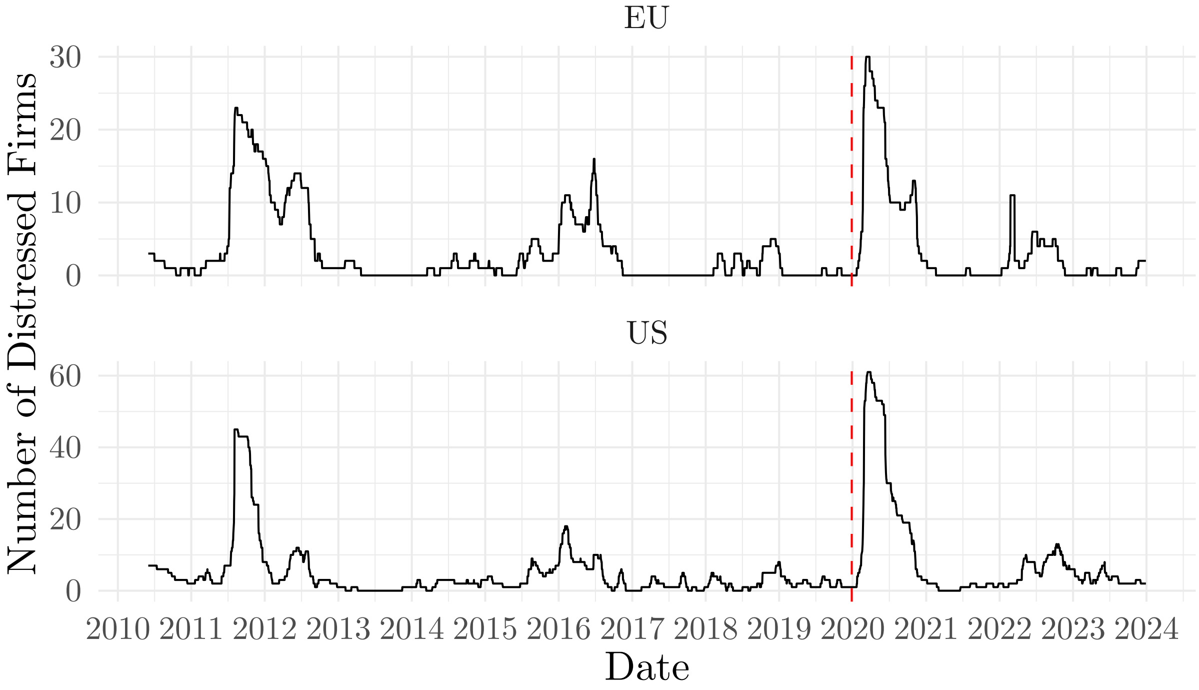


Figure 3: Distress Prediction Results

This figure shows the pointwise prediction results. Each panel represents a different model. The y-axis shows the logarithmic value of the mean absolute error (MAE), and the x-axis shows multiple selection thresholds. For each selection threshold, the procedure applies the variables from the bootstrapped regularization models up to that threshold. Colored paths within the panels correspond to the regions and specifications. The longer specification allows for fewer missing values per variable, resulting in more observations but fewer variables. The maximum number of missing values is reported in parentheses.

