Climate Stress Testing Vietnamese Banks Using a Blended Modeling and Scenario Based Approach

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Abstract

The determinants of bank failure are well researched, and a number of important balance-sheet indicators of bank health have been found and are widely in use by regulators and investors when evaluating the risks banks face. It is less clear how to integrate large-scale macroeconomic risks, including the effects of climate shocks, into these well-studied models. To bring these approaches together, we use a blended modeling approach that combines scenario-based macroeconomic modelling with a longitudinal model of bank non-performing loans (NPL). By transforming climate scenarios into a set of macroeconomic shocks, we stress test the change in the NPL ratios of 29 Vietnamese banks. We identify several individual Vietnamese banks that appear at greater risk to climate-induced macroeconomic shocks.

Keywords

Climate stress testing; DSGE; Bayesian hierarchical modeling; Vietnamese banking; CAMELS analysis; Scenario-based modeling

JEL Classification

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F47, G21, G28, Q54

I. Introduction

Accurate identification and measurement of risk factors facing financial sector institutions, particularly banks, is of obvious importance to a wide variety of stakeholders. The banking system plays a key economic role at all stages of the business cycle, serving either as an engine of economic growth or as ground zero for financial crises that damage growth (Ongore and Kusa, 2013). Given the potential downside risk, early identification of weak banks for additional regulatory scrutiny is desirable.

In Vietnam, the banking sector fills both of these roles, on one hand accounting for 16-18% of annual Vietnamese GDP (Stewart, Matousek & Nguyen 2016), while on the other contributing to economic instability via under capitalization and excess non-performing loans (Le and Law, 2017). Since the “Doi Moi” market reforms in 1986, Vietnam has enjoyed an average annual GDP growth rate of over 6%. The Vietnamese banking sector transformed over this period, introducing specialized state owned banks, joint-stock commercial banks, and foreign banks into the once-centralized system. During these economic good times, banking oversight loosened, leading to increasingly weak balance sheets and riskier investments, especially among loans issued to state-owned enterprises (Katagiri, 2019). This culminated in a “near-crisis” in 2012, that saw arrests and fines for top bank executives, as well as new banking oversight and regulation. This episode highlights the need for early warning systems in the Vietnamese banking sector.

Financial early warning systems have a rich literature, stretching back at least to Altman (1968), who used logistic regression to predict bank failure as a function of financial ratios. Since then, a wide variety of statistical methodologies and financial ratios have been explored; see Liu et al. (2021) for an exhaustive review. One popular technique is to use financial variables that proxy for CAMELS factors. Developed by the Federal Reserve in the mid-1990s, the CAMELS components -- capitalization, asset quality, management, earnings, liquidity, and sensitivity to market risk -- are thought to summarize the financial health of a bank. In the United States this is true by definition, as secret CAMELS scores are used by regulators to decide whether to close problem banks. Outside of the US, the CAMELS framework has also been applied as an early warning system with success.

Despite the power and popularity of the CAMELS rating system to predict bank failure, the framework does not provide researches an obvious way to integrate risk from a wide variety of exogenous shocks. Consider climate risk; how would an increased propensity for extreme weather events affect bank health? It is likely that it would. Banks and their customers hold physical capital assets at risk of damage or destruction, driving otherwise healthy loans into non-performing status. The physical capital of the banks themselves would potentially be at risk. But how would these effects appear in the balance sheet factors proposed by CAMELS? On cursory inspection, it is not clear how.

To address this limitation, we extend the CAMELS framework to include a suite of macroeconomic factors, including GDP, household consumption, investment, terms of trade, interest rates, inflation, the VND/USD exchange rate, and the stock of physical capital. These factors were chosen for two reasons. First, there is a clear connection between large-scale climate shocks like typhoon and flood and macroeconomic disruption. Second, these indicators are all common outputs from nearly all macroeconomic models, for example Dynamic Stochastic General Equilibrium (DSGE) models in the spirit of Smets and Wouters (2003).

Adding these factors effectively allows the problem to be split in two integrable parts. First, we develop and estimate a model of bank NPL ratios that includes macroeconomic factors. Second, we use a macroeconomic model to produce disaster scenarios to generate post-shock macroeconomic trajectories. Using the NPL model, these trajectories can be converted to estimates of bank impacts, conditioned on pre-shock bank balance sheets, as represented by CAMELS factors.

The addition of macroeconomic factors poses challenges for CAMELS modeling. These factors are shared by all banks, meaning it is not possible to apply common maximum likelihood longitudinal estimation techniques, such as the within estimator. To avoid numerical issues arising from perfect autocorrelation between unobserved effects and individual-invariant effects, we apply Bayesian hierarchical models (Gelman et al. 2014). Aside from allowing the inclusion of bank-invariant macroeconomic time series in the estimation, these techniques also allow for the estimation of bank-specific slopes, as well as the usual bank-specific intercepts (“fixed effects”). Together with strong prior regularization, such a model allows policymakers and stakeholders to explore heterogeneity in the response of various banks to a given macroeconomic shock.

Using a hierarchical Bayesian model to estimate the effect of CAMELS ratios and macroeconomic variables also has the effect of allowing us to credibly propagate uncertainty through our models. DSGE models are also estimated using full-information Bayesian techniques, producing posterior estimates of so-called “deep parameters” that can be used to generate posterior distributions over post-shock macroeconomic trajectories. These distributions can be fed into our NPL model, combining the uncertainty from the macroeconomic model with uncertainty from the NPL model. As a result, our mixed approach is fully transparent, and does not over- or under-state the strength of the evidence for bank-level risk exposures to a given scenario.

Our paper is not the first to use DSGE models to examine climate shocks, nor the first to estimate Vietnamese bank health using longitudinal regression, but we are, to our knowledge, the first to fuse these two models. When examining rare shocks, such as hurricanes, macroeconomists have typically made the shocks endogenous, as in Keen and Pakko (2011) and Farhi and Gabaix (2008). Not only are these approaches are computationally onerous (see Levinthal 2017 and Maih 2015), but they also rest on the assumption that rational agents internalize risks from 1-in-100 or 1-in-500 year shocks and plan their consumption choices accordingly. Evidence from behavioral experiments suggests that these horizons, exceeding even one-in-a-lifetime, far exceed the planning horizon of most humans. Benartzi and Thaler (1995), for example, memorably noted that investors acted as if their planning horizons were only 1 year. On the subject of disasters, Meyer and Kunreuther’s 2017 book, *The Ostrich Paradox*, give multiple examples of how people fail to prepare adequately for rare events, and trace them back to well-studied biases in behavioral economics. Fully bringing rare disasters into models, then, might very well serve to understate their harmful economic potential.

To implement the cognitive bias of agents who fail to account for rare events, and to avoid computational difficulties associated with estimating rare-event models, we elect to take a scenario-based approach to rare disaster effect estimation. We build and estimate an open economy DSGE model of Vietnam model without disaster shocks. Post-estimation, we introduce these shocks. Using disaster risk models developed for use in Vietnam, we estimate the direct macroeconomic effects of a specific event: a 1-in-100 year flood in downtown Hanoi. We then convert these damage estimates into percentage shocks to national Vietnamese output, capital stock, imports, and exports. These shocks are used to run Bayesian impulse response functions (IRF). Finally, the resulting trajectories are passed back to the NPL model to estimate the potential impact of the event on bank health.

II. Literature Review

CAMELS analysis has been applied to Vietnamese banks as well. Le and Law (2017) rank Vietnamese banks in each CAMELS dimension to see which Vietnamese banks are relatively more or less healthy. Nguyen and Liu (2019) use CAMELS ratings as a dependent variable, measuring bank health, and run logistic regression to search for financial ratios and macroeconomic variables that explain financial health, so measured. Nguyen and Dang (2020) use CAMELS ratios in a dynamic panel regression of loan growth, allowing them to explore the role of the six factors on bank lending behavior.

None of these studies take up the question of crisis detection via early warning systems as such. This is partly due to data limitations. Early-warning type studies using US data, such as Le and Viviani (2018) or Jing and Fang (2018), use large cross-sectional datasets with bank failure as the dependent variable. In stark contrast to the competitive US banking market, the Vietnamese market remains dominated by state-owned banks, with significant barriers to entry and exit (Kovsted et al. 2003). As a result, there is no heterogeneous pool of banks, with a subset of failures, to study.

