

1 Research project’s background

This project studies how external uncertainty shocks originating in the United States and China are transmitted to Taiwan, which external sources matter most for Taiwan’s domestic uncertainty, and whether the dominant transmission channel changes over time. These questions are especially important for Taiwan because it is deeply integrated with both the U.S. and Chinese economies. As a result, Taiwan lies directly in the path of major policy and geopolitical developments between the two countries. When the U.S. Federal Reserve tightens monetary policy, when trade disputes between the U.S. and China escalate, or when cross-strait political tensions rise, Taiwan often faces immediate consequences for its trade, investment, and financial flows.

However, major policy shifts and geopolitical realignments rarely move from initial proposal to a well-defined policy trajectory overnight. Central banks move in sequences of decisions, trade conflicts unfold through rounds of negotiation and retaliation, and cross-strait relations evolve over extended periods rather than at a single point in time. As a result, there is often a long interval between the announcement or anticipation of a policy change and the point at which a stable policy regime actually emerges. Along the way, planned policy changes may be revised, delayed, or even cancelled altogether. For example, rounds of U.S.–China tariff threats have repeatedly ended with smaller or postponed tariff increases than initially announced, and cross-strait initiatives have at times been shelved after domestic political opposition. During this interval, firms, households, and investors face heightened uncertainty about the future path of policy, demand, and financial conditions. This heightened uncertainty, in turn, affects their investment, consumption, and portfolio decisions (Bloom, 2009, 2014). One prominent example is trade policy uncertainty, which strongly influences firms’ trade and investment decisions (Handley and Limao, 2022). To capture these evolving dynamics without sacrificing the macroeconomic dimension, this project utilizes a monthly dataset. Monthly data are granular enough to capture short-lived spikes in uncertainty during negotiation periods that quarterly data often smooth out, while still allowing the analysis to include key real variables such as industrial production and trade balances that are generally unavailable at daily frequency.

Empirically, however, identifying external uncertainty shocks and quantifying their effects on Taiwan presents several methodological challenges. First, external and domestic sources of uncertainty are tightly intertwined, creating a severe challenge for identification. A single geopolitical event, such as a shift in U.S.–China relations, often simultaneously triggers global financial volatility and shifts in Taiwan’s domestic political landscape. In a small-scale model that lacks sufficient domestic controls, the economic impact of these internal political shifts would be erroneously attributed solely to the external shock. This form of omitted variable bias can lead to a misdiagnosis of the true drivers of uncertainty, potentially overstating the direct influence of external factors while neglecting local transmission mechanisms (Carriero, Clark and Marcellino, 2018). Addressing this issue requires expanding the information set to include a rich array of both domestic and external variables, necessitating the use of a large-scale econometric model.

Second, while a large-scale model is necessary to address this bias, it introduces identification trade-offs. In large systems, standard identification methods based on Cholesky decomposition become problematic because the results are sensitive to variable ordering, creating a conceptual flaw known as order dependence. Addressing this issue requires an order-invariant framework. However, order invariance is mathematically incompatible with the strict block-exogeneity restrictions commonly used in small open economy models to prevent domestic variables from affecting global ones. Consequently, instead of imposing these rigid constraints, we employ the data-driven identification strategy proposed by Davidson, Hou and Koop (2025), treating external drivers as

“unclassified variables”. This avoids arbitrary restrictions on the contemporaneous relationships between variables, allowing for a data-determined structure that can accommodate potential feedback loops, rather than ruling them out by assumption. This approach suits Taiwan’s pivotal role in global technology supply chains, where strict zero restrictions might assume away significant feedback effects originating from the supply side.

Third, many existing approaches face two related limitations. One is their reliance on proxy measures of uncertainty. The other is their use of a two-step procedure that first estimates uncertainty and then evaluates its macroeconomic effects in a separate model. Regarding the former limitation, widely used text-based indices built from international news may not reflect domestic conditions. For example, during Nancy Pelosi’s 2022 visit, international coverage emphasized imminent war risk, while sentiment in Taiwan remained relatively calm. Such reliance on external proxies can create a “perception gap” and distort estimates of uncertainty’s impact on the local economy. Regarding the latter limitation, the two-step design treats the estimated uncertainty series as observed data, ignores estimation uncertainty, and can induce measurement-error bias and model inconsistency (Carriero, Clark and Marcellino, 2018). To address these issues, we employ the proposed stochastic volatility in mean vector autoregression (SVMVAR) framework to jointly estimate uncertainty and its economic effects in a single step. By modeling uncertainty as a latent factor driven by the data itself, we avoid reliance on potentially misaligned external proxies, ensuring that our measure reflects actual domestic economic and financial conditions.

Finally, existing uncertainty measures, such as global financial volatility indices or country-specific policy uncertainty indices, do not distinguish between the *channels* through which uncertainty transmits to the economy. Widely adopted indices such as the VIX or the Baker, Bloom and Davis (2016) Economic Policy Uncertainty index compress the multidimensional nature of uncertainty into a single scalar, obscuring whether a given shock propagates through real activity or financial markets. For a small open economy like Taiwan, this distinction carries different policy implications. When external shocks operate primarily through **macroeconomic channels**, affecting trade flows, export demand, and production linkages, the appropriate policy response involves instruments oriented toward the real economy, such as export facilitation and structural adjustment support. When shocks instead propagate through **financial channels**, disrupting capital flows, asset prices, and credit conditions, the Central Bank of China (Taiwan) faces a different set of imperatives, including foreign exchange intervention and liquidity management. Existing empirical frameworks, however, are ill-equipped to make this distinction in a time-varying setting, leaving policymakers without a systematic basis for identifying which channel is dominant at any given point in time. This constitutes the fourth and most substantive methodological gap that the present project is designed to fill.