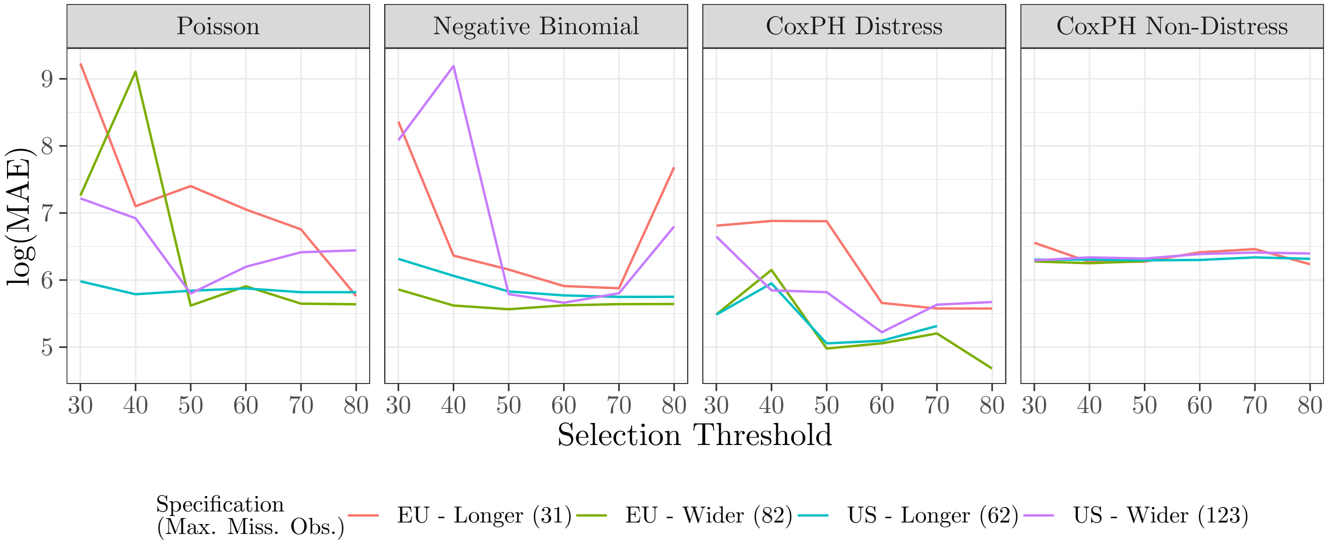
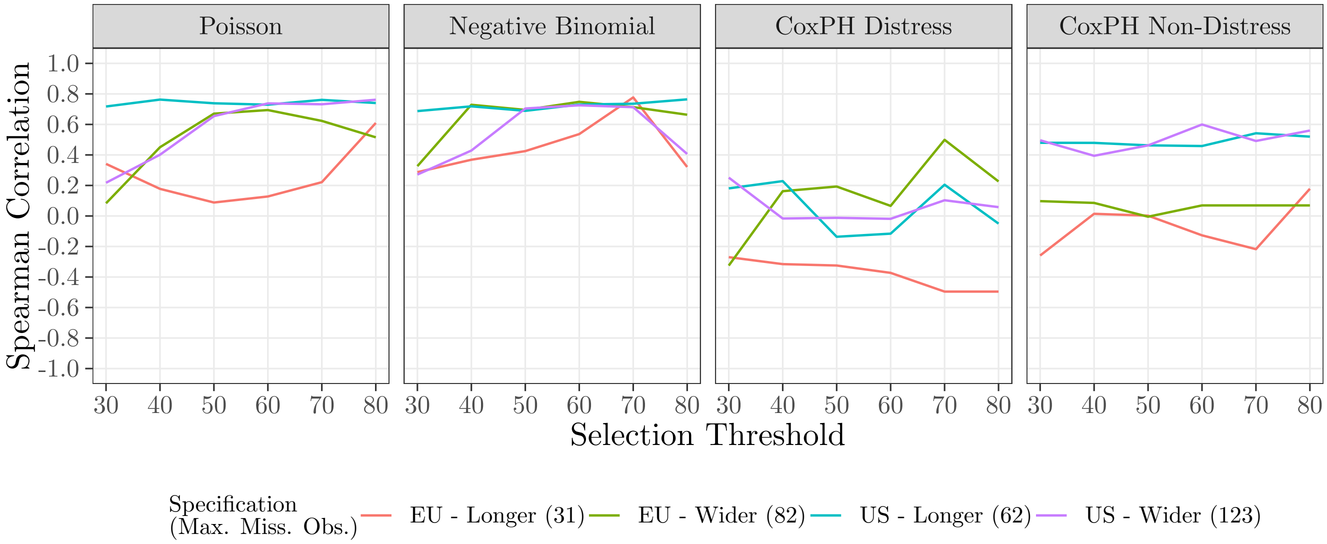


Figure 4: Distress Prediction Results

This figure shows the pointwise prediction results. Each panel represents a different model. The y-axis shows the Spearman rank correlation of the predicted recovery times, and the x-axis shows multiple selection thresholds. For each selection threshold, the procedure applies the variables from the bootstrapped regularization models up to that threshold. Colored paths within the panels correspond to the regions and specifications. The longer specification allows for fewer missing values per variable, resulting in more observations but fewer variables. The maximum number of missing values is reported in parentheses.