Despite this data limitation, it is still possible to evaluate bank failure risk using a proxy measure of bank health. Nguyen et al. (2018) assess Vietnamese bank risk using the non-performing loan (NPL) ratio. The NPL ratio is a natural candidate, given the 2012 crisis and the emphasis Vietnamese supervisory authorities put on this ratio. In 2013, decree No. 53/2013/ND-CP established the Vietnam Asset Management Company (VAMC), a state-owned clearinghouse for bad loans. The mission of the VAMC, to purchase toxic assets from credit institutions. More recently, document No. 6561/NHNN-TTGSNH, issued to banking and credit institutions in response to the COVID epidemic, called on banks to limit their NPL ratio to under 3%. The very existence of the VAMC creates a moral hazard problem, whereby bad loans written by banks become public liabilities. Vietnamese policy makers thus have a first order reason to control the NPL ratio – financial system stability – as well as a second order reason. These factors make the NPL ratio a natural choice for measuring risk to the Vietnamese banking sector.

A second limitation of previous studies using CAMELS ratios in a regression framework has been a lack of analysis at the level of the individual bank. The econometric approach of choice in this literature has been dynamic panel analysis, which produces risk estimates common to all banks. This is in contrast to non-parametric analysis, such as the CAMELS analysis performed by Le and Law (2017), or Data Envelopment Analysis studies, such as Huang (2007), Vu an Turnell (2010), or Steward et al. (2016). Bank-level analysis is valuable to policymakers, as it can help to allocate limited supervisory resources to institutions in accordance with their risk profiles.

With respect to macroeconomic modeling, several DSGE models of the Vietnamese macroeconomy have been developed, recently Nugyen (2021). This model includes the usual New Keynesian frictions made common by Smets and Wouters (2003): price stickiness, investment adjustment costs, and under-utilization of capital. It extends the usual model to include international trade by considering Vietnam as a small open economy. Given the important role that trade and international investment have played in the economic growth of Vietnam at least since 2000 (Nguyen 2020), including open economy dynamics is essential. Furthermore, given the role of the financial system in facilitating international trade and investment, it stands to reason that shocks to trade might have important spillovers to bank health.

III. Data

We seek to measure the sensitivity of Vietnamese banks to changes in CAMELS factors and macroeconomic conditions. For each CAMELS factor, we construct a balance sheet ratio that serves to proxy for that factor. Balance sheet data for 29 banks was provided by FiinGroup. Table 1 shows a list of banks included in this study, sorted by total assets, along with the legal status of the bank. With the exception of the Vietnam Bank for Agriculture and Rural Development, all banks in our sample are joint-stock banks. No foreign branch banks are included in our study.

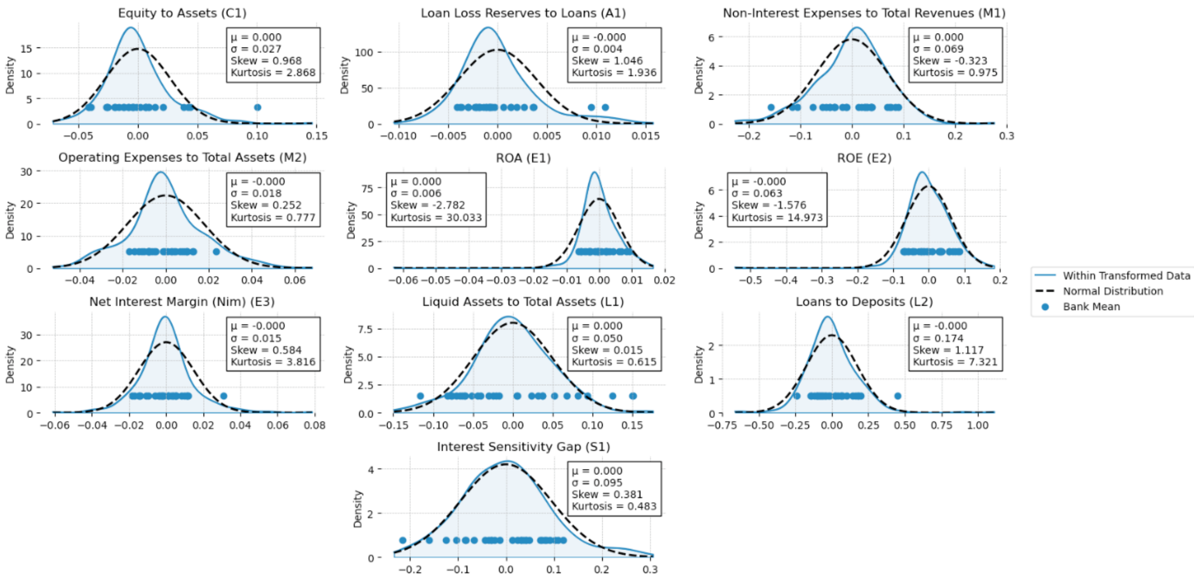
The ratios we use are taken from Nguyen and Dang (2020), and include equity to assets (capital adequacy), loan-loss reserves to total loans (asset quality), return on equity (earnings), liquid assets to total assets (liquidity), and difference between interest-sensitive assets and liabilities to total assets (sensitivity). Like these authors, we consider three possible metrics for earnings: return on assets, return on equity, and the net-interest margin, as well as two metrics for liquidity: liquid assets to total assets, and loans to deposits.

Table 1: Vietnamese banks included in our sample, sorted by total assets in 2020.

Size Rank (2020)	**Bank**	**Ticker**	**Total Assets (Billion VND, 2020)**
1	Vietnam Bank for Agriculture and Rural Development	AGRB	1,568,126.91
2	Joint Stock Commercial Bank for Investment and Development of Vietnam	BID	1,516,685.71
3	Vietnam Joint Stock Commercial Bank for Industry and Trade	CTG	1,341,436.47
4	Joint Stock Commercial Bank for Foreign Trade of Vietnam	VCB	1,326,230.09
5	Sai Gon Commercial Joint Stock Bank	SCB	633,796.97
6	Military Commercial Joint Stock Bank	MBB	494,982.16
7	Saigon Thuong Tin Commercial Joint Stock Bank	STB	492,516.03
8	Asia Commercial Joint Stock Bank	ACB	444,530.10
9	Vietnam Technological and Commercial Joint Stock Bank	TCB	439,602.93
10	Vietnam Prosperity Joint Stock Commercial Bank	VPB	419,026.53
11	Saigon-Hanoi Commercial Joint Stock Bank	SHB	412,679.59
12	Ho Chi Minh City Development Joint Stock Commercial Bank	HDB	319,127.48
13	Vietnam International Commercial Joint Stock Bank	VIB	244,675.68
14	Lienviet Post Commercial Bank	LPB	242,342.95
15	Tien Phong Commercial Joint Stock Bank	TPB	206,314.59
16	Southeast Asia Commercial Joint Stock Bank	SSB	180,207.29
17	Vietnam Maritime Commercial Joint Stock Bank	MSB	176,697.62
18	Vietnam Export Import Commercial Joint Stock Bank	EIB	160,435.18
19	Orient Commercial Joint Stock Bank	OCB	152,528.88
20	Nam A Commercial Joint Stock Bank	NAB	134,315.20
21	North Asia Commercial Joint Stock Bank	BAB	117,189.39
22	An Binh Joint Stock Commercial Bank	ABB	116,366.98
23	Vietnam Thuong Tin Commercial Joint Stock Bank	VBB	91,505.11
24	National Citizen Commercial Joint Stock Bank	NVB	89,601.24
25	Viet A Commercial Joint Stock Bank	VAB	86,537.43
26	Ban Viet Bank	BVB	61,101.56
27	Kien Long Commercial Joint Stock Bank	KLB	57,281.99
28	Petrolimex Group Commercial Joint Stock Bank	PGB	36,153.02
29	Saigon Bank for Industry and Trade	SGB	23,942.79

Figure 1 shows distributions and summary statistics for all CAMELS ratios considered. Three ratios, non-interest expenses to total revenues, loans to deposits, and the interest sensitivity gap, appear roughly normally distributed. Other variables show evidence of heterogeneity between banks. Equity to assets, loan loss reserves to loans, operating assets to total assets, and NIM, for example, have several bank means skewed to the right, suggesting that these variables do not share a common distribution, at least for some banks.

