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Research article

Interpretable deep learning for modeling policy uncertainty and firm-specific risk: Evidence from advanced and emerging markets

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Abstract: This study examines how multidimensional policy-related uncertainty influences firm-specific risk by integrating econometric analysis with interpretable deep learning. Using daily stock-level data for Nikkei 225 firms from 2000–2023, we construct measures of idiosyncratic volatility (IVOL) and combine them with a multisource policy uncertainty index capturing seven domains: economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical risk. To model nonlinear interactions and temporal persistence across uncertainty dimensions, we employ a long short-term memory (LSTM) autoencoder and benchmark its performance against principal component analysis (PCA) and kernel PCA (KPCA). The LSTM-based composite index exhibits the strongest explanatory power, showing that higher policy uncertainty systematically amplifies IVOL. Model transparency is ensured through SHapley Additive exPlanations (SHAP), which highlight fiscal, monetary, and geopolitical uncertainty as the dominant contributors. Heterogeneity analyses reveal that the sensitivity of IVOL to uncertainty varies by sector, firm size, and profitability. To evaluate external validity, we extend the analysis to several advanced and emerging markets, including the United States, Germany, South Korea, India, and Indonesia, and find a consistent uncertainty-IVOL relationship, with Japan displaying the highest sensitivity. The results underscore the value of combining deep learning with explainable artificial intelligence (AI) for financial risk assessment in uncertainty-driven environments.

Keywords: idiosyncratic volatility; policy uncertainty; interpretable machine learning; LSTM autoencoder; SHAP; nonlinear dimensionality reduction; financial risk forecasting; advanced and emerging markets

JEL Codes: C45, D81, E44, G12, G15, G32

1. Introduction

In an increasingly volatile and interconnected global landscape, policy uncertainty has emerged as a pivotal determinant of firm-level financial risk. Economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical risks all shape expectations about future cash flows and discount rates, and thus influence idiosyncratic volatility (IVOL), the component of firm-level return variance that is not explained by systematic market factors (Ang et al., 2009). Understanding how such multidimensional policy uncertainty affects IVOL is central for financial stability, asset pricing, and portfolio management (Ludvigson et al., 2021).

Most existing studies document that macroeconomic and policy uncertainty matter for aggregate activity and marketwide volatility (Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Pastor and Veronesi, 2012) but typically rely on linear econometric frameworks and focus on single uncertainty dimensions, often in U.S. data. Evidence for Japan is more limited and has largely concentrated on macroeconomic aggregates or index-level volatility (Arbatli et al., 2017), with only a few recent contributions linking policy uncertainty to firm-level IVOL in a linear setting (Shin et al., 2024). At the same time, a growing literature shows that monetary policy uncertainty in particular is an important source of stock market risk (Bouri et al., 2020; Liu et al., 2025). Taken together, these findings suggest that policy uncertainty is important, but they leave open how multiple uncertainty dimensions jointly shape firm-specific risk in Japan and how nonlinear, persistent effects should be modelled.

Japan provides a particularly compelling laboratory for studying these questions. Since the late 1990s, the Bank of Japan has implemented an unusually prolonged sequence of unconventional monetary measures, including quantitative and qualitative easing, negative policy rates, and yield-curve control (YCC). These measures have been accompanied by repeated fiscal stimulus packages against a backdrop of high and rising public debt and by exposure to global trade tensions, geopolitical events, and energy price shocks. Structural features of the Japanese financial system, such as the main bank system, cross-shareholding arrangements, and strong bank–firm linkages, can further amplify the transmission of policy news into firm-level funding conditions, balance sheets, and cash flow expectations. These characteristics suggest that Japanese firms may exhibit heightened sensitivity to policy-related uncertainty relative to firms in other advanced and emerging markets, motivating both our focus on Japan and a comparative cross-country analysis.

In this study, we construct a comprehensive policy uncertainty index for Japan and examine its effect on firm-level IVOL for Nikkei 225 firms over the period of 2000–2023. We compile seven policy-based indicators—economic policy uncertainty (EPU), fiscal policy uncertainty (FPU), monetary policy uncertainty (MPU), trade policy uncertainty (TPU), exchange rate policy uncertainty (ERPU), energy-related uncertainty (ERU), and geopolitical risk (GPR)—based on established indices that link policy risk to financial volatility (Caldara and Iacoviello, 2022; Kang et al., 2017; Siddiqui et al., 2024). To summarize this high-dimensional information, we compare linear principal component analysis (PCA), nonlinear kernel PCA (KPCA), and a long short-term memory (LSTM) autoencoder designed to capture temporal persistence and nonlinear interactions in the uncertainty series (Gu et al., 2020; Rapach and Zhou, 2020). To address the interpretability challenge associated with deep learning, we approximate the mapping from the seven indices to the LSTM-based latent factor with a tree-based model and use SHapley Additive exPlanations (SHAP) to quantify the contribution of each uncertainty dimension (Lundberg and Lee, 2017).

Empirically, we document a strong and statistically significant relationship between the composite uncertainty indices and firm-specific volatility. The LSTM-based index explains IVOL substantially better than PCA- or KPCA-based indices, both in sample and out-of-sample prediction exercises. SHAP-based decompositions reveal that economic, fiscal, and monetary policy uncertainty and geopolitical risk are the dominant drivers of the LSTM index, and trade, exchange rate, and energy-related uncertainty play a more modest but still nonnegligible role. Heterogeneity analyses show that the contribution of specific uncertainty dimensions varies systematically across sectors, firm size, and profitability. Robustness checks using exponential generalized autoregressive conditional heteroskedastic (EGARCH) based volatility measures, alternative lag structures, and subperiod splits yield qualitatively similar conclusions. A cross-country extension for the United States, Germany, India, Indonesia, and South Korea further indicates that the uncertainty–IVOL link is present in other markets but is particularly pronounced in Japan, in line with its distinctive policy regime and financial structure.

Our contribution is fourfold. First, we develop a multidimensional policy uncertainty index for Japan that jointly aggregates economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical risks. Second, we benchmark alternative ways of summarizing this information—standard PCA, nonlinear KPCA, and an LSTM autoencoder—and compare how well the resulting indices account for firm-level idiosyncratic volatility of Nikkei 225 firms over 2000–2023. Third, we bridge traditional econometrics and modern machine learning by opening the black box of the LSTM model: SHAP-based decompositions and heterogeneity analyses across sectors, firm size, and profitability link the latent index back to economically interpretable uncertainty channels. Fourth, although the focus is on Japan, cross-country extensions provide comparative evidence for other major markets and highlight the particularly strong role of policy uncertainty in the Japanese setting, yielding actionable insights for investors, portfolio managers, and regulators.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and situates our contribution in the context of prior work on policy uncertainty and firm risk, with particular emphasis on Japan. Section 3 describes the data, variables, and construction of the multidimensional uncertainty index. Section 4 presents the main empirical results, including the comparison of composite indices and the SHAP-based interpretation of the LSTM index. Section 5 discusses the economic mechanisms and heterogeneity patterns. Section 6 outlines implications for investors and policymakers, and Section 7 reports robustness checks. Section 8 concludes with limitations and directions for future research.

2. Literature review and research hypotheses

2.1. Idiosyncratic volatility and its determinants

Idiosyncratic volatility (IVOL) denotes the firm-specific component of return variance that is not captured by common risk factors. It plays a central role in asset pricing, capital allocation, and risk management, as it reflects firm-level uncertainty about cash flows, financing conditions, and growth prospects. A large literature has documented that IVOL is shaped by both firm fundamentals and broader macroeconomic and policy conditions.

2.1.1. Firm-specific factors and IVOL

Firm-level characteristics are important drivers of idiosyncratic volatility. Higher financial leverage, stronger growth opportunities, and elevated market-to-book ratios are typically associated with higher IVOL, as they increase sensitivity to earnings shocks and funding risk (Ferreira and Laux, 2007; Chen and Zhao, 2006). By contrast, robust corporate governance, effective monitoring, and transparent disclosure tend to dampen IVOL by reducing information asymmetry and investor disagreement (Lins et al., 2017).

Market structure also matters: firms in more concentrated industries often enjoy greater pricing power and face fewer competitive shocks, leading to lower idiosyncratic risk (Gaspar and Massa, 2006).

The firm life cycle provides an additional lens. Early-stage and declining firms generally exhibit greater IVOL due to uncertain earnings streams and volatile fundamentals, whereas mature firms experience more stable risk profiles (Hasan and Habib, 2017). There is also evidence that IVOL is related to expected returns and earnings dynamics: firms with high IVOL often trade at lower valuations and face higher required returns, and IVOL tends to be negatively associated with subsequent earnings surprises (Jiang et al., 2009; Liang and Tang, 2018). These results underscore that IVOL is deeply linked to firm-specific fundamentals, but they do not fully capture how macro-level and policy-related uncertainty interacts with those fundamentals.

2.1.2. Macroeconomic and policy uncertainty

Macro-level uncertainty has a pronounced effect on financial markets and firm-specific risk. Elevated economic uncertainty is associated with higher market volatility and a stronger sensitivity of asset prices to news (Li et al., 2021). Policy uncertainty, in particular, can undermine regulatory clarity and implicit guarantees, raising required risk premia and amplifying idiosyncratic responses to shocks (Pastor and Veronesi, 2012; Baker et al., 2016). Different policy domains affect firms in distinct ways: fiscal policy uncertainty introduces ambiguity about future taxation and government spending; trade policy uncertainty disproportionately affects export-oriented firms; and exchange rate policy uncertainty is especially relevant for firms with currency-mismatched revenues and costs (Caldara et al., 2020; Krol, 2014).

A growing strand of the literature emphasizes the role of monetary policy uncertainty for stock market risk. Bouri et al. (2020) showed that monetary policy uncertainty is strongly associated with jumps in advanced equity markets, highlighting that surprise components in policy communication can trigger abrupt repricings of risk. From a forecasting perspective, Liu et al. (2025) documented that both conventional and unconventional monetary policy rate uncertainty have significant predictive power for stock market volatility in advanced economies. These studies reinforce the view that monetary policy uncertainty is a distinct driver of equity market risk and motivate our inclusion of a dedicated monetary policy uncertainty (MPU) component in the Japanese multidimensional index. Our approach differs by focusing on firm-level idiosyncratic volatility, allowing for nonlinear temporal dynamics via LSTM autoencoders, and interpreting the resulting uncertainty index using SHAP-based decompositions and heterogeneity analysis.

Uncertainty is also linked to broader financial indicators such as the VIX and cross-asset volatility correlations, suggesting that policy-driven shocks can propagate across asset classes (Tong et al., 2023). Complementing this, Kumar et al. (2023) documented strong liquidity commonality among emerging Asian equity funds, indicating that regional markets often respond jointly to macrofinancial shocks. This further motivates our cross-country analysis of uncertainty transmission. For Japan specifically, recent evidence indicates that policy uncertainty, especially in the fiscal and monetary domains, significantly increases firm-level volatility (Arbatli et al., 2017; Saxegaard et al., 2022; Shin et al., 2024). Overall, the literature points toward a strong conceptual and empirical connection between multidimensional policy uncertainty and firm-specific risk, but most existing work focuses on single uncertainty dimensions and relies on linear models.

2.2. *Conceptual framework and hypotheses*

Building on this literature, we consider a framework in which multiple policy uncertainty dimensions jointly affect firm-level IVOL. Figure 1 summarizes the key relationships. Seven uncertainty categories—economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical—enter a composite index that serves as the main predictor of firm-specific risk. The index is constructed using PCA, KPCA, and an LSTM autoencoder to capture both linear comovement and nonlinear, time-dependent interactions among the underlying uncertainty measures. Firm characteristics such as size, leverage, profitability, and growth are included as controls to isolate the incremental effect of uncertainty on IVOL.