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A Appendix

A.1 Further Tables and Figures

Table A.1: Variable Definitions (Glossary)

Variable Name	**Variable Description**
`afs_secs`	Available-for-sale securities (balance sheet item)
`bad_news_mcq`	Bad news count; multi-classifier for equity sentiment
`bad_news_ess`	Bad news count; event sentiment score
`business_lah` | `lh_bin`	Binary: life & health business indicator
`business_multi` | `mlt_bin`	Binary: multi-line business indicator
`business_pac` | `pc_bin`	Binary: property & casualty business indicator
`cash_equiv`	Cash and cash equivalents
`coverage`	News coverage by number of articles
`cpi_lvl`	Consumer price index (level)
`d_m1_lvl`	One month domestic government bond yields (level)
`d_m3_lvl`	Three months domestic government bond yields (level)
`d_termst_slp`	Term structure slope; 10-year minus 3-months
`d_y10_hpr`	10-year domestic government holding period return
`d_y10_lvl`	10-year domestic government yield (level)
`distress_bin`	Binary: Financial distress indicator
`drawdown_ppts`	Stock price drawdown in percentage points
`equity_invest`	Equity investments (balance sheet item)
`estx.ins`	Euro Stoxx insurance index return
`fx_lvl`	Foreign exchange rate (level)
`int_div_inc`	Interest and dividend income
`invest_in_re`	Investment in real estate
`invest_inc`	Investment income
`lh_prem`	Life & health premium income
`liq_high_bin`	Binary: high liquidity indicator (90% quantile)
`liq_low_bin`	Binary: low liquidity indicator (10% quantile)
`ln_assets`	Natural log of total assets
`m_cpi_lvl`	Monthly CPI level
`m_indprod_lvl`	Monthly industrial production index (level)
`m_y10_lvl`	Monthly 10-year Treasury yield (level)

Continued on next page

Table A.1 – *continued from previous page*

Variable Name	**Variable Description**
`market_crisis_bin`	Binary: market crisis indicator
`medcpi_lvl`	Median CPI level
`net_inc`	Net income
`news_mcq_maj`	News sentiment multi-classifier for equities; majority-vote
`prem_inc`	Premium income
`return`	Daily stock return
`solv_ratio`	Solvency Ratio
`sep_acct_assets`	Separate account assets
`sp500`	S&P 500 index return
`tot_inv`	Total investments
`total_assets`	Total assets
`total_oper_exp_cm`	Total operating expenses
`trad_net_us_gov`	Net trading position in US government securities
`vix_lvl`	VIX volatility index (level)
`vol.abs_foreigngov't`	Absolute volume/volatility in foreign government bonds
`vol.abs_industrial`	Absolute volume/volatility in industrial bonds
`vol.abs_usfederalgov't`	Absolute volume/volatility in US federal government bonds
`vstoxx_lvl`	VSTOXX Euro volatility index (level)

Suffix Conventions:

- `_lvl` — level (not differenced)
- `_1q` | `_4q` — 1 or 4 quarter trends, respectively
- `_bin` — binary (0/1) indicator variable

Suffix Conventions:

- `d_` — daily frequency
- `m_` — monthly frequency
- `ln_` — natural logarithm transformation
- `vol.abs_` — absolute volume or volatility by asset class

Figure A.1: Distress Prediction Results – Panel A: European sample
This figure illustrates the final distress periods for all firms in the European sample according to the MIX method. Each panel represents an individual firm, and the black path shows that firm's price development. Light blue areas represent non-distress phases and red areas represent distress phases.