Figure 1: Summary statistics and sample distributions for within-transformed CAMELS factors, $\hat{x}_{i,t} = x_{i,t} - \bar{x}_i$ with cross-sectional (between-transformed) means, $\hat{x}_i = \bar{x}_i - \bar{x}$, with normal distribution fit via MLE to the pooled data.



In addition to CAMELS ratios, we are also interested in macroeconomic risk factors facing Vietnamese banks. To measure this, we include nine macroeconomic variables, including GDP, imports, exports, inflation, household consumption and investment, the national capital stock, CPI inflation, the VND/USD exchange rate, and the policy interest rate. To expose only the innovations in these economic time series, we follow data preparation procedures common to the macroeconomic literature. Non-rate variables were first logged, then de-meaned and de-trended using a simple OLS regression, rendering all variables stationary, expressed in percent change from the sample mean. Importantly, these transformations render the observed time series consistent with the outputs of a log-linearized DSGE model, allowing conditional posterior predictive samples from a DSGE to be used in place of observed data.

As a final preprocessing step, we scaled all independent variables by subtracting the pooled mean and pooled standard deviation so that all variables have a mean of 0 and standard deviation of 1. This is known to assist in numerical stability when estimating posterior distributions via MCMC and assists in the selection of prior distributions over parameter values by removing the scale of the variable. The sample mean and standard deviation were saved to allow transformation of posterior predictive DSGE outputs in the same fashion.

To select a final model with identified parameters, a single CAMELS specification, with a single variable representing each factor, needs to be selected. Nguyen and Dang (2020) consider several candidate factors, and we adopt the same list as well. This includes two possible measures of management quality, three measures of earnings, and two measures of liquidity. Within each factor, the potential candidates are highly correlated, so that including multiple ratios for a single factor would result in a poor identification of the NPL risk associated with that factor. The correlation matrix among CAMELS factors is shown in the online appendix.

There are extremely strong pairwise correlations among the nine macroeconomic time series we consider. All components of GDP – consumption, investment, imports, and exports – are mechanically linked via accounting identity. In additional, the Taylor rule followed by the monetary authority immediately suggests a linear-quadratic linkage between the interest rate, inflation, and potentially GDP and the exchange rate. Macroeconomic theory also expects a link between inflation and the exchange rate (via Purchasing Power Parity), and between investment and interest rates (via the Euler equation describing household consumption trajectories). As a result, identification of the response of the NPL ratio to changes in any one of these factors is not possible.

To include a maximum amount of macroeconomic information without facing confounding in our identification, we use principal component analysis (PCA) to construct orthogonal linear combinations of the nine available time series. Of the nine principal components available, we include the first four in our model. These four components account for 95% of the variance in the data. In addition, the effective rank of the covariance matrix between all macroeconomic factors, as defined by Roy and Vetterli (2007), is 3.77. Figure 2 shows the first four components, along with the weights associated with that component.

Figure 2: First four PCA components of macroeconomic time series. Time series were first log transformed (when necessary) then detrended using OLS: $\hat{y}_t = \alpha + \gamma t + \epsilon_t$. Residuals were then scaled by their standard deviation so that all time series were mean zero and standard deviation 1. PCA was performed on the resulting covariance matrix. The four components shown are associated with the four largest eigenvalues, together accounting for 95% of total variance in the untransformed data.

Based on the weights associated with each component shown in figure 2, a rough economic interpretation of each component is possible. The first component is primarily built from negative national account variables. The second is built from prices, inflation and the exchange rate, moderated by the interest rate. The third and fourth components are less clear. The third component appears related to the law of motion of capital, relating investment and capital stock, but also includes the exchange rate. The inclusion of the exchange rate in the law of motion of capital is consistent with a rapidly developing economy like Vietnam, with significant inflows of foreign capital funding industrial expansion, reflected in fixed capital formation. The fourth component links interest rates and the capital stock. Thus, whereas the third component links the price of foreign capital to investment, the fourth links the price of domestic capital to investment.

Many studies of bank health using CAMELS ratios include a lag of the dependent variable. This should only be necessary if there is evidence of autocorrelation in in dependent variable, after conditioning on regression covariates, including (potentially) a deterministic trend. Figure 3 plots the time series of NPL ratios for all 29 banks in our sample. It is not at all obvious on inspection that is significant unconditional autocorrelation in the NPL ratio, especially after 2013-2014 and the establishment of the VAMC. We present autocorrelation and partial-autocorrelation plots for all the banks in the online appendix. Applying the Ljung-Box test, we find that only three banks - BID, TCB, and VCB - have significant autocorrelation at the first lag at a 1% level of significance. Four more – ACB, MBB, TPB, and VPB – are significant at the 5% level of significance. Testing the OLS residuals from a constant-trend model of NPL ratio, however, we find that no banks have significant autocorrelation at the first lag.

As an additional robustness check, we also consider all possible combinations of macroeconomic covariates such among all included variables, no pair has a correlation greater than 0.2 in absolute value. To choose the best model, we use the Pareto-smoothed importance sampled leave-one out (PSIS-LOO) cross validation metric of Vehatri et al. (2016). The LOO score provides a fully Bayesian approximation of a model's ability to generalize to new data, similar to the Frequentist AIC and BIC statistics. The list of considered models, along with their PSIS-LOO values, is provided in the online appendix. Using this methodology, the best model included three variables: household consumption, inflation, and the USD/VND exchange rate. These three variables correspond to the four components identified by PCA. While using this specification would be more interpretable, it would sacrifice some of the richness in macroeconomic dynamics that could be used in climate stress testing. Primarily for this reason, we choose the somewhat more opaque PCA components for our primary specification.

To select between CAMELS specification, we directly compare the goodness-of-fit for each possible specification, given the variables presented in figure 1. Using the model specification described in (3), we fit all combinations of CAMELS specifications, 12 models in total, and compare the resulting PSIS-LOO scores. All models include the first four principal components of the macroeconomic time series shown in figure 6.

Table 2 shows the LOO scores for each model. So measured, the difference between the CAMELS specifications is extremely marginal, with only a 16 point difference between the best and worst specification. Given that the standard error of the best model is 22 points, all of the models can be considered statistically equivalent. As a result, we choose to select the model ranked 8th by the LOO. This is because, per figure 4, this combination of variables has the lowest amount of confounding between the exogenous covariances, avoiding high pairwise correlations between L_2 and S_1, as well as between M_1 and S_1 or E_1.

IV. Modeling and Prior Selection

A significant contribution of this paper is to use a hierarchical Bayesian model to model bank-specific slopes and intercepts. We begin by assuming that the NPL ratio is logit-normal distributed in logit space with mean $\mu_{i,t}$ and standard deviation σ_{NPL}, or $NPL_{i,t} \sim Logistic^{-1}\left(N\left(\mu_{i,t}, \sigma_{NPL}\right)\right)$. We choose the logit-normal distribution because it has support on the unit interval, and because it allows us to model the variance of the NPL ratio as independent of the mean.

We model the mean of the NPL ratio as a linear function of a constant, trend, CAMELS ratios, macroeconomic variables as follows:

$$\mu_{i,t} = \alpha_i + \gamma_i \cdot t + CAMELS_{i,t-1}\beta_i + MACRO_t\, \delta_i \qquad (1)$$

We follow the timing convention of Nguyen and Dang (2020), who, like Adesina (2019), Ben Naceur et al. (2018), and Roulet (2018), assume that CAMELS ratios enter with a lag, while macroeconomic environment enters contemporaneously. This assumes that bank managers are not able to respond to changes in their balance sheets in real-time. On the other hand, they do observe the current business climate, although perhaps imperfectly, and respond accordingly.