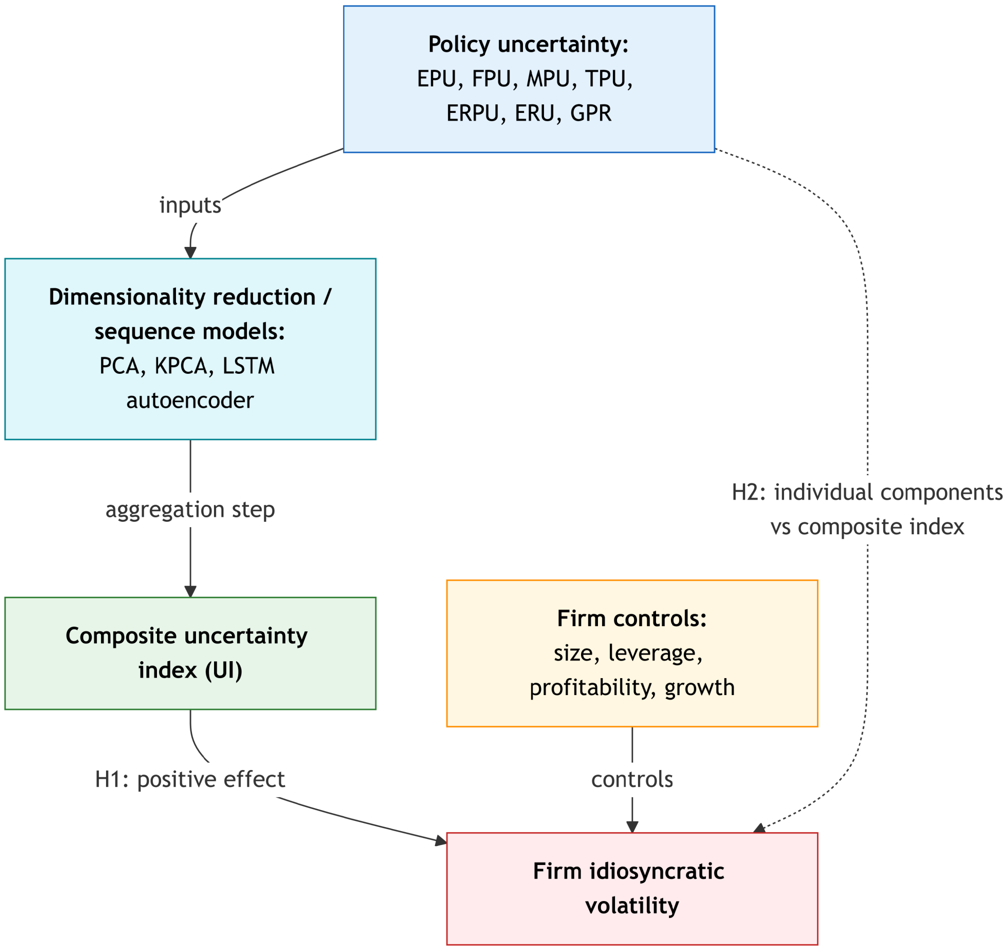

Figure 1. Conceptual framework linking policy uncertainty to firm-level IVOL.

Note: The seven uncertainty dimensions are aggregated into a composite index using PCA, KPCA, and an LSTM autoencoder. The index enters regressions for IVOL together with standard firm-level controls (size, leverage, profitability, and growth), allowing us to quantify the incremental contribution of policy uncertainty to firm-specific risk.

This framework leads to two main hypotheses. The first concerns the overall link between uncertainty and firm-specific risk; the second emphasizes the value of aggregating multiple uncertainty dimensions into a composite index.

- **H1**: *There is a positive relationship between the composite uncertainty index and firm-specific idiosyncratic volatility (IVOL).*
  Theoretical and empirical work suggests that policy uncertainty increases information frictions and investor disagreement, raising required risk premia and amplifying firm-specific reactions to shocks (Pastor and Veronesi, 2012; Baker et al., 2016). As uncertainty rises, firms face more volatile investment and financing environments, which contributes to greater dispersion in expected returns and hence higher IVOL.
- **H2**: *The composite uncertainty index outperforms individual uncertainty components (e.g., EPU, FPU, MPU) in explaining IVOL.*
  Policy uncertainty is multidimensional: fiscal, monetary, trade, exchange rate, energy-related, and geopolitical risks can interact and reinforce each other. A composite index constructed from all seven dimensions can therefore capture joint effects and nonlinear interactions that single-dimension indices miss. Drawing on multifactor risk theory and evidence that nonlinear models can extract richer predictive structure from economic time series (Gu et al., 2020; Rapach and Zhou, 2020), we expect the aggregated index to exhibit superior explanatory power for IVOL.

Our empirical strategy is designed to test these hypotheses using Japanese firm-level data, while also comparing the performance of different index-construction methods (PCA, KPCA, and LSTM autoencoder).

2.3. Research status of policy uncertainty and firm risk in Japan

Whereas the global literature documents substantial effects of policy uncertainty on investment, asset prices, and macroeconomic activity, the evidence for Japan remains comparatively limited and fragmented. Existing Japanese studies typically focus either on aggregate macroeconomic outcomes or on single-policy uncertainty dimensions, and they predominantly rely on linear econometric frameworks.

A first strand examines how uncertainty affects business conditions and investment. Using firm-level survey data, Morikawa (2016a) constructed measures of business uncertainty for Japanese companies and showed that heightened uncertainty significantly depresses investment. In related work, Morikawa (2016b) distinguished between alternative types of policy uncertainty and found that trade and macroeconomic policy uncertainties are particularly salient for Japanese firms. From a broader macrofinancial perspective, Shiratsuka (2001) highlighted the role of uncertainty surrounding asset price fluctuations and monetary policy during Japan's bubble episode, demonstrating how policy misperceptions can amplify financial instability.

A second line of work evaluates the macroeconomic consequences of policy uncertainty more directly. Arbatli et al. (2017) developed a news-based index of Japanese economic policy uncertainty (EPU) and showed that uncertainty shocks significantly affect output and investment. Similarly, Saxegaard et al. (2022) used text-based methods to construct an EPU index and document its effects on macroeconomic dynamics. More specific channels have also been considered: Bahmani-Oskooee and Nayeri (2020) showed that policy uncertainty affects money demand in Japan in a nonlinear manner, and Ghosh and Adebayo (2024) found that global policy uncertainty and geopolitical risks shape Japan's export-led growth.

Only a small number of studies have begun linking policy uncertainty to financial market outcomes at the firm or sector level. Khan et al. (2025) showed that EPU significantly affects sectoral returns in

Japan using cross-quantilogram methods, and Shin et al. (2024) provided the first evidence that policy uncertainty raises firm-level idiosyncratic volatility (IVOL) for Nikkei 225 constituents. However, these studies share two limitations relevant to our research question. First, they rely on linear modelling approaches such as vector autoregression (VAR), ordinary least squares (OLS), or quantile-based dependence measures, which cannot capture nonlinear interactions, regime shifts, or long-memory dependencies—features that are especially important in Japan's prolonged low-rate, unconventional policy environment. Second, virtually all existing studies focus on a single uncertainty dimension, most often aggregate EPU, without modelling fiscal, monetary, trade, exchange rate, energy-related, or geopolitical sources of policy uncertainty simultaneously.

Our study addresses both gaps. We construct a multidimensional policy uncertainty framework for Japan which covers seven domains and employs nonlinear representation learning techniques (PCA, KPCA, and LSTM autoencoders) to capture complex temporal interactions. We further provide SHAP-based interpretability of the learned uncertainty factor and analyze heterogeneity across sectors, firm size, and profitability. As such, we significantly extend the Japanese literature by (i) moving beyond linear modelling and (ii) jointly modelling multiple policy uncertainty channels in explaining firm-level idiosyncratic volatility (table 1).

Table 1. Selected studies on policy uncertainty and firm risk in Japan.

Study	Methodology	Uncertainty Dimension(s)	Limitation Relative to This Study
Morikawa (2016a)	Firm survey; regressions	Business and investment uncertainty	Focus on investment; no policy-domain separation; no firm-level IVOL modelling.
Morikawa (2016b)	Firm-level survey analysis	Multiple policy-uncertainty categories	Descriptive survey-based evidence; no financial-market or nonlinear modelling.
Shiratsuka (2001)	Macro-financial analysis	Asset price and monetary policy uncertainty	Macro focus; does not examine firm-level risk or multidomain uncertainty.
Arbatli et al. (2017)	VAR / macroeconomic regressions	Aggregate Japanese EPU	Macroeconomic aggregates only; linear specification; no firm-level IVOL.
Saxegaard et al. (2022)	Text-based EPU index; linear models	Economic policy uncertainty	Single dimension; no modelling of other policy domains or nonlinear effects.
Bahmani-Oskooee and Nayeri (2020)	Nonlinear money demand estimation	Policy uncertainty (macro)	Focus on money demand; unrelated to firm-level volatility or multidomain risks.
Ghosh and Adebayo (2024)	Wavelet local multiple correlation	World policy uncertainty, GPR	Macroeconomic channel (exports); no firm-level risk and no multidomain modelling.
Khan et al. (2025)	Cross-quantilogram approach	Economic policy uncertainty	Sectoral returns only; single-dimension uncertainty; nonlinear dependence but no IVOL.
Shin et al. (2024)	Panel regressions for Nikkei 225	Aggregate policy uncertainty	First IVOL evidence for Japan, but linear and single-dimension.
This study	PCA, KPCA, LSTM autoencoders + SHAP	Seven domains (EPU, FPU, MPU, TPU, ERPU, ERU, GPR)	Models nonlinear, time-dependent effects on firm-level IVOL; integrates multidomain uncertainty with interpretable deep learning and full firm-level heterogeneity.

3. Methodology

3.1. Sample, data, and variable construction

Our empirical analysis combines firm-level data for Japanese listed companies with policy uncertainty indices and standard asset pricing factors. Monthly policy uncertainty measures for Japan are obtained from the Economic Policy Uncertainty (EPU) website (`https://www.policyuncertainty.com/`) and related sources, as detailed in Table 2. Firm-level financial and return data for Nikkei 225 constituents are drawn from Datastream. Fama–French five-factor returns for the Japanese market are taken from the Kenneth French data library (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`). The sample spans January 2000 to December 2023 at a monthly frequency, covering multiple macroeconomic and policy regimes, including the global financial crisis, the introduction and expansion of unconventional monetary policy (zero and negative rates, QQE, and YCC), Abenomics, and the COVID-19 period.

We focus on Nikkei 225 firms for three reasons. First, index constituents are large, liquid blue chip stocks with reliable and relatively complete data over a long horizon. Second, using a well-defined, large-cap benchmark facilitates comparability with prior work on idiosyncratic volatility and policy uncertainty in major markets. Third, these firms account for a substantial share of aggregate investment, employment, and market capitalization in Japan, so understanding how policy uncertainty affects their risk is of first-order relevance for financial stability. As discussed in Section 8.2, this design likely yields conservative estimates of uncertainty–IVOL sensitivity relative to the broader universe of smaller and less liquid firms.

Before constructing the composite uncertainty index and estimating the econometric models, we apply a series of standard data-cleaning procedures. All time-series variables entering the dimensionality-reduction models (PCA, KPCA, and LSTM) are standardized to have zero mean and unit variance, ensuring comparability across dimensions. Missing observations in the monthly uncertainty series are imputed using linear interpolation. Stationarity is assessed using augmented Dickey–Fuller (ADF) and Levin–Lin–Chu (LLC) panel unit-root tests; nonstationary series are differenced as appropriate. To limit the influence of extreme observations, firm-level variables are winsorized at the first and 99th percentiles. Table 2 summarizes the main variables used in the analysis.

Idiosyncratic volatility (IVOL) is adopted as our proxy for firm-specific risk because it isolates the component of total stock-return variability that is not explained by common risk factors. This is consistent with a large literature linking IVOL to firm fundamentals, information asymmetry, and expected returns (e.g., Ang et al., 2006; Fu, 2009; Jiang et al., 2009). The formal construction of IVOL follows standard factor-model residual methods and is described in the next subsection.

3.2. Measuring idiosyncratic volatility

We measure firm-specific risk using idiosyncratic volatility derived from the Fama and French (2015) five-factor model, in line with recent empirical studies (e.g., Liu et al., 2019; Tabatabaei Poudeh et al., 2022; Liu et al., 2024). For each stock i, daily excess returns are regressed on the market and factor returns:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t \\ + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the return on stock i at day t, $R_{f,t}$ is the corresponding risk-free rate, and $(R_{m,t} - R_{f,t})$ denotes the market risk premium. The factors SMB_t and HML_t capture size and value effects, and RMW_t and CMA_t represent profitability and investment factors. The residual $\varepsilon_{i,t}$ is the firm-specific component of returns unexplained by these common risk factors.

Following Ang et al. (2006), monthly idiosyncratic volatility for firm i is defined as the standard deviation of daily residuals within month m:

$$\text{IVOL}_{i,m} = \text{Stdev}(\varepsilon_{i,t\in m}) \times 100, \tag{2}$$

where multiplication by 100 expresses IVOL in percentage terms. This construction yields a panel of firm-month observations capturing the nonsystematic risk that is most relevant for investors concerned with firm-level uncertainty.

To assess the robustness of our IVOL measure and to allow for time-varying volatility, we also estimate an EGARCH(1,1) model for the residuals from Eq (1) (Bali and Cakici, 2008),

$$\varepsilon_t = v_t \sqrt{h_t}, \tag{3}$$

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \lambda_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \beta_1 \ln(h_{t-1}), \tag{4}$$

where h_t denotes the conditional variance of ε_t. EGARCH accommodates volatility clustering and asymmetric responses to shocks and avoids explicit nonnegativity constraints on h_t. In robustness checks (reported in Section 7), we also consider standard GARCH(1,1) and TGARCH(1,1) specifications and confirm that our main conclusions about the uncertainty–IVOL relationship are not sensitive to the particular volatility estimator used.