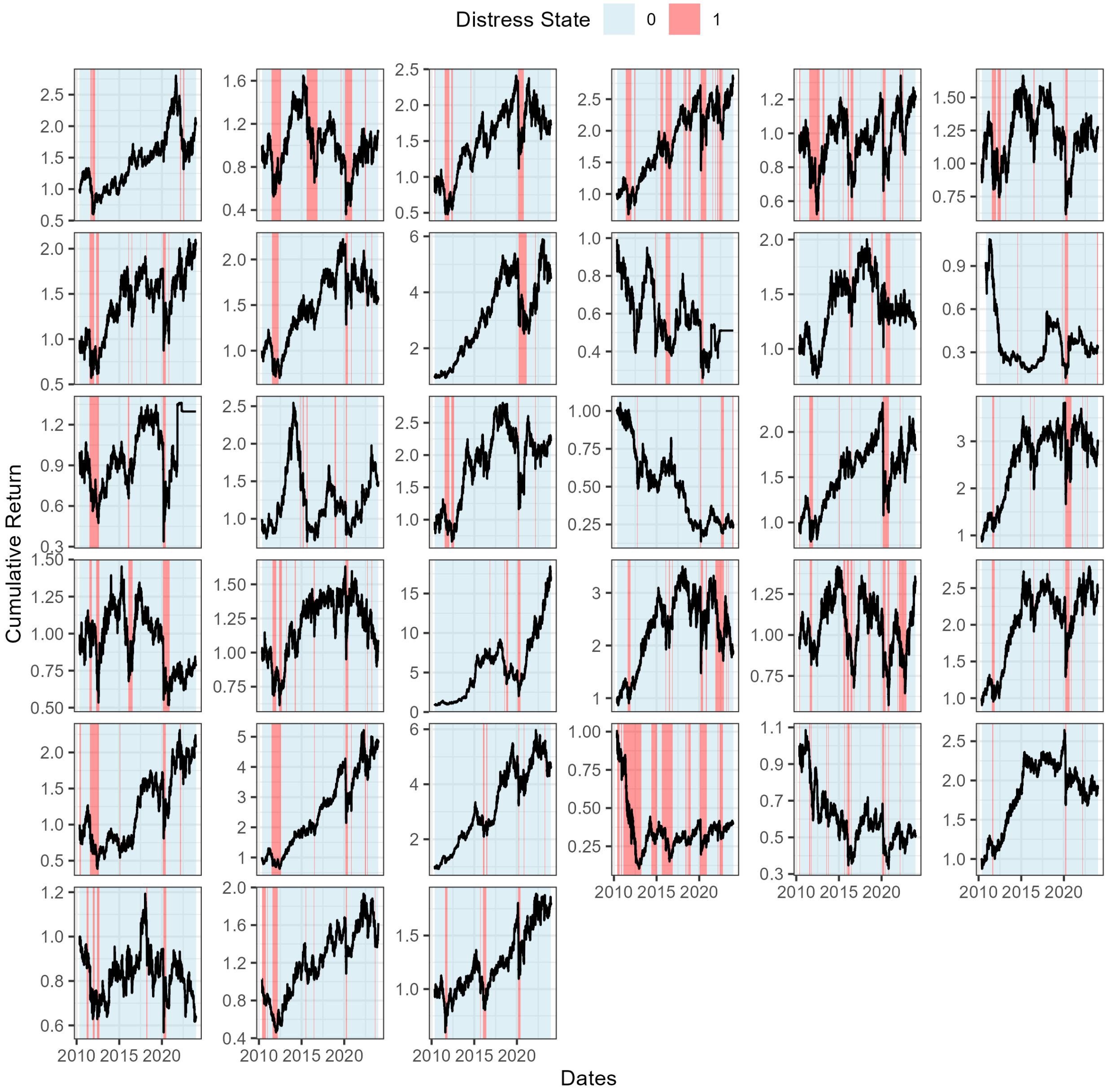


Figure A.2: Distress Prediction Results – Panel B: US sample
This figure illustrates the final distress periods for all firms in the US sample according to the MIX method. Each panel represents an individual firm, and the black path shows that firm's price development. Light blue areas represent non-distress phases and red areas represent distress phases.