Estimation of a unique intercept, trend, and slope coefficients for each bank is infeasible in the standard OLS framework, as it requires estimation of $\left(n_{coef} + 2\right) \times n_{banks}$ parameters. For large-N small-T panel data sets, this value may exceed the number of observed datapoints, but even in cases when $T > \left(n_{coef} + 2\right) \times n_{banks}$, the model is certain to be over-specified. Hierarchical models circumvent this model via partial pooling of parameters values. We assume that each parameter for each bank is drawn from a common distribution with the following prior structure:

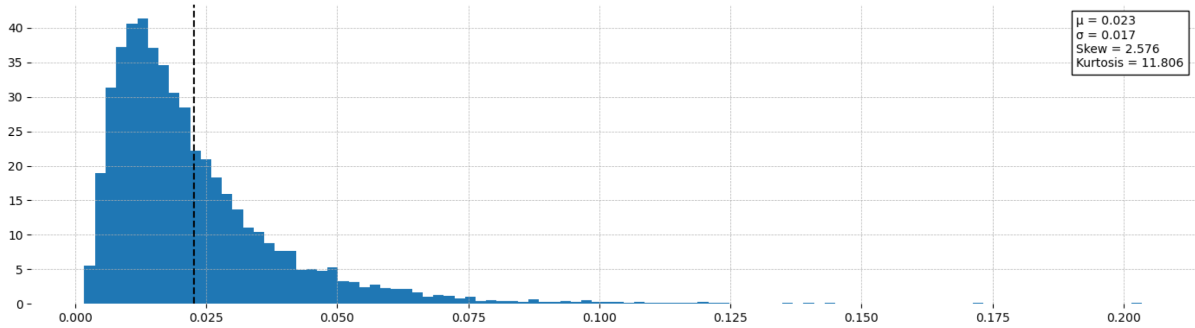
$$\begin{aligned} \mu_{\beta_j} &\sim N(0, 0.5) \\ \sigma_{\beta_j} &\sim Gamma(2, 4) \\ \beta_{j,i} &\sim N\left(\mu_{\beta_j}, {\sigma_{\beta_j}}^2\right) \end{aligned} \tag{2}$$

μ_{β_j} and σ_{β_j} are so-called hyperpriors. This hierarchical structure "shrinks" all estimates of β_j towards the group mean μ_{β_j}, which is itself centered on zero. As a result, although we estimate individual parameters for each bank, the value of these parameters are informed by data from all banks, through the estimation of the group mean and group standard deviation. If the data support significant heterogeneity in parameter estimates, this can be accommodated via larger values of σ_{β_j}. On the other hand, if NPL response to a given covariate is heterogeneous across banks, the estimate for each bank will be drawn towards the common effect, μ_{β_j}. For an exhaustive treatment of this class of models, see Gelman et al. (2014).

The mean and standard deviation of μ_{β_j} are not estimated. We center all slopes, as well as the time-trend, on zero. This is consistent with the typical econometric null hypothesis of no effect. The bank intercepts were centered on -4, which corresponds to a prior expected NPL ratio of 1.8%. Although the NPL ratio is mathematically constrained on the unit interval, it is not economically possible for a bank with an NPL ratio above 10-20% to survive. We therefore use the mean parameter to pull posterior estimates towards the lowest range of the support. This is consistent with the observed data, which has a pooled average NPL ratio of 2.1%, and a maximum value of 8.8%. The standard deviation of 0.5 allows for the marginal effect of a standard-deviation shock in a covariate to cover essentially the entire range of economically feasible NPL ratios, not ruling out any sensitivities a priori.

Figure 3 plots prior NPL ratios for an orthogonal one-sigma covariate shock, given $\alpha \sim N(-4, 0.5)$ and $\beta \sim N(0, 0.5)$. The mass of the prior response distribution is below the empirical maximum NPL ratio, while extreme outliers responses are not ruled out. Such priors are called "weakly informative" by Gelman et al. (2015); it is, "set up so that the information it does provide is intentionally weaker than whatever actual prior knowledge is available." In our case, it is almost certainly an economic impossibility that a 1-standard deviation change in, for example, the equity to assets ratio ($\sigma = 4\%$), could result in an NPL ratio of 20%. Our prior choices nevertheless allow for this possibility, while biasing the model towards much more modest parameter values.

Figure 4: Prior distribution over NPL ratio given a one-sigma shock to a single covariate, represented as $Logistic^{-1}(\alpha + \beta)$, with $\alpha \sim N(-4, 0.5)$ and $\beta \sim N(0, 0.5)$. Prior predictive NPL ratios are shown on the x-axis, as a fraction of total loans. The mean of the prior predictive distribution is marked with a dashed line.



Our choice of hierarchical standard deviation, $\sigma_{\beta_j} \sim Gamma(2, 4)$, is likewise weakly informative. As noted in Chung et al. (2013), estimates of group-level parameter bank variance are noisy and often zero when the number of groups is small. In our case, with only 29 banks, we wish to bias the model away from estimates of zero group variance. Despite significant uncertainty around these parameters, it is extremely unlikely that there is no heterogeneity at all among bank response to changes in the macroeconomic climate, or to changes in bank health, as proxied by balance sheet ratios. These heterogeneities could come from differences in geographic or sectoral distribution of loans, management, business strategy, or arise from unmodeled interactions between variables. Chung et al. (2013) advise a $Gamma\ (2, A)$ prior, where A is set such that the mode of the distribution, $\frac{1}{A}$, is at a "reasonable" level of group dispersion. We choose $A = 4$, so that the prior mode is at 0.25 with a mean of 0.5. As shown in figure 4, this level of variance in slope coefficients, given a one-sigma shock to a single covariate, produces NPL ratios mostly in the 1-5% range, with a long right tail up to about 20%.

We also allow for interactions between variables by jointly sampling CAMELS and macroeconomic slope coefficients from a multivariate normal distribution. We model the covariance matrix of the slopes using the LKJ distribution of Lewandowski et al. (2009), a distribution over correlation matrices. We parameterize the LKJ distribution to place uniform prior probability over all possible correlations, allowing for potentially strong covariance between beta coefficients.

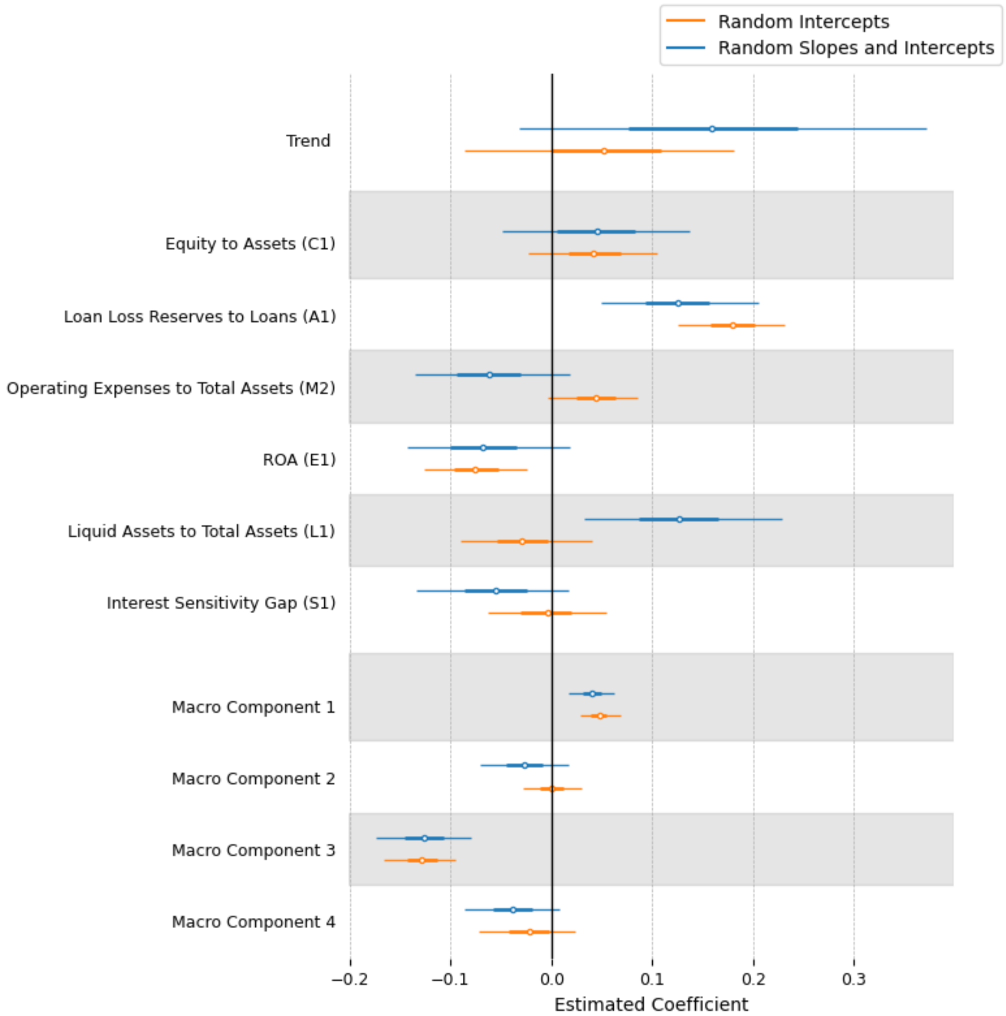
Finally, we use an outlier-robust half-Student T distribution to model the standard deviation of the NPL process, $\sigma_{NPL} \sim T_3^+(0.1)$. The prior parameterization was chosen by maximum likelihood estimation of a Student T distribution using the pooled NPL data for all banks and years. Three degrees of freedom were chosen to allow a long right tail, making the likelihood function robust to the "bursts" of NPLS observed in figure 3. Our model is fully summarized as follows:

$$
\begin{gathered}
\mu_\alpha \sim N(-4, 0.5) \\
\sigma_\alpha \sim Gamma(2, 4) \\
\alpha_i \sim N(\mu_\alpha, \sigma_\alpha^2) \\
\\
\mu_\gamma \sim N(0, 0.5) \\
\sigma_\gamma \sim Gamma(2, 4) \\
\gamma_i \sim N\left(\mu_\gamma, \sigma_\gamma^2\right) \\
\\
\mu_\beta \sim N(0, 0.5) \\
\sigma_\beta \sim Gamma\ (2, 4) \\
\beta \sim N\left(\mu_\beta, \sigma_\beta\right) \\
\\
\mu_{i,t} = \alpha_i + \gamma_i t + X_{i,t}^T \beta_i \\
\sigma_{NPL} \sim HalfT_3(0.1) \\
NPL_{i,t} \sim LogitNormal\left(\mu_{i,t}, \sigma_{NPL}^2\right)
\end{gathered}
\tag{3}
$$

V. Estimates and Results

To obtain risk coefficients, we estimate the posterior distribution over the system described in (3) using Markov Chain Monte Carlo, with sampling proposals generated by the No-U Turn Sampler (NUTS) algorithm. Estimation was done in Python, using the PyMC package of Salvatier et al. (2016). The NUTS algorithm uses gradient information to generate joint proposals over all parameters simultaneously, allowing for swift and efficient sampling of potentially complex posterior geometries. Multiple chains were sampled to compute diagnostics ensuring the sampler had converged to the true posterior. All variables had r-hat statistics of 1.0, with effective sample sizes above 2000, suggesting the sampler converged, generated non-correlated samples, and can be used for valid inference. Full diagnostic information is included in the online appendix.

Figure 7: Posterior distribution over group-level average effect, in random intercepts and random intercepts and random slopes models, with 90% highest-density interval (HDI). Thick lines show the interquartile range, while thin lines show the 90% HDI. Coefficients whose distributions do not contain zero in the HDI can be considered "statistically significant" at a 90% level. All CAMELS variables enter the model with a one-year lag, while macroeconomic variables enter contemporaneously.



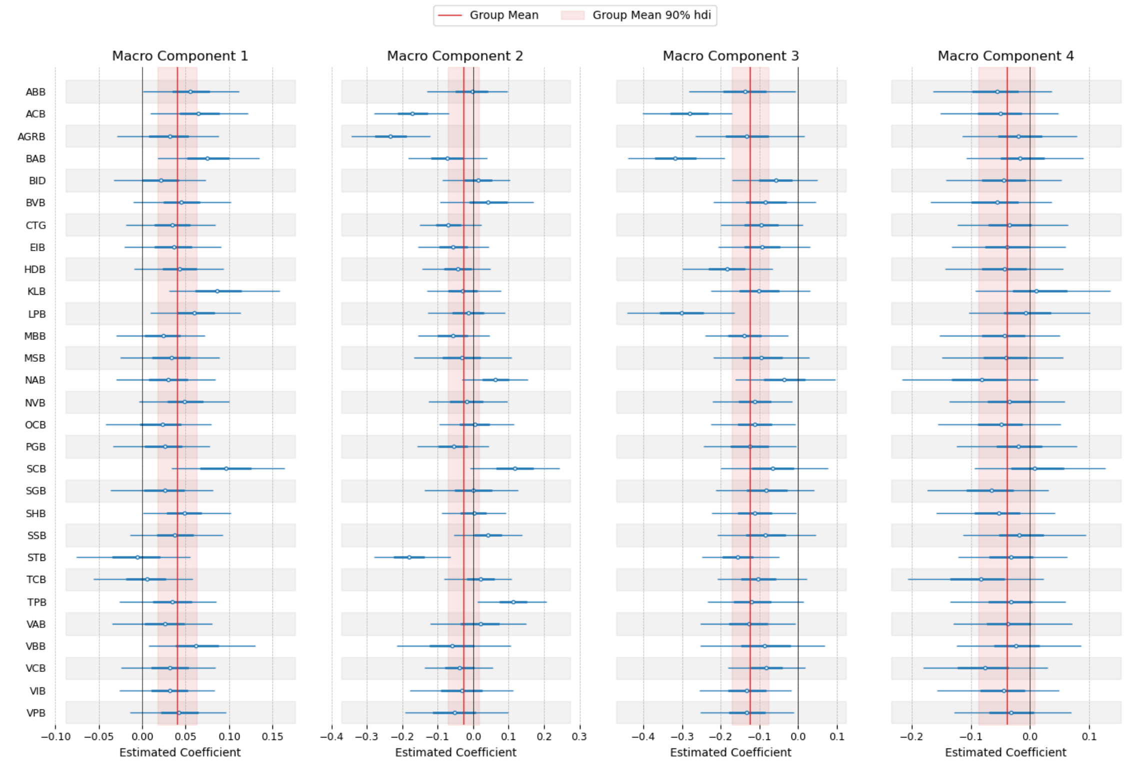
In addition to the full model (3), we also consider a "fixed-effects" model common to panel econometrics, with only random intercepts. This corresponds to setting σ_γ and σ_β to zero in (3), and assigning the group mean, μ_γ or μ_β, to all banks. Figure 7 shows the estimated distribution over group-level mean for each parameter for the random intercept ("fixed effect") model, and the full model with both random slopes and intercepts, along with 90% highest-density intervals (HDI), which provides a range of values our model views as plausible given the data and the priors. In the restricted model, asset quality, management, and earnings are all “statistically significant”, in the sense that their 90% HDI does not contain zero. In addition, the signs of the estimated effects match economic intuition: increased loan-loss reserves is associated with a high NPL ratio in the following year, as is more wasteful management. Increased earnings is associated with a low NPL ratio. Note that because we use a non-linear transformation of our estimated coefficients, it is not possible to directly interpret the marginal effect of a unit change.

Among macroeconomic variables, the restricted model estimates that components one and three are significantly different from zero. Component 1 contains primarily national account variables, with negative factor loadings, suggesting that when economic activity increases, NPL ratios fall. Component 3 contains the exchange rate, investment, and negative capital stock, suggesting that when foreign investment falls, bank NPL ratios increase.

The estimated group-level average macroeconomic effects are robust to the inclusion of bank-level heterogeneity. Components 1 and 3 remain significant after bank slopes are allowed to vary around the group mean. CAMELS average effect estimates, on the other hand, are significantly distributed allowing heterogeneous effects. This is not surprising, as CAMELS data varies in the bank and time dimensions, while macroeconomic data varies only in the time dimension. Allowing for heterogeneity allows for a group estimate that is robust to outliers, and large observed shifts in estimated group means validate the inclusion of random slopes.

After random slopes are included, mean estimates of management and liquidity reverse sign and significance. Liquidity, which has a negative mean but whose 90% HDI includes zero in the becomes statistically significant and positive when random slopes are included. Management quality, on the other hand, becomes negative with zero included in the HDI. Estimates for capital adequacy, asset quality, earnings, and interest rate sensitivity are robust to the inclusion of random slopes.

Figure 8: Estimated posterior distribution over individual bank macro risks (blue), with interquartile range (thick blue band) and 90% highest density interval (thin blue band), with estimated group mean (red). A bank can be considered “statistically different” from zero when its estimated 90% hdi does not include zero, and statistically different from the group mean when its 90% hdi does not include the mean of estimated group average.