3.3. Constructing the multidimensional policy uncertainty index

To quantify policy-related uncertainty in Japan, we compile seven monthly indices covering economic policy uncertainty (EPU), fiscal policy uncertainty (FPU), monetary policy uncertainty (MPU), trade policy uncertainty (TPU), exchange rate policy uncertainty (ERPU), energy-related uncertainty (ERU), and geopolitical risk (GPR). These measures are based on news-based or text-based indices developed in prior work (e.g., Saxegaard et al., 2022; Dang et al., 2023; Caldara and Iacoviello, 2022) and are summarized in Table 2. Together, they provide a multidimensional view of policy and geopolitical risk that can influence firm-level volatility.

Because the seven indices are highly correlated and likely interact in nonlinear ways, we construct composite uncertainty indices using three complementary approaches: principal component analysis (PCA), kernel PCA (KPCA), and an LSTM autoencoder. This composite approach allows us to benchmark a simple linear summarization against more flexible nonlinear and dynamic representations.

3.3.1. Principal component analysis (PCA)

PCA serves as a transparent linear benchmark. Let X denote the $n \times p$ matrix of standardized monthly uncertainty measures, with $p = 7$. PCA finds an orthogonal transformation,

$$Z = XW, \tag{5}$$

where W is the $p \times k$ matrix of eigenvectors of the covariance matrix of X, and Z contains the k principal components. We retain the first principal component (PC1), which captures the largest share of common variance among the seven uncertainty series, as the PCA-based uncertainty index. This index is widely used in the construction of composite macroeconomic and policy uncertainty measures and provides a useful baseline for comparison.

3.3.2. Kernel principal component analysis (KPCA)

To capture potential nonlinear comovements among the uncertainty dimensions, we extend PCA using kernel PCA. KPCA implicitly maps the data into a higher-dimensional feature space via a kernel function and then performs PCA in that space. We use a radial basis function (RBF) kernel,

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \tag{6}$$

where x_i, and x_j are rows of X and σ is a bandwidth parameter. Eigenvalue decomposition of the centred kernel matrix K yields nonlinear principal components; the first component is taken as the KPCA-based uncertainty index. KPCA can capture curvature and interaction effects in the joint distribution of the uncertainty measures that linear PCA may miss.

3.3.3. LSTM autoencoder

Policy uncertainty is inherently dynamic: shocks tend to be persistent, and the effect of one type of uncertainty can depend on the recent history of others. To model such temporal and nonlinear structure, we use a long short-term memory (LSTM) autoencoder applied to rolling sequences of the seven standardized uncertainty indices. The encoder maps sequences of length T into a low-dimensional latent representation, and the decoder attempts to reconstruct the original sequence from that representation. The latent encoding thus summarizes the information in the uncertainty sequence that is most relevant for reconstructing its joint dynamics.

In the main text, we focus on the conceptual role of the LSTM autoencoder as a sequence model capturing long-memory and nonlinear interactions. Technical details of the architecture, including the number of layers, hidden units, activation functions, regularization (dropout), optimizer, learning rate, batch size, number of epochs, and early stopping criteria, are provided in Appendix Appendix 1, along with the training and validation loss curve. The first latent dimension from the encoder is used as the LSTM-based uncertainty index.

3.3.4. Rationale for combining PCA, KPCA, and LSTM autoencoders

Our three index-construction methods are chosen to span a spectrum of modelling assumptions. PCA summarizes the seven uncertainty dimensions under a linear, static structure and provides an interpretable baseline. KPCA relaxes the linearity assumption by allowing for nonlinear comovements via kernel mappings but remains static in time. The LSTM autoencoder further incorporates temporal dependence and long-memory effects, which are central to the persistence and clustering of policy shocks. Comparing these indices allows us to assess the incremental value of modelling nonlinear and dynamic features in macrofinancial uncertainty, in line with recent work that integrates machine learning into empirical asset pricing and risk modelling (Gu et al., 2020; Rapach and Zhou, 2020).

3.4. Control variables

To isolate the incremental contribution of policy uncertainty to firm-specific risk, we control for standard firm-level characteristics known to affect idiosyncratic volatility. Following Cao et al. (2008) and Rajgopal and Venkatachalam (2011), we include firm size (FSIZE; logarithm of market capitalization), market-to-book ratio (MBR), financial leverage (LEVG; total debt to total assets), and return on equity (ROE). These variables proxy for firm scale, growth opportunities, balance-sheet risk, and profitability, respectively. Larger, more mature firms with stronger balance sheets and less aggressive investment opportunities are typically expected to exhibit lower IVOL than smaller, high-growth, or highly leveraged firms (Zhang, 2010).

Time-invariant unobserved heterogeneity at the firm level (e.g. governance quality, business model) is captured using firm fixed effects in the panel regressions, whereas common macroeconomic shocks are absorbed by time fixed effects. Table 2 provides precise definitions and data sources for all variables.

Table 2. Variable definitions.

Variable	Symbol	Definition
Dependent variable		
Idiosyncratic volatility	IVOL	Monthly standard deviation of daily residuals from the Fama–French five-factor model (Equation 1).
Uncertainty variables		
Economic policy uncertainty	EPU	News/text-based index for Japan, Saxegaard et al. (2022).
Monetary policy uncertainty	MPU	News/text-based index for Japan, Saxegaard et al. (2022).
Fiscal policy uncertainty	FPU	News/text-based index for Japan, Saxegaard et al. (2022).
Trade policy uncertainty	TPU	News/text-based index for Japan, Saxegaard et al. (2022).
Exchange rate policy uncertainty	ERPU	News/text-based index for Japan, Saxegaard et al. (2022).
Energy-related uncertainty	ERU	News-based energy uncertainty index, Dang et al. (2023).
Geopolitical risk	GPR	Geopolitical risk index, Caldara and Iacoviello (2022).
Composite uncertainty indices		
Uncertainty index (PCA)	UI_PCA	First principal component of the seven uncertainty variables.
Uncertainty index (KPCA)	UI_KPCA	First nonlinear principal component (RBF kernel) of the uncertainty variables.
Uncertainty index (LSTM)	UI_LSTM	First latent dimension from the LSTM autoencoder encoder.
Control variables		
Firm size	FSIZE	Logarithm of firm market capitalization.
Market-to-book ratio	MBR	Ratio of market value to book value of equity.
Leverage	LEVG	Ratio of total debt to total assets.
Return on equity	ROE	Net income divided by average total equity.

Note: This table summarizes the main variables used in the analysis. See text for details on construction.

3.5. Summary statistics and correlations

Table 3 reports summary statistics for the main variables. Panel A describes firm-specific variables, Panel B the seven uncertainty indices, and Panel C the Fama–French factors and risk-free rate. The data exhibit substantial cross-sectional and time-series variation in firm-level risk and fundamentals, as well as in policy uncertainty, providing a rich environment for identifying the uncertainty–IVOL relationship.

Table 3. Summary statistics.

Variable	Mean	St. Dev	Max	Median	Min	Obs.
A. Firm-specific variables						
Returns	0.0059	0.0101	1.9012	0.0029	-0.7881	59,976
IVOL	2.5651	0.8611	6.2256	2.4510	0.8511	59,976
FSIZE	0.0099	0.1122	3.5321	0.0032	-0.7824	59,976
MBR	0.0021	0.0055	0.5341	0.0015	-0.0488	59,976
LEVG	0.5723	0.2144	1.2411	0.6103	0.0312	59,976
ROE	0.0761	0.3472	17.9940	0.0753	-8.4401	59,976
B. Uncertainty variables						
EPU	0.0193	0.1968	0.7715	0.0076	-0.4515	287
FPU	0.0288	0.2502	1.0545	0.0015	-0.5723	287
MPU	0.0775	0.4366	1.9189	-0.0104	-0.8590	287
TPU	0.0682	0.4138	2.1256	0.0149	-0.6141	287
ERPU	0.1288	0.6525	4.1316	-0.0139	-0.7471	287
ERU	0.1038	0.6036	3.3421	-0.0031	-0.7211	287
GPR	0.2425	1.1116	12.1440	-0.0256	-0.8404	287
C. Factor variables						
Mkt–RF	0.0015	0.0458	0.1504	0.0039	-0.1354	287
SMB	0.0030	0.0244	0.0821	0.0031	-0.0647	287
HML	0.0052	0.0322	0.1459	0.0037	-0.0787	287
RMW	-0.0003	0.0172	0.0406	0.0002	-0.0670	287
CMA	0.0025	0.0210	0.0755	0.0019	-0.0677	287
RF	0.0013	0.0016	0.0057	0.0008	0.0000	287

Note: This table reports descriptive statistics for the main variables used in the empirical analysis.

Panel A indicates substantial cross-sectional dispersion in IVOL and in firm fundamentals such as leverage and ROE, suggesting that firm-specific risk and financial conditions vary markedly across firms and over time. Panel B shows that the seven uncertainty indices display sizeable variation and occasional extreme values, particularly for GPR and ERPU, indicating episodes of elevated policy and geopolitical tension. Panel C confirms that the Fama–French factors exhibit the expected properties for Japanese equity returns over the sample.

Table 4 reports Pearson correlations among the seven uncertainty measures and the three composite indices (PCA-, KPCA-, and LSTM-based). EPU and FPU are highly correlated, as are EPU and MPU, reflecting common macroeconomic policy influences. By contrast, ERU and GPR are only weakly correlated with the core policy uncertainty measures, suggesting that energy-related and geopolitical risks provide additional, relatively independent information.

Table 4. Correlation matrix: uncertainty measures and composite indices.

Variable	EPU	FPU	MPU	TPU	ERPU	ERU	GPR	PCA	KPCA	LSTM
EPU	1.00									
FPU	0.94^{***}	1.00								
MPU	0.74^{***}	0.66^{***}	1.00							
TPU	0.33^{***}	0.35^{***}	0.18^{***}	1.00						
ERPU	0.37^{***}	0.42^{***}	0.48^{***}	-0.02	1.00					
ERU	0.09	0.06	0.24^{***}	0.14^{**}	0.02	1.00				
GPR	-0.03	-0.05	0.05	0.13^{**}	0.01	0.10^{*}	1.00			
PCA	0.78^{***}	0.82^{***}	0.64^{***}	0.37^{***}	0.38^{***}	0.04	0.01	1.00		
KPCA	0.88^{***}	0.90^{***}	0.73^{***}	0.47^{***}	0.40^{***}	0.10	0.02	0.76^{***}	1.00	
LSTM	0.99^{***}	0.97^{***}	0.89^{***}	0.57^{***}	0.66^{***}	0.33^{**}	0.24^{**}	0.92^{***}	0.88^{***}	1.00

Note: Pairwise Pearson correlations are reported. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

PCA and KPCA indices are strongly correlated with EPU and FPU, indicating that fiscal and economic policy uncertainty are key drivers of the common component of policy risk. The LSTM-based index exhibits the highest and most balanced correlations with all seven uncertainty measures, suggesting that it captures a richer blend of macroeconomic and geopolitical uncertainty, including nonlinear and dynamic interactions. Although the high correlations among some uncertainty dimensions raise concerns about multicollinearity in regressions that use them individually, this is precisely what motivates our use of composite indices and dimensionality-reduction techniques.

3.6. Econometric specification

To quantify the effect of policy uncertainty on firm-specific risk, we estimate a two-way fixed-effects panel regression of monthly IVOL on the composite uncertainty index and firm-level controls. Our baseline specification is:

$$IVOL_{i,t} = b_0 + b_1 UI_{t-1} + \beta CV_{i,t-1} + \eta_t + \varphi_i + \epsilon_{i,t}, \tag{7}$$

where $IVOL_{i,t}$ is the idiosyncratic volatility of firm i in month t, UI_{t-1} is the one-month-lagged uncertainty index (PCA-, KPCA-, or LSTM-based), and $\mathbf{CV}_{i,t-1}$ is a vector of lagged firm-level control variables (FSIZE, MBR, LEVG, and ROE). Time-fixed effects η_t capture common macroeconomic shocks, and firm fixed effects φ_i absorb time-invariant firm characteristics. The error term $\epsilon_{i,t}$ is assumed to be mean zero and heteroskedasticity-robust.

All firm-level explanatory variables enter the regression with a one-period lag to mitigate concerns about reverse causality between contemporaneous volatility and firm characteristics, following established practice in empirical finance (e.g., Jiang et al., 2018; Chen et al., 2020; Xie et al., 2024). Using lagged regressors also strengthens the interpretation of b_1 at capturing the effect of prior-period uncertainty on current-period firm-specific risk.