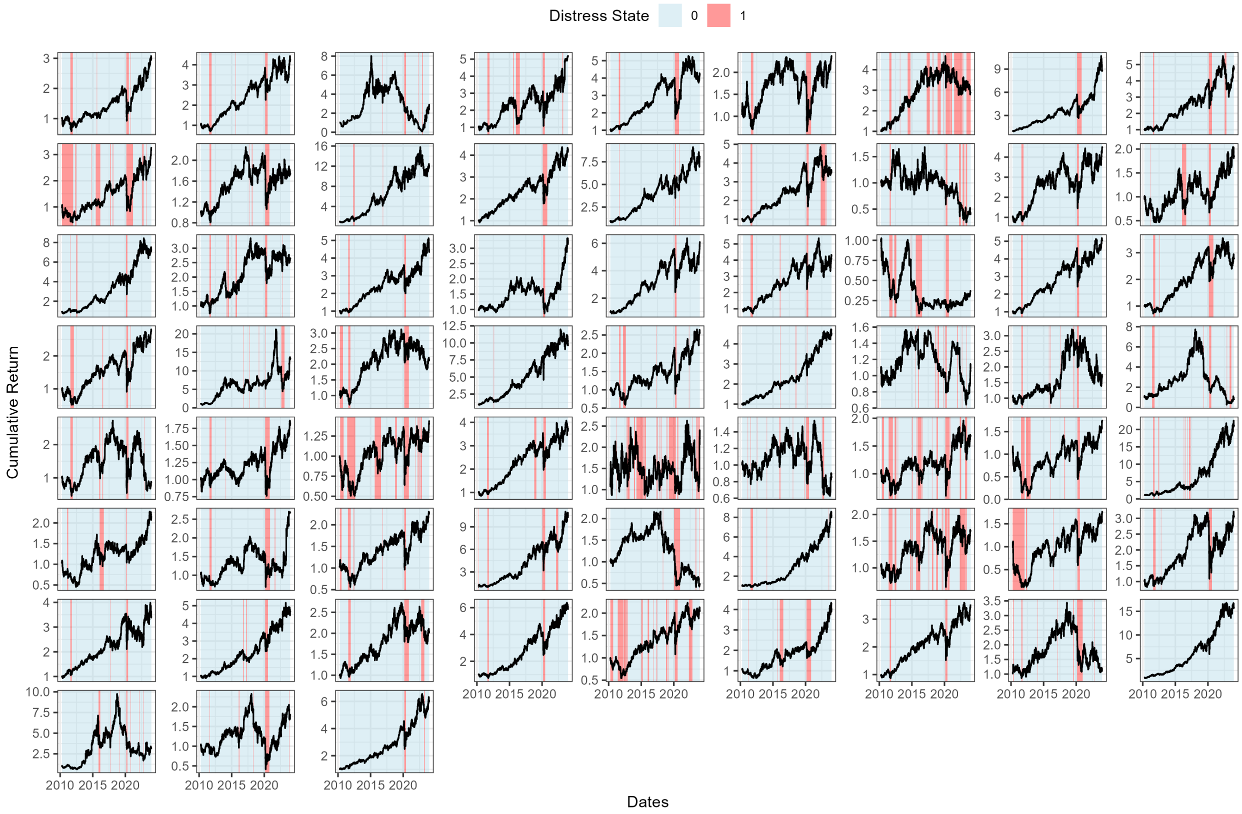


Figure A.3: Within-firm deviation by specification, EU sample

The figure illustrates the sampling dependence of the MIX distress definition without minimum sequence length, by the within-firm deviation for the European sample. I set a firm-invariant reference window during the Covid-19 market crash and shrink the available past observations in 20 steps with a square-root scaling, making early steps larger and later steps smaller. Each boxplot on the x-axis shows how much firms deviate, in that specification, from their own average across all specifications. Thus, a value of zero means that, for a given specification, a firm is exactly at its own average across all specifications. Each box represents 33 firms. Due to strong high concentration of zeros, the boxplots are re-adjusted to range from the 5% to 95% quantiles, whiskers range from minimum to maximum observations. The first panel shows the within-firm deviation for the number of state changes during the reference window. The second panel shows the number of days spend in distress state during the reference window. The third panel shows the first date identified as distress state.