Inclusion of random slopes allows us to inspect the risk exposure of each individual bank to changes in balance sheets and macroeconomic climate. Figure 8 shows the response of each bank to changes in the macroeconomy, as represented by the first four principal components described above. The estimated group averages shown in figure 7 are reproduced as red bands, while the estimated distribution over each bank's coefficient is show in blue. As seen in figure 7, the estimated 90% hdi for the average group effect for components 1 and 3 does not include zero, while those of components 2 and 4 do. Nevertheless, many bank-level estimates for responses to changes in national accounts (component 1) and foreign capital flows (component 3) do include zero.

The NPL ratios of three banks - BAB, KLB, and SCB - appear to be particularly sensitive to changes in national accounts, which we interpret as business cycle effects. On the other hand, STB and TCB appear to be particularly robust to the "business cycle". In addition, the majority of individual bank estimates include zero in the 90% HDI, even though the group mean estimate does not. Indeed, only 7 out of 29 banks do not include zero in the hdi. Whereas the pooled model suggested a systematic risk to business cycle fluctuations, the estimation of heterogeneous responses to these fluctuations shows that the risk is concentrated in only a handful of institutions.

This pattern of concentrated risk repeats in components 2 and 3, price levels and international capital investment, respectively. The estimated average effect of changes in price levels is zero, but three banks (ACB, AGRB, and STB) have negative coefficients significantly different from zero, while one, TPB, has a positive coefficient significantly different from zero. In component 3, the group mean is pulled down by strongly negative estimated coefficients of three banks: ACB, BAB, and LPB. Including these, about half, 14 out of 29, do not include zero in the HDI. Only in the case of component 4 do we see a homogeneous response across the entire sector, with bank-level effects clustering closely around the group-level mean of zero.

Figure 9: Estimated posterior distribution over individual bank CAMELS risks (blue), with interquartile range (thick blue band) and 90% highest density interval (thin blue band), with estimated group mean (red). A bank can be considered “statistically different” from zero when its estimated 90% hdi does not include zero, and statistically different from the group mean when its 90% hdi does not include the mean of estimated group average.

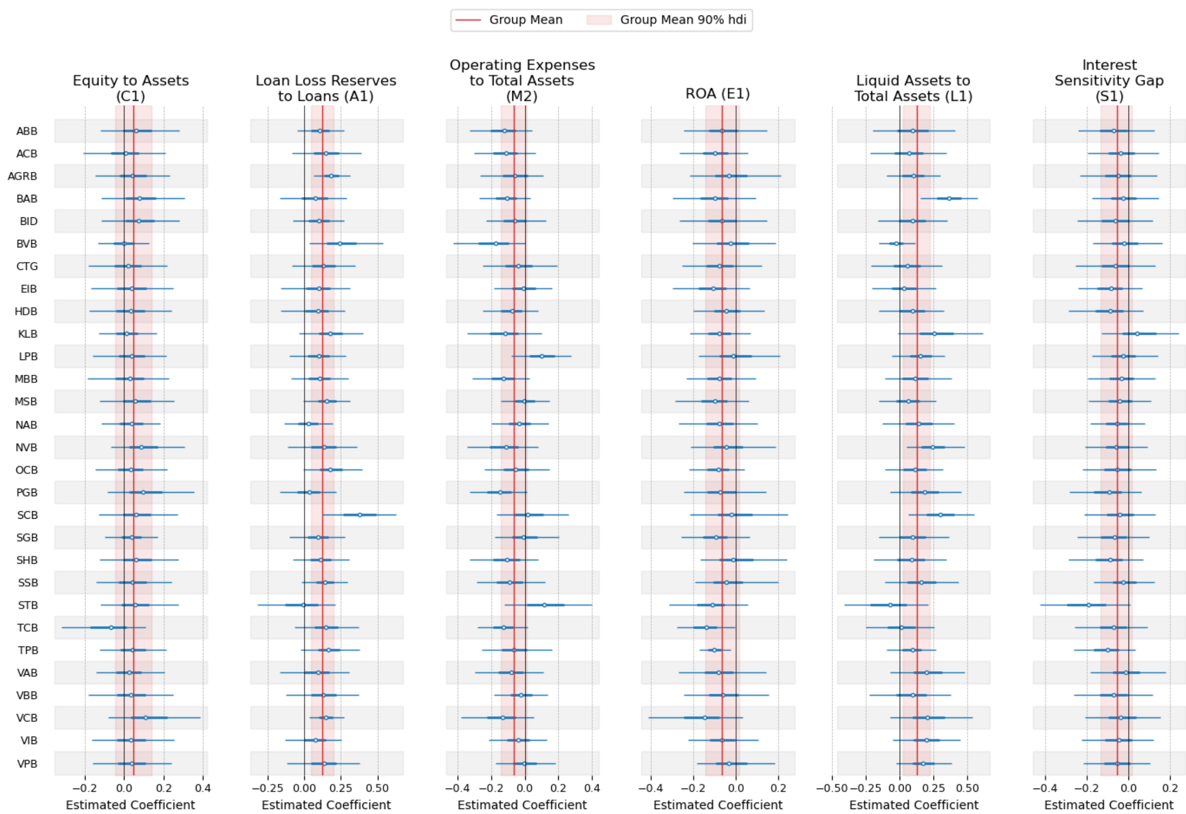


Figure 9 shows posterior estimates for individual bank CAMELS risk coefficients (blue), along with the estimated group mean (red). Compared to cofficients associated with macroeconomic factors show in figure 8, estimates of CAMELS coefficients are much more clustered around group means. There are, however, notable exceptions. SCB appears more significantly more sensitive to changes in asset quality than the average bank. Two banks stand out in the liquidity factor: BAB, which sees an stronger increase in its NPL ratio when share of liquid assets increases, and BVB, which is centered on zero and excludes the group mean from its HDI. Evidence for a link between NPLs and liquidity factor is weak across, the board, but only BVB seems to rule it out entirely. We find no evidence that any bank's NPL ratio is significantly affected by changes in the previous year's capital adequacy or interest rate sensitivity gap. Table 3 summarizes our bank-level risk exposure findings.

Table 3: Summary of bank-level coefficient estimates. All coefficients "statistical different" from zero, defined as those parameters whose posterior HDI excludes zero, are listed. Banks marked with (*) also exclude the group mean from the HDI.

	90% HDI of Group Mean Excludes Zero	90% HDI of Estimate Excludes Zero	
Factor		Coefficient negative	Coefficient positive
Equity to Assets (C1)			
Loan Loss Reserves to Loans (A1)	X		AGRB, BVB, MSB, OCB, SCB*, VCB
Operating Expenses to Total Expenses (M2)		BVB	
ROA (E1)		TCB, TPB	
Liquid Assets to Total Assets (L1)	X		BAB*, NVB, SCB,
Interest Rate Sensitivity Gap (S1)			
Macro Component 1 (National Accounts)	X		ABB, ACB, BAB, KLB, LPB, SCB, SHB, VBB
Macro Component 2 (Price Level)		ACB*, AGRB*, STB*	TPB*
Macro Component 3 (International Investment)	X	ABB, ACB*, BAB*, HDB, LPB*, MBB, NVB, OCB, PGB, SHB, STB, VAB, VIB, VPB	

Macro Component 4 (Domestic Investment)			

VI. Application: Climate Stress Test

With bank-level slope estimates to bank-invariant, i.e. macroeconomic, risk factors, it is possible to examine how individual banks might be expected to fare in the face of different macroeconomic scenarios. We choose to demonstrate such an analysis with the example of a climate shock. A growing body of literature argues that the financial sector should pay close attention to risk exposures to climate change and its attendant consequences Indeed, the "attendant consequences" are what make "climate stress testing" so difficult in the first place. Monasterolo (2020) identifies many transmission channels by which financial institutions might be impacted by climate change, including via changes in the NPL ratio resulting from natural disasters, changes in investor preferences, or carbon transition technology shocks. Battiston et al. (2021) also highlight increased exposure to socio-economic shocks resulting from extreme weather events. Analyzing risk exposure to Vietnamese banks from these types of climate risks is the goal of the current exercise.

Extreme weather events, such as droughts, floods, or typhoons, are complex events whose shockwaves can travel through the social and economic fabric for years. They can, however, be decomposed into two components, which we label as direct effects and indirect effects. Direct effects are the immediate capital destruction, human displacements, and productivity interruptions that result from the destruction or disabling of housing and productive capital. Indirect effects are the consequent shockwaves and ripples that travel through the socio-economic fabric. Of the two, direct effects are unambiguously easier to measure, as they can be at least partially observed, and do not suffer from attribution challenges inherent in measuring after-shocks in complex dynamic systems. When stress testing the impacts of extreme weather events on financial institutions, we therefore begin from direct damages.