To assess the robustness of our inferences, we conduct a set of diagnostic and specification checks (full results available upon request). Variance inflation factors (VIFs) indicate that multicollinearity among the regressors is not problematic. Stationarity of the panel variables is supported by Levin–Lin–Chu (LLC) tests. We estimate the model using firm-clustered robust standard errors to account for heteroscedasticity and serial correlation within firms (Cameron and Miller, 2015). Finally, we replicate the baseline specification using IVOL measures based on alternative volatility models (GARCH, TGARCH, and EGARCH) and obtain qualitatively similar estimates for b_1, as reported in Section 7.

4. Results

This section presents the empirical evidence on the relationship between policy-related uncertainty and firm-specific risk, measured by idiosyncratic volatility (IVOL), for Nikkei 225 firms. We proceed in four steps. First, we examine the effect of each uncertainty dimension individually. Second, we compare composite uncertainty indices constructed via PCA, KPCA, and an LSTM autoencoder. Third, we use SHAP to open the black box of the LSTM-based index and quantify the contribution of each uncertainty dimension. Finally, we analyze SHAP-based heterogeneity across sectors, firm size, and profitability.

4.1. Baseline regressions with individual uncertainty predictors

Table 5 reports panel fixed-effects regressions of IVOL on individual uncertainty variables—EPU, MPU, FPU, TPU, ERPU, ERU, and GPR—including firm- and time-fixed effects and the full set of control variables described in Section 3. Each column uses a single uncertainty dimension as the main regressor.

Table 5. Regression results for individual uncertainty predictors.

Variable	(1)EPU	(2)MPU	(3)FPU	(4)TPU	(5)ERPU	(6)ERU	(7)GPR
Uncertainty variable	0.0018***	0.0016***	0.0011***	0.0001	-0.0002**	0.0003**	0.0009**
	[0.0000]	[0.0000]	[0.0034]	[0.1010]	[0.0320]	[0.0490]	[0.0400]
FSIZE	1.0423***	1.0401***	1.0429***	1.0434***	1.0403***	1.0450***	1.0419***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LEVG	1.8334*	1.8301*	1.8342*	1.8310*	1.8365*	1.8293*	1.8302*
	[0.0524]	[0.0571]	[0.0486]	[0.0562]	[0.0513]	[0.0580]	[0.0579]
MBR	22.0452***	22.0215***	22.0810***	22.0355***	22.0020***	22.1111***	22.0845***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ROE	0.1512***	0.1530***	0.1525***	0.1544***	0.1521***	0.1537***	0.1523***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	1.6581***	1.6522***	1.6550***	1.6535***	1.6593***	1.6572***	1.6544***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Firm FE / Time FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
No. of obs.	59,974	59,974	59,974	59,974	59,974	59,974	59,974
Adjusted R^2	0.3314	0.3218	0.3412	0.3256	0.3142	0.3351	0.3401

Note: This table reports two-way fixed-effects panel regressions of IVOL on individual policy uncertainty variables and firm-level controls for Nikkei 225 firms. Robust standard errors are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficients on EPU, MPU, and FPU are positive and statistically significant at the 1% level, indicating that higher economic, monetary, and fiscal policy uncertainty are associated with higher idiosyncratic volatility. For example, in column (1), a one-unit increase in EPU is associated with an increase in IVOL of around 0.18 percentage points. This is consistent with earlier work showing that macroeconomic and policy uncertainty raise risk premia and firm-level volatility (e.g., Baker et al., 2016; Pastor and Veronesi, 2012).

Energy-related uncertainty (ERU) and geopolitical risk (GPR) also enter with positive and statistically significant coefficients, suggesting that shocks to energy markets and geopolitical tensions contribute to firm-specific risk, particularly for firms with high exposure to global supply chains and imported energy. By contrast, trade policy uncertainty (TPU) is not statistically significant at conventional levels, pointing to a more muted direct effect of trade policy news on Nikkei 225 firm volatility once other controls and fixed effects are taken into account.

The coefficient on exchange rate policy uncertainty (ERPU) is small and negative but statistically significant. One interpretation is that episodes of heightened exchange rate policy attention may coincide with policy measures that dampen exchange rate volatility and, in turn, partially stabilize firm-level risk, for example through interventions or communication that anchors currency expectations. We view this as an interesting deviation from the otherwise uniformly positive pattern rather than as evidence that ERPU systematically reduces firm risk.

Adjusted coefficient of determination (R^2) values range between 0.31 and 0.34, indicating that individual uncertainty dimensions explain a nontrivial but still limited portion of the total cross-sectional and time-series variation in IVOL. This motivates the construction of composite indices that capture joint and potentially nonlinear effects across uncertainty dimensions.

4.2. Composite uncertainty indices: PCA, KPCA, and LSTM

Table 6 reports regression results when the seven uncertainty dimensions are summarized into a single composite index using PCA, KPCA, or the LSTM autoencoder. The econometric specification is identical to Equation (7), with the composite index entering in place of individual uncertainty variables.

Table 6. Regression results for composite uncertainty indices.

Variable	(1) PCA	(2) KPCA	(3) LSTM
Uncertainty index	0.0023***	0.0028***	0.0031***
	[0.0000]	[0.0000]	[0.0000]
FSIZE	1.0421***	1.0489***	1.0513***
	[0.0000]	[0.0000]	[0.0000]
LEVG	1.8312*	1.8457*	1.8542*
	[0.0581]	[0.0504]	[0.0472]
MBR	22.0552***	22.1742***	22.2345***
	[0.0000]	[0.0000]	[0.0000]
ROE	0.1531***	0.1575***	0.1593***
	[0.0000]	[0.0000]	[0.0000]
Constant	1.6572***	1.2415***	1.2153***
	[0.0000]	[0.0000]	[0.0000]
Firm FE / Time FE	Yes / Yes	Yes / Yes	Yes / Yes
No. of obs.	59,974	59,974	59,974
Adjusted R^2	0.3812	0.4285	0.4713

Note: This table reports two-way fixed-effects regressions of IVOL on composite uncertainty indices constructed via PCA, KPCA, and an LSTM Autoencoder, along with firm-level controls. Robust standard errors are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

All three composite indices enter with positive and highly significant coefficients. In the PCA model, a one-unit increase in the PCA-based uncertainty index is associated with a 0.23 percentage point increase in IVOL. The KPCA index yields a larger coefficient of 0.0028 and a higher adjusted R^2 of 0.4285, indicating that allowing for nonlinear comovements among the uncertainty dimensions improves the fit relative to the linear PCA benchmark.

The LSTM-based index produces the largest coefficient (0.0031) and the highest adjusted R^2 (0.4713). Economically, this implies that a one-unit increase in the LSTM uncertainty index is associated with a 0.31 percentage point increase in idiosyncratic volatility. The increase in explanatory power from PCA to KPCA and from KPCA to LSTM suggests that accounting for both nonlinear relationships and temporal dependence in policy uncertainty yields a materially richer description of firm-specific risk. These results support Hypothesis H2 that composite indices, particularly those derived from flexible sequence models, outperform individual uncertainty components in explaining IVOL.

4.3. SHAP-based decomposition of the LSTM uncertainty index

PCA and KPCA offer interpretability through component loadings, but the LSTM autoencoder, by design, is a nonlinear sequence model with limited intrinsic transparency. To open this "black box", we employ SHAP (SHapley Additive exPlanations; Lundberg and Lee, 2017), which decomposes the LSTM-based uncertainty index into the marginal contributions of the seven underlying policy uncertainty dimensions. Because SHAP requires a model with tractable structure, we adopt the standard surrogate modelling approach and approximate the LSTM mapping using a flexible tree-based regressor. The resulting SHAP values quantify, for each month, how much each uncertainty dimension contributes to the fitted LSTM index. Full methodological details, including the surrogate model specification, hyperparameters, and the computation of normalised mean absolute SHAP values, are provided in Appendix Appendix 2.

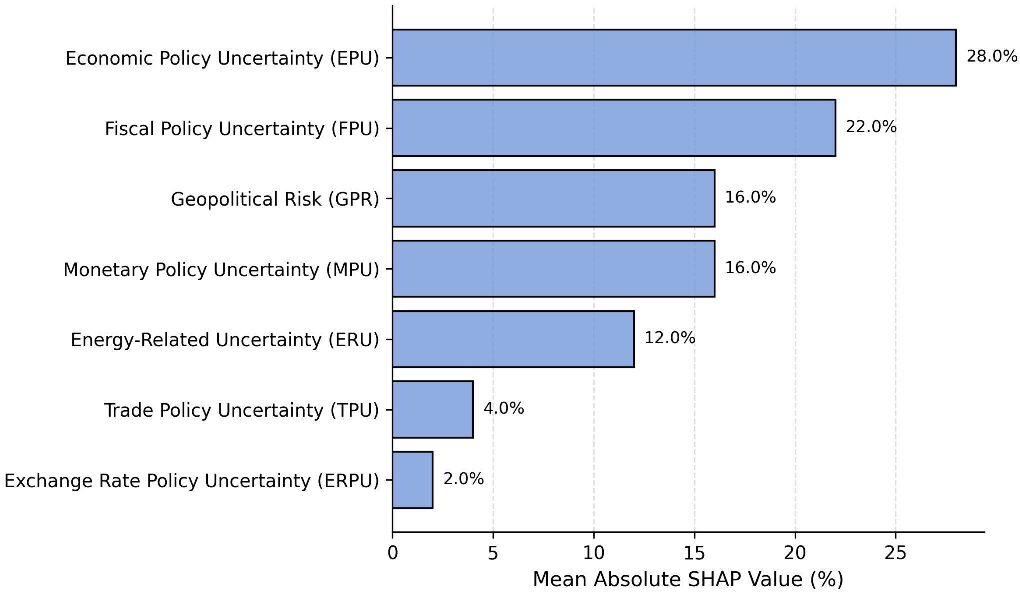

Figure 2. Global SHAP importance for the LSTM-based uncertainty index.

Note: Bars report the normalized mean absolute SHAP values for the seven policy uncertainty dimensions, expressed as percentages that sum to 100%. EPU, FPU and GPR are the dominant contributors, followed by MPU and ERU, whereas TPU and ERPU have comparatively smaller importance.

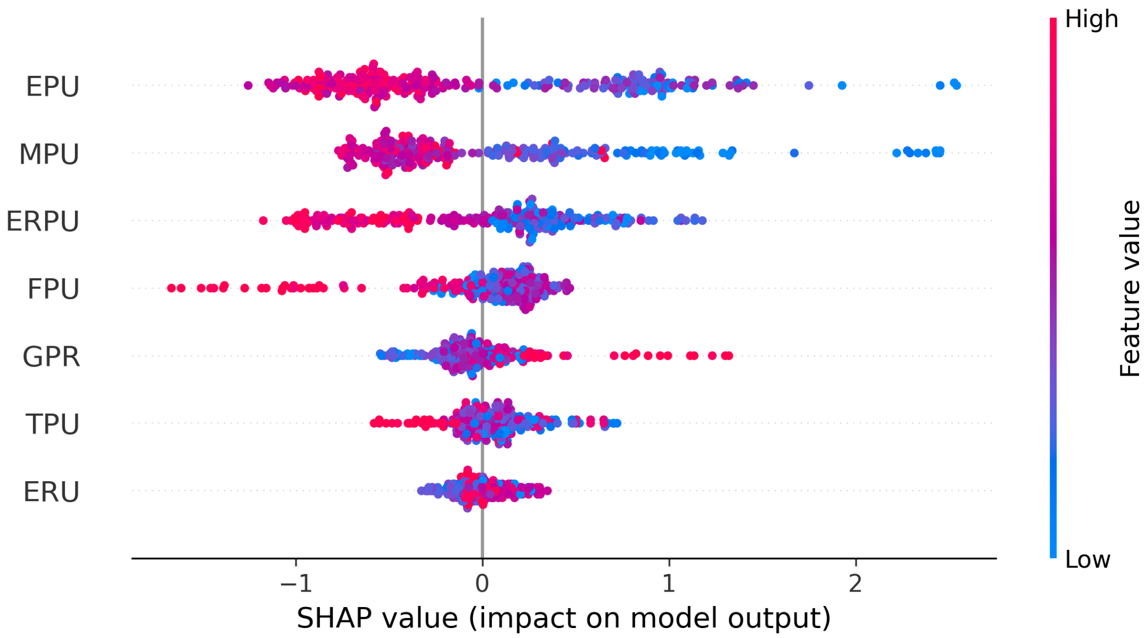

Figure 3. SHAP summary plot for the LSTM-based uncertainty index.

Note: Each point represents a monthly observation. The horizontal axis shows the SHAP value for a given policy uncertainty dimension (its marginal contribution to the fitted LSTM-based index), and colour encodes the standardized value of that uncertainty variable (red = high, blue = low). Variables are ordered by mean absolute SHAP value, with EPU, FPU, and GPR emerging as the most influential contributors, consistent with Figure 2.