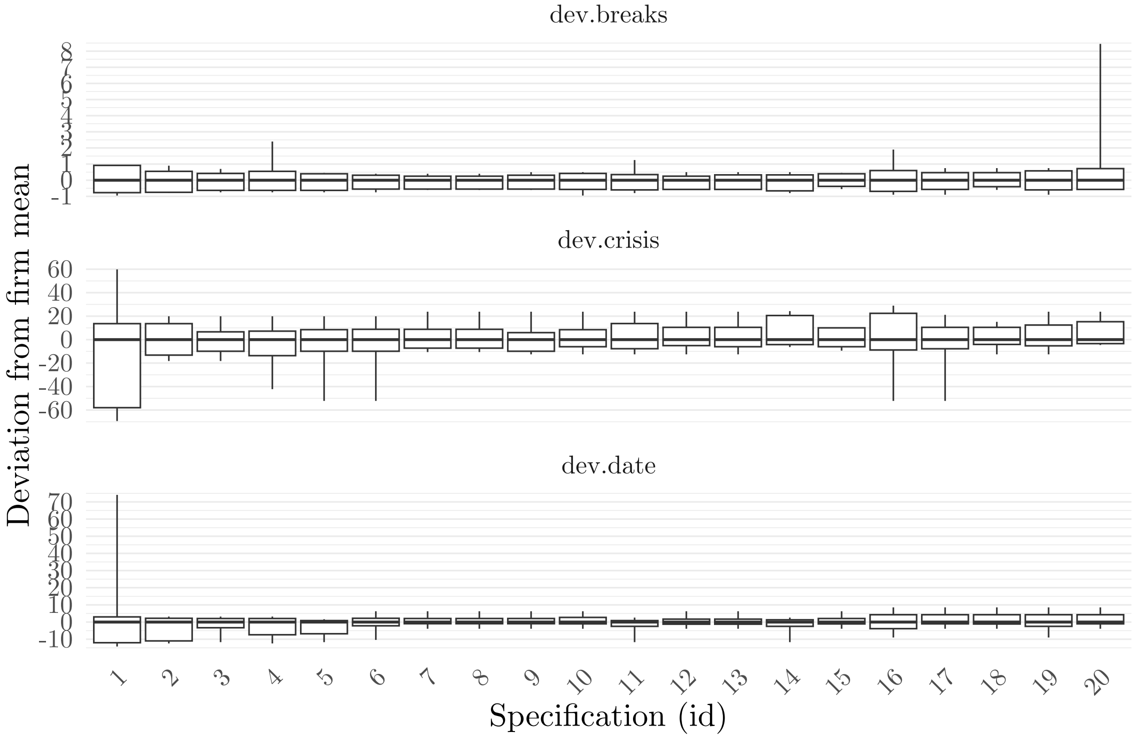
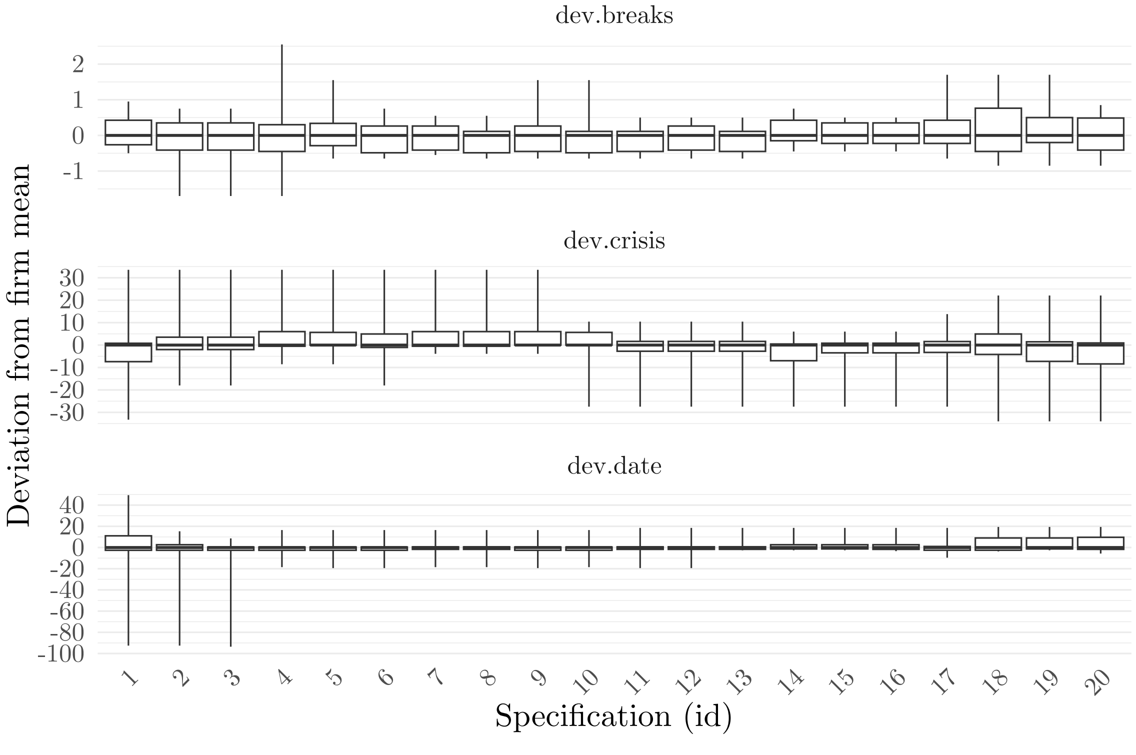