For an extreme weather event, we choose a 250-year return period flood in the city of Hanoi. Vietnam is part of the tropical monsoon sea belt, exposed flooding resulting from tides, typhoons, and storm surges. As the city has grown, infrastructure and populations have moved into more flood-prone areas (Tyler et al. 2016). The combined effects of heavy rainfall, typhoons, tides, and sea level rise are projected to lead to greater flood risk for urban areas in Vietnam. These floods can trigger landslides that cause further destruction and economic disruption. Using historical disaster data provided by the World Bank, we estimate that a 250-year return period flood would flood 47% of the surface area of Hanoi, effecting nearly 600,000 dwellings and causing probable maximum losses of $2.7 billion. Table 4 summarizes the key direct effects of our disaster scenario.

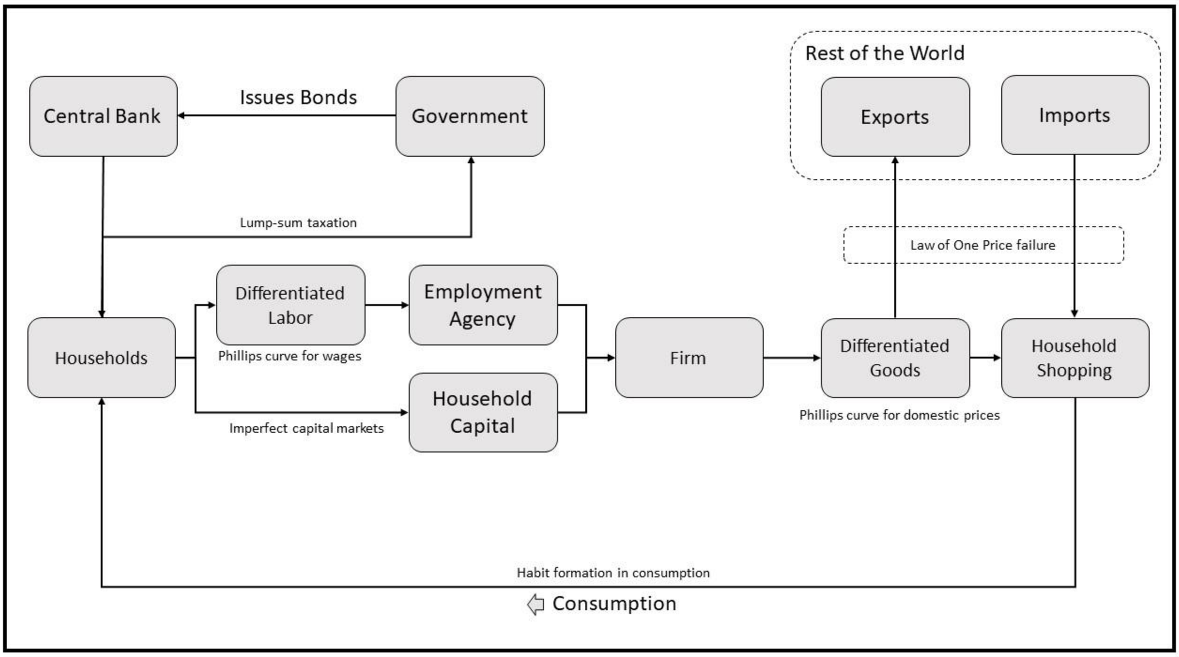
Table 4: Summary of the assumed effects of a 250-year return period flood in Hanoi, based on data courtesy of the World Bank.

Dwellings affected	580,000
Inundated Area	47% of total Hanoi surface area. 10% of total Hanoi surface area with water depth greater than 1 meter.
Critical infrastructure affected	Roads and public transportation River embankment Irrigation dams and resevoirs Electricity distribution Telecommunications Water treatment and distribution Schools and hospitals Noi Bai International Airport
Half-life of infrastructure disruption	3 months
Probable Maximum Loss (PML) from direct damages	USD $2.6 billion

Although easier to quantify, it is unlikely that immediate direct damage from extreme weather events pose a larger risk to banks than indirect effects. As shown above, changes in prices and disruptions to trade or production can impact the health of bank balance sheets. As these indirect effects are difficult to observe, we employ a Dynamic Stochastic General Equilibrium (DSGE) model to provide estimates of what the indirect effects of an extreme weather event might be.

Battiston et al. (2021) is extremely critical of the use of DSGE models in modeling climate risk. Our use of a DSGE model, however, is significantly different from previous studies. First, we do not include fat-tailed climate shocks in the model endogenously. That is, the expectations of agents within our model is that these shocks do not occur at all. Secondly, we do not include a financial sector endogenously in our model. Conclusions about the effects of climate shocks on the financial sector are instead drawn from the interplay between our two models, rather than from the endogenous decision of utility maximizing financial managers in the DSGE framework. Our DSGE model only shows how a given extreme weather shock might propagate through the economy. As agents within the model economy are totally unprepared for the shock, it represents a kind of upper-bound on the severity of these transmissions. Figure 10 shows the high-level structure of our DSGE model. Full derivation of the model is available in the online appendix.

Figure 10: Structure of the DSGE model used to approximate indirect effects of extreme weather events.



The model shown in figure 10 is admittedly simple relative to recent DSGE models of the Vietnamese economy, for example Nguyen (2021). We made the choice to use a simplified model in the present example because our aim is merely to show how a blended model framework can be used to perform a climate stress test. Our model is the simplest possible, while still retaining three important features for this context: an open economy, stocks of physical capital, and the standard suite of new Keynesian frictions. We leave expansion to the model, including the addition international capital and financial flows, Uncovered Interest Parity frictions, disruptive taxation, and differentiated firms and/or households, to future work.

Our DSGE model is comprised of 55 equations, with 32 parameters and 11 stochastic shocks. The model was solved as in first order approximation using the Python gEcon.py package[6]. Of the 34 parameters, we estimated 32, along with 11 variance parameters, using Bayesian inference. The two calibrated parameters were the household discount factor, set to 0.98, and the depreciation rate of capital, set to 0.025. Prior distributions were selected using posterior mean and variance estimates reported in Nguyen (2020) and Nguyen (2021) where possible. The resulting posterior density was estimated via Markov Chain Monte Carlo (MCMC), using the Affine-Invariant Ensemble Sampler of Goodman and Weare (2010), implemented in the emcee package (Foreman-Mackey et al. 2013). This sampler is much more sample efficient than the standard Gaussian Metropolis-Hastings random walk algorithm, and also deals with multimodality more effectively. This is important because the typical posterior geometry of a DSGE model's likelihood function is made discontinuous by stability requirements not present in typical economic models. Parameters must solve the steady state, which potentially involves numerical approximation, and produce a stable perturbation solution to the first-order linear approximate model, and a candidate linear approximate solution must satisfy the conditions given by Blanchard and Kahn (1980). A random walk algorithm can easily become stuck at these discontinuities, whereas an ensemble sampler is able to traverse them. Prior and posterior parameter distributions, as well a trace plots and sampler diagnostics, are available in the online appendix.

To compute the indirect effects of the flood, we represent the damages shown in table 4 as set a exogenous shocks that can be entered into the DSGE model. The indirect effects are then taken to the be impulse response function (IRF) that results from this set of shocks. Table 5 shows the shocks used to represent the flood. The GDP shock was computed by taking the 2018 fraction of Hanoi regional GDP to 2018 national GDP, 22%, and multiplying by the affected land-area fraction of the flood, 47%, so the final impact is a 10% negative output disruption. Capital destruction, a shock omitted during model estimation, is the PML as a fraction of the Vietnamese physical capital stock, as estimated by the Penn World Table

[6] https://github.com/jessegrabowski/gEcon.py

10.0 (Feenstra, Inklaar & Timmer, 2015), or 0.25%. Finally, import and export shocks were computed by assuming that 35% of all international trade is conducted by air freight[7], that Vietnamese air freight operations are evenly split between Noi Bai International and Tan Son Nhat International (in Ho Chi Min City), and that flood-related disruptions would totally halt airport activity for one week. Taken together, we enter the effect at a 4.3% disruption to both imports and exports into the model.