Figure 2 reports the global SHAP importance shares. Economic policy uncertainty (EPU), fiscal policy uncertainty (FPU), and geopolitical risk (GPR) dominate the contribution to the LSTM index, jointly accounting for the majority of total SHAP importance. monetary policy uncertainty (MPU) and energy-related uncertainty (ERU) play secondary but non-negligible roles, while trade policy uncertainty (TPU) and exchange rate policy uncertainty (ERPU) have comparatively modest influence. This ranking aligns with the regression evidence and supports the interpretation that macrofinancial, and geopolitical conditions are key drivers of firm-specific risk in Japan.

Figure 3 complements these results with a SHAP "beeswarm" plot showing the full distribution of SHAP values for each policy uncertainty dimension. High values of EPU and FPU (red markers) are systematically associated with large positive SHAP values, indicating that episodes of elevated economic and fiscal uncertainty strongly increase the fitted LSTM index. In contrast, TPU and ERPU exhibit tightly clustered SHAP values near zero, consistent with their limited global importance in Figure 2. Overall, the SHAP analysis provides an economically intuitive decomposition of the LSTM latent factor and reveals that the model is most sensitive to macroeconomic and geopolitical uncertainty.

4.4. SHAP heterogeneity across sectors, firm size, and profitability

The aggregate SHAP ranking provides a useful global summary but may mask important cross-sectional differences in how policy uncertainty translates into firm risk. To study heterogeneity, we group firms along three dimensions that are particularly relevant in the Japanese context: industry sector (based on the six Nikkei sectors), firm size, and profitability.

For each group g (sector, size, or profitability), we construct a group-level IVOL series as the cross-sectional average of firm-level IVOL within the group and estimate a random forest model,

$$\mathrm{IVOL}_t^{(g)} = f_g(U_t) + \eta_t^{(g)},$$

where U_t collects the seven uncertainty indices. We then compute SHAP values $\phi_{k,t}^{(g)}$ and summarize them via the normalized mean absolute contribution

$$I_k^{(g)} = \frac{\frac{1}{T}\sum_t |\phi_{k,t}^{(g)}|}{\sum_{j=1}^{7} \frac{1}{T}\sum_t |\phi_{j,t}^{(g)}|},$$

so that, for each group g, the shares $I_k^{(g)}$ sum to one. This yields a set of "SHAP weight profiles" that can be compared across sectors, size groups, and profitability buckets.

Industry-sector heterogeneity. Figure 4 displays the normalized SHAP contributions by Nikkei sector. Trade- and energy-intensive sectors such as Capital Goods/Others, Materials, and Transportation & Utilities exhibit relatively larger contributions from TPU and ERU, consistent with their exposure to export demand, global supply chains, and energy prices. By contrast, Consumer Goods and Financials place greater weight on FPU and MPU, reflecting their dependence on domestic demand conditions and interest rate policy. Technology firms show a relatively high contribution of GPR and ERU, in line with their sensitivity to geopolitical tensions and input cost shocks. These patterns suggest that the multidimensional uncertainty index loads onto economically plausible channels at the sector level.

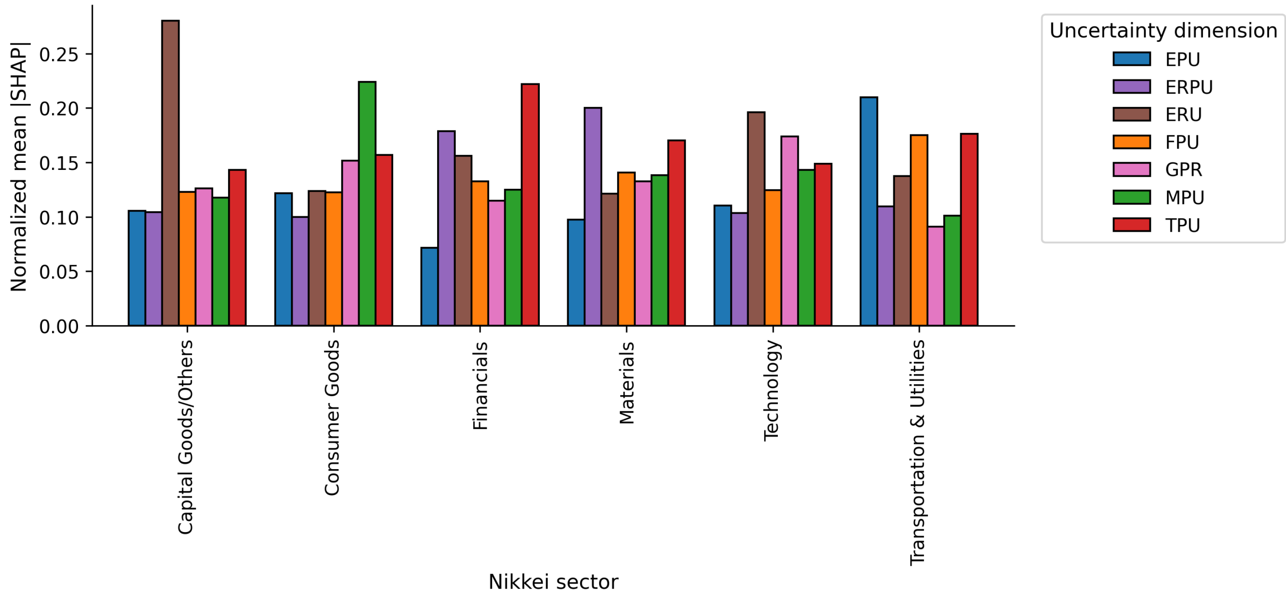

Figure 4. SHAP feature importance by sector.

Note: Bars show the normalized mean absolute SHAP contributions of the seven policy uncertainty dimensions within each Nikkei sector, summing to one for a given sector. Trade- and energy-intensive sectors (Capital Goods/Others, Materials, Transportation & Utilities) display relatively larger contributions from TPU and ERU, whereas Consumer Goods and Financials place more weight on FPU and MPU. Technology firms load more strongly on GPR and ERU, consistent with supply chain and input cost exposure.

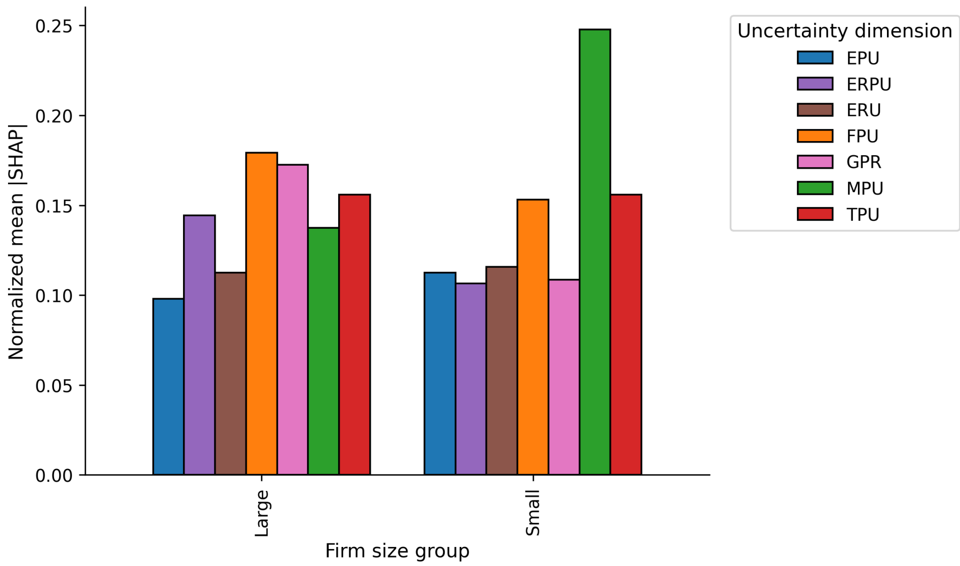

Figure 5. SHAP feature importance by firm size.

Note: Firms are split into Large and Small groups using the cross-sectional median market capitalization. Bars show the normalized mean absolute SHAP contributions of the seven policy uncertainty dimensions within each size group. Small firms exhibit relatively larger contributions from MPU and FPU, and large firms show higher contributions from GPR and ERPU, consistent with stronger exposure to global and currency-related shocks.

Size-based heterogeneity. We next split firms into "Large" and "Small" groups based on the cross-sectional median market capitalization. Figure 5 shows that small firms exhibit relatively higher SHAP shares for MPU and, to a lesser extent, FPU, whereas large firms display somewhat higher contributions of GPR and ERPU. This is intuitive: smaller firms tend to be more financially constrained and more sensitive to policy-driven changes in interest rates and government demand, whereas large firms are more internationally diversified and therefore more exposed to geopolitical and exchange rate risk.

Profitability-based heterogeneity. Finally, we classify firms into High-ROE and Low-ROE groups based on the cross-sectional median return on equity. Figure 6 indicates that Low-ROE firms have relatively larger SHAP contributions from FPU and ERU, suggesting that weaker firms are more vulnerable to fiscal and energy-related shocks that compress cash flows and margins. High-ROE firms, by contrast, load more strongly on MPU and GPR, consistent with a greater sensitivity to interest rate policy and global geopolitical developments that affect investment opportunities and overseas operations.

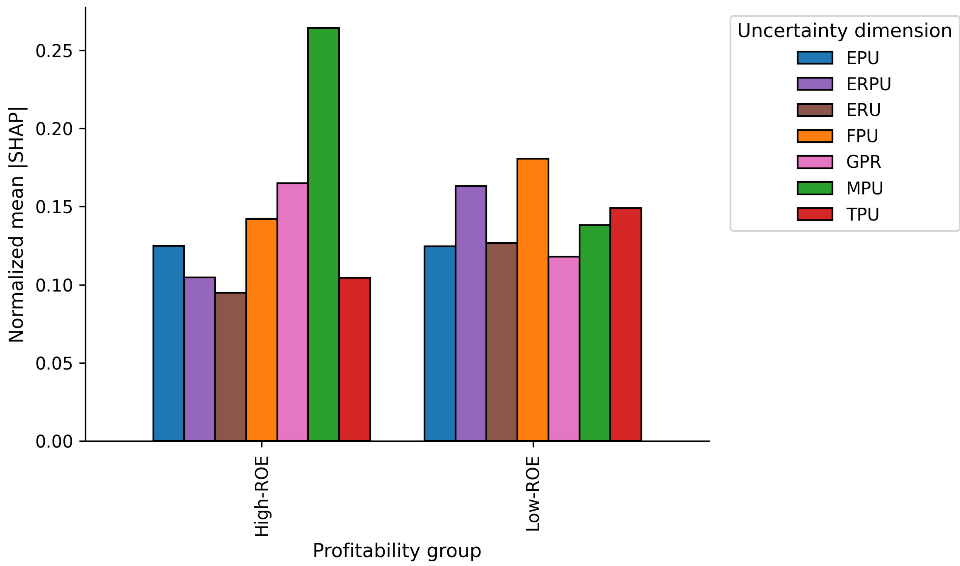

Figure 6. SHAP feature importance by profitability.

Note: Firms are classified as High-ROE or Low-ROE using the cross-sectional median ROE. Bars report the normalized mean absolute SHAP contributions of the seven policy uncertainty dimensions within each profitability group. Low-ROE firms exhibit relatively larger contributions from FPU and ERU, and High-ROE firms load more strongly on MPU and GPR, suggesting that balance sheet strength shapes the transmission of policy uncertainty into firm-specific risk.

Overall, the heterogeneity analysis demonstrates that the positive and economically meaningful link between policy uncertainty and IVOL documented in the aggregate masks rich cross-sectional structure. Manufacturing-style and trade-exposed sectors are particularly sensitive to TPU and ERU; small and low-ROE firms respond more strongly to fiscal and monetary uncertainty. These findings reinforce the interpretation that policy uncertainty affects firm-level risk through several channels whose relative importance depends on firms' business models, scale, and financial strength, and they motivate the policy and portfolio implications discussed in Section 6.

5. Discussion

This section interprets the empirical findings in light of the broader literature on uncertainty, asset pricing, and firm-specific risk. Overall, the results show that (i) multidimensional policy-related uncertainty is a first-order driver of idiosyncratic volatility (IVOL) for Japanese firms, (ii) nonlinear, sequence-based machine learning models extract substantially more predictive structure from uncertainty data than linear benchmarks, and (iii) firm-level fundamentals and heterogeneity remain crucial in shaping how policy shocks are transmitted to firm-specific risk.