Figure A.4: Within-firm deviation by specification, US sample

The figure illustrates the sampling dependence of the MIX distress definition, by the within-firm deviation for the US sample. I set a firm-invariant reference window during the Covid-19 market crash and shrink the available past observations in 20 steps with a square-root scaling, making early steps larger and later steps smaller. Each boxplot on the x-axis shows how much firms deviate, in that specification, from their own average across all specifications. Thus, a value of zero means that, for a given specification, a firm is exactly at its own average across all specifications. Each box represents 66 firms. Due to strong high concentration of zeros, the boxplots are re-adjusted to range from the 5% to 95% quantiles, whiskers range from minimum to maximum observations. The first panel shows the within-firm deviation for the number of state changes during the reference window. The second panel shows the number of days spend in distress state during the reference window. The third panel shows the first date identified as distress state.



A.2 Poisson Results

Table A.2 presents the selection based on Poisson-distributed errors for EU data. In the longer specification, with a smaller number of missing observations, the sample size is 286 and the minimum selection rate among the ten most frequently selected variables is above 78%. This changes in the wider specification that allows more missing observations, where the sample reduces to 221 and the minimal selection rate shrinks to 62%. The reduction when moving from the longer to the wider specification is intuitive, given the combination of fewer observations and more variables. This intuition also reflects the increase in the regularization parameter, which rises from 7.74 in the longer specification to 11.12 in the wider specification.

In the longer specification, firm-specific variables primarily relate to liquidity and investment details. Meanwhile, influential macro variables include inflation and 10-year government bond yields. Of the ten most commonly selected variables, the only selected interaction term is the share of cash and cash equivalent holdings in total assets, which has a selection rate above 97%. The coefficients indicate that larger shares of cash and equivalents at the start of each period increase the length of non-distress periods and decrease the length of distress periods. This result is consistent with the theory that ex-ante more liquid firms are less constraint during downturns.

Including trend variables in the wider specification increases the importance of stock market and income-related variables, although the overall selection rate decreases. Interestingly, the model does not select cash and equivalents, even though it is included in nearly all iterations of the longer specification. The model likely excludes cash and equivalents because other variables explain the effects that lead to higher shares of cash and equivalents, and these variables assume its explanatory power. Regarding recovery, the model selects equity investments as a factor that reduces the length of the distress period in 82% of cases. The model selects the lowest decile of firms' absolute cash holdings and firms with a higher share of interest and dividend income in total assets less commonly, and both factors reduce distress period length. The former observation aligns with the size effect, and the latter aligns with the selection of equity investments. The finding that greater equity holdings and increased interest or dividend income are associated with shorter periods of financial distress may be unexpected at first, as these asset classes and income sources are generally linked to elevated risk exposure. One potential explanation is that equity investments tend to be pro-cyclical and sensitive to short-term market fluctuations. This could cause firms with larger exposures to experience distress more frequently, yet recover more quickly. Another possibility is that stricter regulatory capital requirements for higher-risk assets mean that these variables partly reflect stronger capitalization levels rather than risk exposure alone.

Table A.3 presents the results for the US sample based on the Poisson distribution. The longer specification features 515 and the wider specification features 430 observations. Unlike the European sample, the longer specification includes more variables more frequently. Securities held for sale have the greatest influence on distress period length, with a selection rate of 95%, which aligns with the scope-of-action argument during distress. In the wider specification, selection rates decrease overall, and regularization parameters increase, consistent with observations for European firms. When trend variables are present, available-for-sale securities move out of the top ten, and the interaction between distress state and the level of the term structure emerges as the most commonly selected variable. This result indicates that, for the US sample, distress periods are shorter during times with a steeper yield curve.

A comparison of the selection results for the European and US samples under a Poisson distribution in Tables A.2 and A.3 shows that selection rates are higher for the US sample. In the longer specification, firm-level balance sheet variables dominate the results for the European sample, while the results for the US sample emphasize macro-financial and market variables among the ten most commonly selected variables. However, when controlling for selection thresholds instead of using the top ten, this tendency disappears. Across both samples, the longer specification mainly selects variables unconditional on distress state. In the wider specification, the model agrees on the importance of interest rate regimes for both samples by selecting interest rate measures most frequently. For the US sample, the term structure measure is the only distress-dependent measure in the top ten. The European sample remains consistent with the longer specification, attributing distress effects to firm-specific variables only.