Table 5: DSGE model shocks used to represent a 250-year return period flood in the city of Hanoi

Shock	**Value**
Domestic Production	-10.3%
Capital Destruction	-0.25%
Exports	-4.3%
Imports	-4.3%

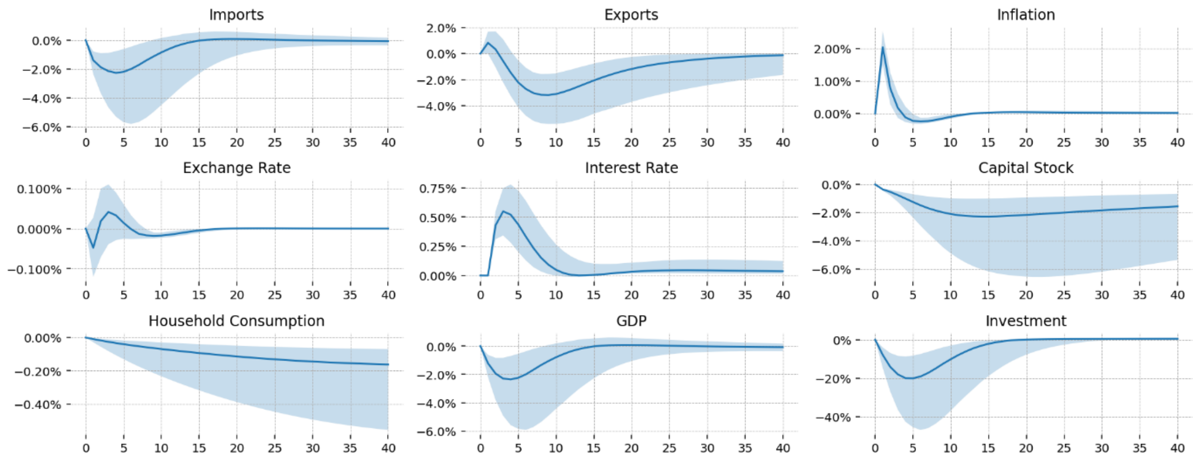
Figure 11 shows quarterly impulse response functions for the nine time series included in our NPL model. Outputs are largely consistent with our a priori assumptions about economic consequences of extreme weather events. Economic output (GDP), imports, and exports all fall immediately following the flood. Inflation increases, and interest rates increase with a lag as the monetary authority reacts. Households, made poorer by the destruction of capital, sell assets (negative investment) to maintain their habitual consumption level as best they can. The combination of capital destruction and dis-investment by households deteriorates the national capital stock, which is slow to rebuild, as households are slow to shift back to the steady-state level of savings. The USD/Dong exchange rate is not estimated to be significantly affected by this scenario.

To stress test banks, we took the outputs of the DSGE IRFs generated by the shocks described and used them in place of observed macroeconomic data. We transformed the DSGE outputs to match the data preprocessing described above. Notably, we scaled each simulated time series by the standard error of its empirical counterpart, then formed the four PCA components with the weigh matrix computed using empirical data. In addition, because the DSGE model was estimated using quarterly data, while the NPL model uses annual data,

[7] This is the global average, as estimated by the International Air Transport Association (IATA).

stock variables output by the DSGE model were summed to produce annual values. For flow variables, the average value for each "year" was used. The simulated flood macroeconomic data was then paired with empirical bank balance sheet data.

Figure 11: Bayesian impulse response functions generated by our DSGE for nine macroeconomic time series, following the 250-year Hanoi city flood scenario. The shocks used to build the flood scenario are given in table 5. The solid blue line shows the median impulse response function of 1,000 draws from parameter posterior distributions, while the 95% credible interval is shaded in blue.

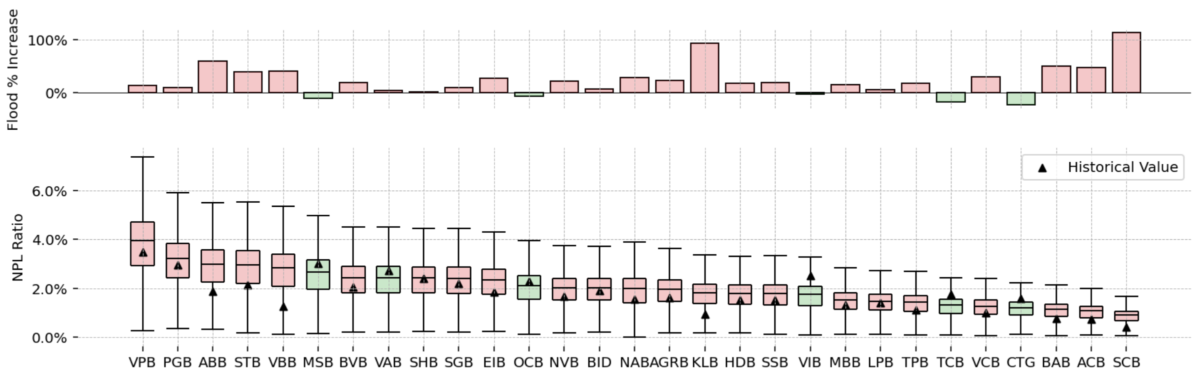


We placed the flood in Q1 of 2018. This date was chosen because it was well after the NPL crisis of 2016 and the associated banking reforms, but prior to the COVID-19 pandemic outbreak. We thus assume that it proves a somewhat "normal" period in which to place our flood. To propagate uncertainty between models, we randomly sampled from the DSGE and NPL model posteriors when computing IRFs and the resulting estimated NPL ratios.

One limitation of our procedure is that there are no dynamic feedbacks between the two models, nor between macroeconomic variables and balance sheet variables. This is a wildly unrealistic assumption, which holds that bank managers would do nothing in the face of counter-factual macroeconomic shocks, nor in the face of changes to their NPL ratio resulting from these shocks. As a result, our method produces a credible estimate only in the period in which we place the shock, Q1 of 2018. After this, errors resulting from holding balance sheets fixed at their observed values compound. As a result, we report results only from 2018Q1 and 2018Q2, but note that even a single quarter forward produces significant errors. It can be view, at best, as an upwardly biased estimate – the consequences to a bank if management is "asleep at the switch".

Figure 12 shows the distribution over NPL ratios that our models estimate would have resulted in the year 2018, along with the percentage change between the mean prediction given the flood data and the observed 2018 NPL ratio. Box plots show 25% to 75% quantiles, along with the mean value, with 1.5 times the IQR shown with whiskers. All observed NPL ratios fall within the IQR, but values for several banks, including ABB, STB, VBB, KLB, BAB, ACB, and SCB are output of the body of the predicted distribution. In the case of KLB and SCB, the mean estimated NPL ratio following the flood is nearly double the observed ratio, suggesting these two banks are particularly exposed to a macroeconomic shock of this type.

Figure 12: Bottom panel: Distribution over estimated NPL ratio in a counter-factual 2018, wherein a 250-year return period flood hit Hanoi. Counterfactual data was generated from the Bayesian impulse response functions of our DSGE model for Vietnam. Top panel: The percent change between the mean of the counter-factual 2018 distribution and the observed 2018 NPL ratio.



VII. Conclusion

A growing consensus among risk analysists is that the financial system is at risk from climate change, including extreme weather events that may become more frequent in the near future. Measuring the risks faced by financial institutions is non-trivial, however, because they are relatively more exposed to the indirect, socio-economic consequences of these events, relative to the direct effects.

To address this difficulty, we constructed a model of Vietnamese bank non-performing loan (NPL) ratios. Importantly, we used Bayesian estimation techniques that allowed us to obtain bank-specific estimates of risk exposure to various well-researched determinants of NPL ratios, as well as risks to shifts in the Vietnamese macroeconomy. We then used a scenario based approach, which modeled a 250-year return period flood as a macroeconomic event. Using a DSGE model, we generated likely “indirect effects” of the flood, defined as the impulse response function generated by inputting a representation of the flood into the model.

This exercise identified seven banks particularly exposed to a risk such as the one we consider: ABB, STB, VBB, KLB, BAB, ACB, and SCB. Our blended model methodology could easily be extended to include different types of climate shocks, more banks, more macroeconomic indicators, and a more robust macroeconomic model. The use of Bayesian estimation techniques in both models allows for the combination of uncertainty from both models. Our results should be of particular interest to bank managers, financial regulators, and policymakers seeking to hedge risk and allocate supervisory resources.

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