5.1. Policy uncertainty and firm-specific volatility

Our baseline regressions confirm a strong positive association between policy-related uncertainty and IVOL. Economic (EPU), fiscal (FPU), monetary (MPU), energy-related (ERU), and geopolitical (GPR) uncertainty all enter with positive and statistically significant coefficients, whereas trade policy uncertainty (TPU) is statistically weak, and exchange-rate policy uncertainty (ERPU) has a small but negative coefficient. This pattern is broadly consistent with theoretical models in which policy uncertainty raises risk premia, increases investor disagreement, and amplifies cash flow uncertainty (Baker et al., 2016; Pastor and Veronesi, 2012).

The prominent role of EPU, FPU, and MPU resonates with existing work showing that macroeconomic and policy uncertainty affect investment, hiring, and financing decisions, and thereby firm-level risk (Baker et al., 2016; Pastor and Veronesi, 2012). In the Japanese context, where unconventional monetary policy and repeated fiscal interventions have become structural features, uncertainty about the timing, scale, and credibility of these policies appears to be priced into firm-specific volatility, as also suggested by recent Japan-focused studies (Shin et al., 2024; Saxegaard et al., 2022). Our results extend this evidence by showing that these policy domains remain important even after controlling for firm fundamentals and fixed effects.

The significant positive coefficients on GPR and ERU highlight the importance of geopolitical and energy-related channels. This is in line with Caldara and Iacoviello (2022) and Ren et al. (2023), who emphasize that geopolitical shocks propagate through trade flows, supply chains, and risk sentiment, and with Siddiqui et al. (2024), who showed that energy-related uncertainty can alter input costs, cash flow expectations, and sectoral risk exposures. For a highly open, energy-importing economy such as Japan, these channels provide a natural explanation for the transmission of global shocks into firm-level volatility.

The negative coefficient on ERPU is more nuanced but economically plausible. One interpretation, consistent with Krol (2014), is that Japanese firms, especially large exporters, engage in systematic currency hedging and operational diversification. When exchange rate policy becomes more salient, policy actions and communication may reduce perceived tail risks in the exchange rate, thereby lowering residual uncertainty around net currency exposure for well-hedged firms. In that sense, ERPU may capture episodes in which policy interventions stabilize rather than destabilize expectations, a pattern that fits the high degree of exchange rate management and guidance in the Japanese environment.

Taken together, these results support the view that policy uncertainty is not a monolithic concept: different dimensions operate through distinct channels, and their combined effect on IVOL depends on both macroeconomic conditions and firm characteristics.

5.2. *Why Nonlinear and temporal models matter*

A key methodological finding is the clear ordering in explanatory power across the three composite uncertainty indices: PCA, KPCA, and the LSTM autoencoder. The LSTM-based index yields the largest effect size and the highest adjusted R^2, followed by KPCA and then PCA. This hierarchy suggests that uncertainty dynamics relevant for firm-specific risk are both nonlinear and path-dependent.

PCA provides a useful linear benchmark but, by construction, captures only static contemporaneous comovements among the uncertainty series. KPCA relaxes this linearity assumption via kernel mappings and thereby improves fit, indicating that nonlinear interactions among uncertainty dimensions matter for IVOL. The LSTM autoencoder goes one step further by exploiting the full time-series structure of the data: it can learn persistent effects, lagged interactions, and regime-like patterns in uncertainty shocks, features that are central in macrofinancial applications (Hochreiter and Schmidhuber, 1997; Gu et al., 2020; Rapach and Zhou, 2020).

The SHAP-based decomposition of the LSTM index bridges the gap between predictive performance and economic interpretation. Globally, SHAP values show that EPU, FPU, and GPR contribute most to the LSTM-based uncertainty index, with MPU and ERU playing a secondary role and TPU and ERPU contributing less. This ranking aligns closely with the regression evidence and with economic intuition: investors react more strongly to broad macroeconomic and geopolitical news than to narrower or more hedged policy domains. In this sense, the LSTM model is not merely a black box that happens to fit the data well; its internal representation of uncertainty is consistent with interpretable and policy-relevant drivers once viewed through the lens of SHAP (Lundberg and Lee, 2017; Ribeiro et al., 2016).

From a methodological perspective, these findings support recent calls to integrate machine learning into empirical asset pricing and risk management while maintaining interpretability. Nonlinear sequence models such as LSTMs are able to extract additional structure from the joint history of policy uncertainty indices that is simply not available to static linear models, and SHAP-type tools make this structure accessible for economic analysis and policy discussion.

5.3. *Firm fundamentals and cross-sectional heterogeneity*

Firm-level fundamentals behave in largely intuitive ways and remain strong predictors of IVOL even after controlling for policy uncertainty. Leverage (LEVG) is positively associated with idiosyncratic volatility, reflecting the amplifying effect of balance sheet fragility on cash flow and discount rate shocks (Bradley et al., 1984; Frank and Goyal, 2009). The market-to-book ratio (MBR) also loads positively on IVOL, consistent with the idea that growth firms , which have more of their value tied to distant, uncertain cash flows, carry higher valuation risk and greater dispersion in expectations (Fama and French, 1992).

The positive association between ROE and IVOL suggests that highly profitable firms, although attractive to investors, are also more sensitive to information flows and policy news. One possible mechanism is that such firms receive more analyst coverage and investor attention, so surprises in earnings or policy announcements translate more sharply into price revisions (Novy-Marx, 2013). In this sense, profitability does not unambiguously insulate firms from uncertainty; instead, it can increase the intensity of market reactions when expectations are revised.

The role of firm size is more nuanced in our sample. Larger firms are typically thought to exhibit lower idiosyncratic volatility due to diversification across products and markets (e.g., Schwert, 1989;

Cao et al., 2008). In our setting, however, Nikkei 225 constituents are all relatively large, internationally active firms, and the positive coefficient on firm size should be interpreted within this restricted universe: within the large-cap segment, bigger firms may be more exposed to global policy and geopolitical news, operate more complex supply chains, and rely more heavily on external finance, all of which can increase the sensitivity of their idiosyncratic volatility to uncertainty shocks.

The SHAP-based heterogeneity analysis reinforces the idea that policy uncertainty is transmitted through channels that depend on firms' economic roles and balance sheet characteristics. Trade- and energy-intensive sectors (such as Materials, Capital Goods/Others, and Transportation & Utilities) show relatively higher SHAP contributions from TPU and ERU, consistent with their exposure to exports, commodity prices, and energy costs. Consumer Goods and Financials place more weight on FPU and MPU, reflecting their dependence on domestic demand and the interest rate environment. Technology firms exhibit larger contributions from GPR and ERU, in line with their sensitivity to global supply chain disruptions and input cost shocks.

Similarly, small firms in the Nikkei 225 are more exposed to monetary and fiscal policy uncertainty than their larger peers, which accords with their tighter financing constraints and greater dependence on bank lending and government demand. Low-ROE firms show relatively higher contributions from FPU and ERU, suggesting that weaker firms are less able to absorb policy and cost shocks and therefore experience more pronounced volatility responses. High-ROE firms, by contrast, load more strongly on MPU and GPR, indicating that profitable, globally integrated firms are particularly sensitive to interest-rate and geopolitical developments that affect investment opportunities and international operations.

Overall, these patterns underscore that the uncertainty–IVOL relationship is both economically meaningful and heterogeneous. Multidimensional policy uncertainty interacts with firm size, profitability, sector, and financial structure, rather than feeding uniformly into firm-specific risk. This has important implications for portfolio construction and policy design, which we explore in Section 6.

6. Implications of research

6.1. Theoretical implications

This study offers several contributions to the theoretical literature on financial risk, policy uncertainty, and the use of machine learning in asset pricing and risk modelling.

First, our results reinforce the view that macroeconomic and policy-related uncertainty behaves like a systematic risk factor with a material impact on firm-specific volatility (IVOL). In line with uncertainty-based asset pricing models (Pastor and Veronesi, 2012; Jurado et al., 2015), we show that policy shocks not only shift expected returns but also increase the dispersion of firm-level outcomes. The fact that multiple dimensions of policy uncertainty, including economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical, all bear on IVOL highlights that uncertainty is inherently multidimensional and transmitted through several economic channels.

Second, the comparative performance of PCA, KPCA, and LSTM autoencoders supports the idea that uncertainty is both nonlinear and persistent. Linear factor structures are able to capture only a portion of the relevant variation. The superior explanatory power of the LSTM-based index is consistent with theoretical arguments that policy and macroeconomic shocks exhibit long-memory dynamics, regime dependence, and interaction effects that are difficult to represent in static linear models (Hochreiter and Schmidhuber, 1997; Gu et al., 2020). In this sense, our findings provide empirical grounding for the use of sequence-based deep learning models in the study of uncertainty and volatility.

Third, by combining the LSTM autoencoder with SHAP (SHapley Additive exPlanations), we help bridge the gap between predictive black-box models and theory-driven interpretation. SHAP decompositions reveal that economic, fiscal, monetary and geopolitical uncertainty are the dominant contributors to the learned uncertainty index, offering a factor-structure interpretation of the LSTM latent space that is consistent with macrofinancial intuition (Lundberg and Lee, 2017; Molnar, 2022). This illustrates how explainable AI can be used not only to validate model behavior but also to inform the design of uncertainty-augmented risk-factor models.

Finally, the robust roles of firm characteristics such as size, leverage, market-to-book, and profitability confirm and extend insights from capital structure and asset-pricing theories. Our evidence suggests that policy uncertainty operates as a structural overlay that interacts with firm fundamentals, rather than replacing them, in determining IVOL. This interaction-based perspective enriches traditional frameworks such as the Fama–French factor model and leverage-based theories by explicitly incorporating uncertainty as a time-varying, multidimensional state variable.

6.2. Practical implications

The results also carry clear implications for corporate managers, institutional investors, and risk practitioners.

For corporate managers, the evidence that policy uncertainty significantly raises firm-specific volatility underscores the importance of integrating macroeconomic and policy scenarios into risk management. Firms in energy-intensive, export-oriented, or geopolitically exposed sectors appear particularly vulnerable. Practical responses include more active use of financial and operational hedging, flexible capital budgeting that conditions on uncertainty regimes, and contingency planning for shifts in fiscal and monetary policy. The heterogeneity results further suggest that smaller and low-ROE firms should devote particular attention to their exposure to fiscal and energy-related uncertainty, and highly profitable and internationally active firms should closely monitor monetary and geopolitical developments.

For investors and portfolio managers, our LSTM-based uncertainty index can be used as a forward-looking signal within risk management and asset allocation frameworks. First, incorporating the index into volatility-forecasting models, value-at-risk systems, and stress tests can help identify episodes in which policy shocks are likely to produce elevated IVOL, allowing for timely adjustments to position sizes, margin requirements, and leverage. Second, the SHAP-based decomposition of the index into its constituent uncertainty dimensions enables more granular portfolio tilts: if, for example, trade policy uncertainty becomes the dominant driver of the index, investors may reduce exposure to export-oriented manufacturers or deploy targeted currency and trade-sensitive hedges; if fiscal or monetary uncertainty rises, rebalancing toward firms with stronger balance sheets and lower refinancing needs becomes more attractive. Third, the sensitivity of IVOL to uncertainty differs across countries, global investors can use relative policy risk metrics to inform capital allocation between Japan and other markets.

More broadly, the study illustrates how interpretable machine learning tools can complement traditional factor models in practice. Rather than replacing existing frameworks, the LSTM–SHAP combination adds a flexible layer that captures nonlinear and time-varying effects while preserving economic interpretability, making it suitable for integration into institutional risk dashboards and investment processes.

6.3. Policy implications for investors and regulators

Beyond firm- and portfolio-level decisions, the findings have several implications for policymakers, supervisors, and regulators, particularly in an environment such as Japan which has persistent unconventional policies and high public debt.

First, the empirical link between policy uncertainty and IVOL implies that uncertainty is not just a macroeconomic concept but a concrete determinant of firm and financial system stability. Clear, credible, and consistent communication about policy objectives, instruments, and exit strategies can reduce unnecessary uncertainty premia and dampen spikes in firm-specific volatility. In the monetary sphere, this includes transparent guidance on the future of yield curve control, negative interest rates, and balance sheet policies; in the fiscal sphere, stable medium-term frameworks for taxation and public spending can anchor expectations about future cash flows and financing conditions.

Second, the multidimensional uncertainty index we construct suggests a role for such measures as part of macroprudential monitoring and early-warning systems. Sharp increases in specific components—for example, exchange rate or energy-related uncertainty—can flag higher vulnerability in sectors that our SHAP heterogeneity analysis identifies as particularly exposed. Supervisory authorities can combine these aggregate indicators with micro-level information to target stress tests, capital buffers, or disclosure requirements at the most sensitive segments of the corporate sector.