Overall, the models that assume Poisson-distributed error terms produce sensible results, but the selection process is volatile to the addition of new variables. Furthermore, the model largely selects variables that do not explain differences between distress and non-distress periods, which is likely due to the overdispersion and the associated underestimation of variance, as outlined in subsection 3.1. This shortcoming is addressed in the models assuming negative binomial distributed errors in the main specification.

Table A.2: European Data: Bootstrapped Lasso Selection Rates under Poisson Distribution This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original European subset data. The columns are grouped by the maximum number of allowed missing observations per variable. Longer refers to a more strict set of variables, where previous quarter changes are excluded, due to missing observations created. The wider specification includes the period change variables at the cost of losing observations. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. The bottom of the table shows the average regularization coefficients and the number of observations in the original dataset, which equals the total number of bootstrap samples created. The errors are assumed to be distributed according to a Poisson distribution with a logarithmic link function. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 31)				Wider (Maximum Missing Obs: 82)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
cash_equiv	98.60	1.17	12.78	d_y10_hpr_4q	86.43	0.25	7.93
cash_equiv × distress	97.20	-27.14	-2.51	return_1q	85.97	0.08	1.81
m_cpi_lvl	90.91	-0.12	-0.00	equity_invest × distress	82.35	-11.11	-0.32
m_y10_lvl	85.31	0.01	2.09	m_y10_lvl	76.47	0.00	0.25
invest_inc	84.27	0.04	38.84	prem_inc_1q	72.85	-74.40	17.52
liq_high_bin1	82.17	-0.62	0.13	liq_low_bin1 × distress	69.68	-0.79	-0.02
ln_assets	80.77	-0.21	0.01	invest_in_re	69.23	-0.46	7.23
invest_in_re	80.07	-1.12	6.28	tot_inv_1q	64.25	-6.19	8.99
sep_acct_assets	80.07	0.04	1.80	int_div_inc × distress	63.80	-46.59	-0.50
lh_prem	78.32	-2.01	3.96	sep_acct_assets_4q	61.99	0.19	7.58
Bootstrap Specs							
Average Regularization Parameter			7.74	Average Regularization Parameter			11.12
Sample Size — Bootstrap Samples			286	Sample Size — Bootstrap Samples			221

Table A.3: US Data: Bootstrapped Lasso Selection Rates under Poisson Distribution

This table shows the ten most commonly selected variables during the Lasso regularization, using bootstrapped samples of the original US subset data. The columns are grouped by the maximum number of allowed missing observations per variable. The columns within each group present the selected variable, the percentage of bootstrap samples in which the variable was selected, and the 2.5% and 97.5% quantiles of the coefficient values. The bottom of the table shows the average regularization coefficients and the number of observations in the original dataset, which equals the total number of bootstrap samples created. The errors are assumed to be distributed according to a Poisson distribution with a logarithmic link function. Error minimizing regularization parameters are selected via cross-validation. The variables only encompass information prior to the period change. Firm specific variables are scaled by total assets. Variable definitions are presented in Table A.1.

Longer (Maximum Missing Obs: 62)				Wider (Maximum Missing Obs: 123)			
Variable	Select. Rate	2.5 CI	97.5 CI	Variable	Select. Rate	2.5 CI	97.5 CI
fx_lvl	100.00	-0.06	-0.01	d_termst_slp × distress	99.77	-0.67	-0.14
afs_secs	99.81	0.23	1.27	indprod_lvl	99.53	-0.12	-0.01
indprod_lvl	96.89	-0.06	-0.00	indprod_lvl_1q	96.28	0.00	0.06
invest_inc	96.31	-62.94	-3.23	fx_lvl	93.26	-0.06	-0.00
market_crisis	96.31	0.00	0.44	afs_secs	93.26	0.04	0.94
afs_secs × distress	95.53	-1.58	-0.15	ln_assets_1q	90.00	0.19	6.49
invest_in_re	94.76	-15.02	0.74	distress	89.77	-1.39	-0.10
d_y10_lvl	91.46	-0.40	-0.02	medcpi_lvl_1q	85.58	-0.24	-0.00
net_inc	90.87	-2.31	28.57	d_m1_lvl	80.70	-0.26	-0.01
pc_bin1	90.68	0.01	0.80	cash_eq_4q	80.70	-0.04	11.13
Bootstrap Specs							
Average Regularization Parameter			3.37	Average Regularization Parameter			5.72
Sample Size — Bootstrap Samples			515	Sample Size — Bootstrap Samples			430