Third, the strong interconnectedness between banks, institutional investors, and large corporations in Japan implies that policy coordination matters. Abrupt or poorly communicated shifts in monetary or fiscal stance can propagate quickly through funding conditions, investment plans, and balance sheets. Coordinated communication across monetary, fiscal, and regulatory authorities can help align expectations and limit amplification of policy shocks into firm-specific volatility. In this sense, reducing unnecessary policy uncertainty can itself be viewed as a form of macroprudential policy, particularly in economies where unconventional tools and structural features heighten the sensitivity of firm-level risk to policy signals.

Finally, the demonstrated usefulness of explainable AI tools such as SHAP has implications for regulatory views on advanced modelling. Encouraging the use of interpretable machine learning in risk management rather than opaque black-box models can help ensure that AI-driven decisions remain auditable, economically grounded, and aligned with financial stability objectives.

7. Robustness analysis

This section reports a series of robustness checks designed to assess whether our main findings are sensitive to alternative volatility estimators, lag structures, sample splits, modelling choices, and country coverage. Across all exercises, the central result, a positive and economically meaningful association between multidimensional policy uncertainty and firm-specific idiosyncratic volatility (IVOL), with the LSTM-based index delivering the strongest explanatory power, remains intact.

7.1. Alternative IVOL measures and lag structures

We first examine whether the estimated impact of uncertainty on IVOL depends on how idiosyncratic volatility is measured. In place of residual standard deviations from the Fama–French five-factor model, we re-estimate IVOL using an EGARCH(1,1) specification, which accommodates volatility clustering, asymmetry, and leverage effects. Table 7 (columns 1–3) reports the corresponding panel regressions for the PCA-, KPCA-, and LSTM-based uncertainty indices.

The coefficients on the uncertainty indices remain positive and highly significant in all three specifications. Their magnitudes are very close to the baseline estimates, and the adjusted R^2 values are virtually unchanged. This indicates that our findings are not an artifact of a particular volatility estimator: conditional variance dynamics captured by EGARCH do not overturn the substantive link between uncertainty and IVOL.

Next, we test the sensitivity of the results to the assumed lag structure. Although our baseline model uses a one-period lag of the uncertainty index and control variables to mitigate endogeneity, we re-estimate the regressions using a two-period lag (columns 4–6 of Table 7). As expected, the coefficients on the uncertainty indices are somewhat smaller in magnitude, reflecting the fact that more distant uncertainty shocks carry less information for current IVOL, but they remain positive and statistically significant at the 1% level. The pattern of adjusted R^2 values is preserved, with the LSTM-based index continuing to outperform PCA and KPCA. These results suggest that the uncertainty–IVOL relationship is not sensitive to reasonable changes in lag length.

Table 7. Robustness: EGARCH-based IVOL and alternative lag structure

Variable	(1) PCA (EGARCH)	(2) KPCA (EGARCH)	(3) LSTM (EGARCH)	(4) PCA (2-lag)	(5) KPCA (2-lag)	(6) LSTM (2-lag)
Uncertainty Index	0.0022***	0.0027***	0.0030***	0.0016***	0.0019***	0.0024***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
FSIZE	1.0365***	1.0354***	1.0349***	1.0349***	1.0342***	1.0344***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LEVG	1.8321**	1.8294**	1.8311**	1.8295**	1.8281**	1.8307**
	[0.0572]	[0.0553]	[0.0541]	[0.0593]	[0.0582]	[0.0570]
MBR	22.0439***	22.0381***	22.0427***	22.0305***	22.0327***	22.0311***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ROE	0.1530***	0.1535***	0.1529***	0.1523***	0.1528***	0.1526***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	1.6543***	1.6538***	1.6532***	1.6531***	1.6527***	1.6524***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Adjusted R^2	0.3817	0.4283	0.4712	0.3601	0.3975	0.4498

Note: This table reports robustness tests for the uncertainty indices (PCA, KPCA, LSTM) using (i) EGARCH-based IVOL (columns 1–3) and (ii) a two-period lag of the uncertainty index and controls (columns 4–6). P-values are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

7.2. Subsample analysis and alternative modelling choices

We next examine whether the uncertainty–IVOL relationship is stable across different market regimes. To this end, we split the sample into precrisis (2000–2007) and postcrisis (2009–2023) subperiods and re-estimate the baseline panel regressions for each uncertainty index. Table 8 summarizes the results.

In both subperiods, the coefficients on the uncertainty indices are positive and statistically significant across PCA, KPCA, and LSTM specifications. The LSTM-based index retains the largest coefficient and highest adjusted R^2 in each subperiod, indicating that its superior performance is not driven by a single crisis episode. If anything, the estimates are somewhat larger in the post-2008 subsample, consistent with the notion that unconventional monetary and fiscal policies have increased the salience of policy uncertainty in the more recent period. Additional subsample checks for the 2015–2023 interval (not tabulated) yield similar conclusions.

Table 8. Robustness: Pre- and post-2008 subsample analysis.

Variable	(1) PCA Pre-2008	(2) KPCA Pre-2008	(3) LSTM Pre-2008	(4) PCA Post-2008	(5) KPCA Post-2008	(6) LSTM Post-2008
Uncertainty Index	0.0017***	0.0021***	0.0026***	0.0025***	0.0030***	0.0034***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
FSIZE	1.0374***	1.0361***	1.0357***	1.0352***	1.0348***	1.0343***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LEVG	1.8344**	1.8310**	1.8325**	1.8310**	1.8297**	1.8309**
	[0.0564]	[0.0542]	[0.0531]	[0.0582]	[0.0574]	[0.0569]
MBR	22.0525***	22.0468***	22.0489***	22.0467***	22.0435***	22.0423***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ROE	0.1538***	0.1534***	0.1531***	0.1527***	0.1531***	0.1529***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	1.6553***	1.6540***	1.6537***	1.6542***	1.6535***	1.6531***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Adjusted R^2	0.3558	0.3821	0.4345	0.4296	0.4758	0.5181

Note: This table reports estimates of the effect of the PCA-, KPCA- and LSTM-based uncertainty indices on IVOL in pre-2008 (columns 1–3) and post-2008 (columns 4–6) subsamples. P-values are in brackets. Significance levels: * 10%, ** 5%, *** 1%.

We also experimented with alternative modelling choices for the construction and use of the uncertainty index. In addition to PCA, KPCA, and the LSTM autoencoder, we estimated ridge and lasso regressions that map the seven uncertainty dimensions into a single composite index. When these alternative indices are used in the panel regressions, the coefficients on uncertainty remain positive and significant, and the ranking of models in terms of adjusted R^2 is preserved, with the LSTM-based index delivering the best fit. Finally, an ablation exercise in which we drop each uncertainty dimension in turn shows that the main conclusions are not driven by any single component: the composite index remains highly predictive of IVOL even when specific policy dimensions are excluded. This indicates that the index captures broad-based uncertainty effects rather than a narrow subfactor.

Taken together, these exercises suggest that the documented uncertainty–IVOL relationship reflects underlying economic mechanisms rather than specific modelling or sample choices.

7.3. Cross-country robustness: Evidence from developed and emerging markets

To gauge external validity, we extend the analysis to five additional markets: the United States, Germany, South Korea, India, and Indonesia. For each country, we construct a country-specific LSTM-based uncertainty index using the same architecture and estimation protocol as for Japan and re-estimate the baseline panel regression of IVOL on the index and control variables.

Table 9 reports the resulting coefficients and adjusted R^2 values. In all markets, the LSTM-based uncertainty index enters positively and significantly at the 1% level, indicating that policy-related uncertainty is a pervasive driver of firm-specific volatility. The magnitude of the coefficient and the explanatory power, however, differ across countries, with Japan lying toward the upper end of the distribution. This pattern suggests that although the uncertainty–IVOL channel is common across institutional environments, its strength is shaped by local policy regimes, financial structures, and exposure to global shocks.

Table 9. Cross-country robustness: LSTM-based uncertainty and IVOL.

Country	LSTM Coefficient	P-value	Adjusted R^2
Japan	0.0031***	0.0004	0.4713
USA	0.0029***	0.0006	0.4689
Germany	0.0027***	0.0009	0.4512
South Korea	0.0026***	0.0012	0.4425
India	0.0024***	0.0020	0.4271
Indonesia	0.0023***	0.0025	0.4215

Note: This table presents countrywise estimates of the effect of the LSTM-based uncertainty index on IVOL. Significance levels: * 10%, ** 5%, *** 1%.

The relatively large coefficient and R^2 for Japan are consistent with its structural exposure to both domestic and global policy shocks: prolonged unconventional monetary policy, high government debt, and strong integration into global supply chains amplify the impact of policy news on firm-specific risk. By contrast, large and highly diversified markets such as the United States and Germany, and emerging markets such as India and Indonesia with different financial structures and policy regimes, exhibit somewhat smaller but still economically meaningful sensitivities.

7.4. Mechanistic analysis of Cross-country differences

The cross-country robustness results raise the question of why Japan appears particularly sensitive to policy-related uncertainty. To shed light on this, we briefly relate the heterogeneity in estimated coefficients to key institutional and policy-regime characteristics.

For each market in the robustness sample, we summarize the dominant monetary and fiscal policy arrangements and selected features of the financial system in Table 10. Japan stands out along several dimensions. First, the Bank of Japan has pursued an extensive and prolonged regime of unconventional monetary policy, including zero or negative policy rates, large-scale asset purchases, and yield curve control (YCC). Uncertainty about the timing, speed, and sequencing of an exit from such a regime can generate substantial variation in expected discount rates and risk premia, particularly for long-lived cash flows. Second, Japanese listed firms are highly exposed to domestic fiscal policy through sizeable public investment, repeated stimulus packages, and a very high government debt stock. Debates about consumption tax hikes and fiscal consolidation therefore translate quickly into uncertainty about future profitability and leverage. Third, the Japanese corporate sector is deeply integrated into global supply chains and energy markets, implying that geopolitical and energy-related shocks are rapidly transmitted to firm-level cash flows and financing conditions.

In contrast, the United States and Germany have operated largely within more conventional interest rate targeting regimes, with unconventional tools used in a more episodic fashion, whereas India and Indonesia combine shallower capital markets with different degrees of capital account openness and fiscal capacity. These institutional differences help explain why a conceptually similar multidimensional policy uncertainty index generates somewhat weaker or more diffuse effects on IVOL in those markets. Overall, the cross-country evidence supports our interpretation that Japan's monetary and fiscal regime, combined with its corporate and financial market structure, magnifies the transmission of policy uncertainty into firm-specific volatility.

Table 10. Country-specific policy uncertainty and institutional characteristics.

Country	Equity index	Monetary policy regime	Fiscal policy features	Financial market characteristics
Japan	Nikkei 225	Prolonged unconventional policy; zero/negative rates; yield curve control; large-scale asset purchases	High government debt; repeated stimulus packages; sizeable public investment; debates about consumption tax hikes and fiscal consolidation	Deep and liquid equity market; strong bank–firm linkages; high export and energy dependence; high foreign investor participation
United States	S&P 500	Conventional interest-rate targeting; large but episodic QE; no YCC	Discretionary fiscal stimulus during crises; regular debt ceiling negotiations	Very deep equity and corporate bond markets; broad investor base; high financialization
Germany	DAX 30	ECB monetary policy; negative rates only in later part of sample; no country-specific YCC	Fiscal rules ("debt brake"); relatively conservative fiscal stance; exposure to euro-area institutional uncertainty	Large, export-oriented firms; high exposure to euro-area policy and global trade cycles
India	NIFTY 50	Inflation-targeting regime; conventional rate-setting; no QE/YCC for most of sample	Large role of government expenditure and subsidies; evolving tax system (e.g. GST introduction)	Rapidly developing but shallower capital markets; capital controls and varying foreign ownership limits
Indonesia	IDX Composite	Policy rate as main instrument; occasional exchange rate and macroprudential interventions	Ongoing fiscal reforms; infrastructure spending; commodity-related revenue dependence	Less deep equity market; higher exposure to commodity-price and exchange rate shocks; more limited foreign participation

8. Conclusion, research limitations, and future directions

8.1. Conclusion

This paper has examined how multidimensional policy-related uncertainty affects firm-specific risk in Japan as measured by idiosyncratic volatility (IVOL). We construct a composite uncertainty index from seven policy domains (economic, fiscal, monetary, trade, exchange rate, energy-related, and geopolitical) and summarize it using three alternative approaches: linear principal component analysis (PCA), nonlinear kernel PCA (KPCA), and a long short-term memory (LSTM) autoencoder. The framework is applied to monthly data for Nikkei 225 firms over the period 2000–2023.

The results show that policy-related uncertainty is a statistically and economically significant driver of firm-level volatility. All three composite indices are positively associated with IVOL, but the LSTM-based index provides the strongest fit: a one-unit increase in this index is associated with roughly a 0.31% rise in idiosyncratic volatility, and the corresponding adjusted R^2 exceeds those of the PCA- and KPCA-based specifications. This supports the view that uncertainty dynamics are nonlinear and state-dependent, and that sequence models are better suited than static linear projections for capturing their impact on firm-specific risk.

To address the usual "black-box" concern surrounding deep learning, we employ SHAP-based decompositions. These reveal that economic and fiscal policy uncertainty, monetary policy uncertainty, and geopolitical risk are the dominant contributors to the LSTM-based index, and trade, exchange rate, and energy-related uncertainty play more moderate but still nonnegligible roles. Heterogeneity analysis across sectors, firm size, and profitability further shows that trade- and energy-intensive sectors, smaller firms, and low-ROE firms are particularly sensitive to specific uncertainty channels. Thus, the latent LSTM index can be linked back to economically interpretable transmission mechanisms rather than treated as a purely statistical construct.

A comprehensive set of robustness checks reinforces these findings. The core results are stable when IVOL is re-estimated using an EGARCH specification, when we vary the lag structure, and when we split the sample into pre- and post-2008 subperiods. A cross-country extension to the United States, Germany, South Korea, India, and Indonesia confirms that policy uncertainty is positively related to IVOL in all markets considered, with Japan lying toward the upper end of the distribution of coefficients. Overall, the analysis bridges traditional econometrics and modern machine learning by combining panel regressions, nonlinear index construction, and explainable AI, and shows that multidimensional policy uncertainty is a key component of firm-specific risk in Japan.

8.2. Limitations and future research

Despite these contributions, several limitations remain, which also point to avenues for future work.

First, the firm-level sample is confined to constituents of the Nikkei 225. These large, liquid, blue chip firms cover an important segment of the Japanese market but do not represent the broader population of small and mid-cap firms, which typically exhibit higher volatility, greater financing frictions, and more pronounced sensitivity to shocks. The estimated uncertainty–IVOL relationship may therefore be conservative for the full Tokyo Stock Exchange universe. Extending the analysis to include mid- and small-cap stocks, and formally comparing size-based subsamples, would allow for a more complete assessment of how policy uncertainty propagates across the market-capitalization spectrum.

Second, the cross-country robustness exercise, although informative, covers only a limited set of institutional environments. Japan is best interpreted as a rich case study of a persistent unconventional policy regime rather than a global benchmark. Future research could build a multicountry panel that combines markets with different monetary and fiscal frameworks, degrees of financial development and capital account openness. Such a design would permit explicit testing of how institutional features condition the strength of the uncertainty–IVOL channel.

Third, the uncertainty measures used in this study are based on news- and text-based indices. These capture an important manifestation of policy-related risk but do not exhaust the space of relevant uncertainties. Option-implied volatility, survey-based expectations, firm-level textual disclosures, and indices of climate, cyber, or supply chain risk could complement the existing indices and help refine the interpretation of the latent uncertainty factor. A natural extension would be to construct a higher-dimensional “risk map” that nests these additional sources of uncertainty alongside the policy indicators employed here.

Fourth, the modelling choices—PCA, KPCA, and an LSTM autoencoder—capture linear, nonlinear, and temporal structure, but they are not unique. On the econometric side, time-varying parameter models, Markov-switching regressions, or state-space frameworks could be used to study how the impact of uncertainty on IVOL evolves over business and policy cycles. On the machine-learning side, transformer-based sequence models or hybrid architectures that jointly process macrofinancial variables (such as interest rates, credit spreads, inflation, and exchange rate volatility) together with the uncertainty indices may yield an even richer representation of the environment in which firm-level risk is generated. Complementary explainability tools (e.g. local interpretable model-agnostic explanations (LIME), integrated gradients, or attention-based explanations) could be employed alongside SHAP to further probe how complex models process uncertainty shocks.

Finally, our focus is deliberately on idiosyncratic volatility and a limited set of firm characteristics (size, leverage, valuation, and profitability). We do not explicitly model the interaction between

IVOL and systematic risk, nor do we explore in depth how governance structures, ownership patterns, disclosure quality, or managerial behavior shape firms' exposure to uncertainty. Future work could extend the framework to study how policy uncertainty feeds into aggregate market volatility, sectoral contagion, and cross-firm spillovers—particularly in crisis episodes—using network-based or multilevel volatility models. Incorporating a broader range of firm attributes and behavioral finance variables would also help explain why ostensibly similar firms sometimes react very differently to the same policy news.

Addressing these limitations would deepen the theoretical and empirical understanding of the uncertainty–IVOL channel and provide more finely targeted tools for investors, policymakers, and corporate decision-makers operating in an increasingly complex and uncertain environment.

Author contributions

All authors contributed equally to the conception and design of the study, data collection, analysis, and interpretation of results. All authors were involved in drafting the manuscript and revising it critically for important intellectual content.

Use of AI tools declaration

The authors declare that generative Artificial Intelligence (AI) tools were used solely to improve the language and clarity of the manuscript. No AI tools were used for content generation, data analysis, or interpretation. All scientific work, tables, and findings were created and validated exclusively by the authors.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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Supplementary Material

Appendix 1. Implementation details

LSTM autoencoder model setup:

To construct a nonlinear policy uncertainty index, we train a sequence-to-sequence long short-term memory (LSTM) autoencoder on the seven monthly policy uncertainty series,

$$U_t = (\mathrm{EPU}_t, \mathrm{FPU}_t, \mathrm{MPU}_t, \mathrm{TPU}_t, \mathrm{ERPU}_t, \mathrm{ERU}_t, \mathrm{GPR}_t)',$$

where $t = 1, \ldots, T$ indexes months. Before estimation each series is standardized to zero mean and unit variance.

Input construction. Rather than learning from one-month snapshots, the autoencoder takes short histories of length $L = 10$ months as input. For month $t \geq L$, we define a sliding window

$$X_t = (U_{t-L+1}, \ldots, U_t) \in \mathbb{R}^{L\times 7},$$

so that the sample consists of $T - L + 1$ sequences $\{X_t\}_{t=L}^{T}$. We split these sequences chronologically into an 80% training set and a 20% validation set. This preserves the time ordering and avoids look-ahead bias.

Network architecture. The autoencoder has a *two-layer encoder* and a *two-layer decoder*. On the encoder side:

- Input layer: sequence of shape $(L, 7)$.
- LSTM layer 1: 64 units, `return_sequences = True`, dropout rate 0.2.
- LSTM layer 2: 64 units, `return_sequences = False`, dropout rate 0.2.
- Dense latent layer: 8 units with linear activation, providing an 8-dimensional latent representation $z_t \in \mathbb{R}^8$.

The decoder mirrors this structure:

- `RepeatVector`: repeats z_t across L time steps.
- LSTM layer 1: 64 units, `return_sequences = True`, dropout rate 0.2.
- LSTM layer 2: 64 units, `return_sequences = True`, dropout rate 0.2.
- Time-distributed dense output layer: 7 units with linear activation, producing the reconstructed sequence $\widehat{X}_t \in \mathbb{R}^{L\times 7}$.

All LSTM layers use the standard LSTM internal activations (tanh for the cell state and sigmoid gates).

Loss function and optimization. The model is trained to minimize the mean squared reconstruction error

$$\mathcal{L} = \frac{1}{(T-L+1)L\cdot 7}\sum_{t=L}^{T}\sum_{l=1}^{L}\sum_{k=1}^{7}(X_{t,l,k}-\widehat{X}_{t,l,k})^2.$$

We use the Adam optimizer with learning rate $\eta = 0.001$, batch size of 32, and a maximum of 40 epochs. To mitigate overfitting, we employ dropout (rate 0.2) in all hidden LSTM layers and adopt *early stopping*: training is terminated if the validation loss does not decrease for three consecutive epochs, and the weights from the epoch with the lowest validation loss are restored. Random seeds for NumPy and TensorFlow are fixed to enhance reproducibility.

LSTM-based uncertainty index. After training, each input sequence X_t is passed through the encoder to obtain its latent vector z_t. We use the first latent component, rescaled to zero mean and unit variance,

$$\text{LSTMUI}_t = \frac{z_{t,1}-\bar{z}_1}{\sqrt{\text{Var}(z_{1,1},\ldots,z_{T-L+1,1})}},$$

as our LSTM-based uncertainty index. Sections 4 and 4.3 show that this index explains idiosyncratic volatility more strongly than linear PCA and KPCA benchmarks.

Training and validation loss. Figure 7 reports the evolution of the training and validation mean squared error across epochs. The validation loss declines initially and then stabilizes; the vertical dashed line marks the early-stopping epoch. The absence of pronounced divergence between training and validation loss suggests that the chosen architecture and regularization are adequate for our application.

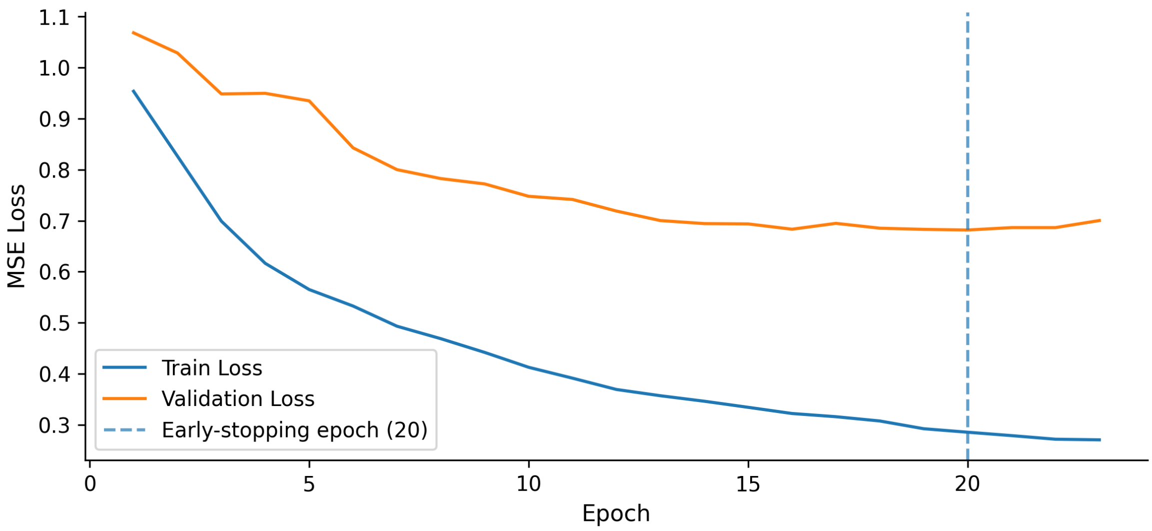

Figure 7. LSTM autoencoder training and validation loss.

Note: The figure plots the mean squared reconstruction error on the training and validation sets across epochs. The vertical dashed line marks the early-stopping epoch, beyond which additional training does not improve validation performance.

Appendix 2. Technical implementation of the SHAP decomposition

This appendix provides the technical details underlying the SHAP decomposition discussed in Section 4.3. Let LSTMUI_t denote the LSTM-based uncertainty index at month t, and let $U_t = (U_{1,t}, \ldots, U_{7,t})'$ be the corresponding vector of standardized policy uncertainty measures (EPU, FPU, MPU, TPU, ERPU, ERU, and GPR).

Following standard practice for interpreting nonlinear deep-learning models, we approximate the mapping $U_t \mapsto \text{LSTMUI}_t$ using a surrogate random forest regressor,

$$\text{LSTMUI}_t = f(U_t) + \varepsilon_t,$$

where $f(\cdot)$ is estimated using 200 trees, the mean squared error split criterion, and bootstrap-based ensemble averaging. All seven inputs are standardized to zero mean and unit variance.

We compute SHAP values using the `TreeExplainer` algorithm. For each observation t and each policy uncertainty dimension $k \in \{1, \ldots, 7\}$, the SHAP value $\phi_{k,t}$ decomposes the fitted value $f(U_t)$ into additive contributions,

$$f(U_t) = \phi_0 + \sum_{k=1}^{7} \phi_{k,t},$$

where ϕ_0 is the model baseline (expected prediction under the training distribution). The SHAP value $\phi_{k,t}$ measures the marginal effect of uncertainty dimension k on the predicted LSTM-based index at time t, holding all other uncertainty dimensions at their background distribution.

Global feature importance is summarized using the mean absolute SHAP values,

$$I_k = \frac{1}{T - L + 1} \sum_{t=L}^{T} |\phi_{k,t}|,$$

which we normalize so that $\sum_{k=1}^{7} I_k = 1$. These normalized values correspond precisely to the percentages plotted in Figure 2 and are used to assess the relative contribution of each policy uncertainty dimension to the LSTM-based index.

This surrogate modelling framework allows for a transparent and computationally efficient decomposition of the LSTM latent factor into its underlying drivers while preserving the flexibility of the original sequence model.