To address these challenges, this project applies the order-invariant stochastic volatility in mean vector autoregression (OI-SVMVAR) framework developed by Davidson, Hou and Koop (2025) to the Taiwan context. This project treats external drivers such as U.S. monetary policy indicators and cross-strait tension indices as unclassified variables and uses their time-varying co-movement with Taiwan’s macroeconomic and financial common factors to identify the operative transmission channel at each point in time. This provides a data-driven reading of the operative transmission channel without requiring the researcher to impose it *ex ante*.

This project makes three contributions. First, the large-scale specification, which includes more than forty domestic, U.S., Chinese, and global variables, helps mitigate the omitted-variable bias that is especially severe when external and domestic sources of uncertainty are tightly intertwined (Carriero, Clark and Marcellino, 2018). Second, the order-invariant identification strategy avoids the distortions associated with variable ordering in large VAR systems. Third, and most impor-

tantly for policy, the models time-varying classification results help identify whether policymakers in Taiwan should respond primarily with real-economy instruments or with financial stability tools, a distinction that conventional single-index measures of uncertainty cannot provide.

The remainder of this proposal proceeds as follows. The first year of the project focuses on data assembly and empirical implementation: we construct a monthly dataset of more than 40 variables spanning Taiwan’s domestic macroeconomic and financial conditions together with U.S., Chinese, and global indicators, adapt the Davidson, Hou and Koop (2025) MCMC estimation algorithm to this dataset, and conduct the three-step analysis comprising time-varying classification probabilities, forecast error variance decomposition (FEVD), and impulse response functions (IRF). The second year extends the analysis by developing and estimating a small open economy dynamic stochastic general equilibrium (DSGE) model with financial frictions, estimated via Bayesian methods, whose structural impulse responses are matched against the data-driven IRFs obtained in year one, providing micro-founded validation of the transmission mechanisms identified empirically.

The First Year

1.1 Methods, procedures, and implementation schedule

(1) Research principles, methods, and the innovation of research methods

(1.1) The OI-SVMVAR Framework

To address the identification challenges outlined in Section 1, this project employs the **order-invariant stochastic volatility in mean vector autoregression** (OI-SVMVAR) framework developed by Davidson, Hou and Koop (2025). We select this framework because it uniquely resolves the three methodological obstacles that confront any attempt to trace external uncertainty shocks through a small open economy: it accommodates a large information set, eliminating the omitted variable bias that confounds small-scale models; its order-invariant identification ensures that results do not depend on arbitrary variable ordering; and its time-varying classification mechanism allows the data—rather than the researcher—to determine whether a given external shock transmits through macroeconomic or financial channels. The model consists of five coupled components, estimated jointly in a single Bayesian step, which we now present in turn.

To capture the direct impact of uncertainty on real economic activity and financial conditions, the observation equation embeds the latent uncertainty factors in the conditional mean of a VAR:

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=1}^p \mathbf{A}_l \mathbf{y}_{t-l} + \mathbf{\Gamma} \mathbf{h}_t + \boldsymbol{\varepsilon}_t, \quad (1)$$

where \mathbf{y}_t is the $N \times 1$ vector of observables (in our application, $N = 43$ variables spanning Taiwan’s domestic economy, U.S. and Chinese indicators, and global risk measures); \mathbf{c} is an $N \times 1$ intercept vector; \mathbf{A}_l are $N \times N$ coefficient matrices at lag $l = 1, \dots, p$; $\boldsymbol{\varepsilon}_t$ is the $N \times 1$ reduced-form disturbance vector; and $\mathbf{h}_t = (h_{m,t}, h_{f,t})'$ is a 2×1 vector containing the two latent common log-volatility factors that represent Taiwan’s **macroeconomic uncertainty** ($h_{m,t}$) and **financial uncertainty** ($h_{f,t}$), respectively. The $N \times 2$ matrix $\mathbf{\Gamma}$ captures the **stochastic volatility in mean** effect: because $\mathbf{\Gamma} \mathbf{h}_t$ enters the conditional mean of \mathbf{y}_t , elevated uncertainty directly shifts the expected path of all observables—output, employment, asset prices, and credit conditions alike. This is what distinguishes the SVMVAR from a standard stochastic volatility model, in which volatility appears

only in the error covariance and thus cannot feed back into the levels of economic variables. The inclusion of $\mathbf{\Gamma} \mathbf{h}_t$ allows us to test the prediction—central to real-options and precautionary-savings theories (Bloom, 2009, 2014)—that heightened uncertainty depresses investment, consumption, and hiring not merely by increasing dispersion but by shifting the conditional mean of economic outcomes.

To ensure that identification does not depend on the arbitrary ordering of variables within \mathbf{y}_t , the contemporaneous relationship between reduced-form and structural disturbances is specified as

$$\mathbf{B}_0 \boldsymbol{\varepsilon}_t = \boldsymbol{\Sigma}_t^{1/2} \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_N), \quad (2)$$

where \mathbf{B}_0 is an $N \times N$ contemporaneous impact matrix and $\boldsymbol{\Sigma}_t = \text{diag}(\sigma_{1,t}^2, \dots, \sigma_{N,t}^2)$ is the diagonal matrix of time-varying, variable-specific conditional variances. The structural disturbances \mathbf{u}_t are homoskedastic by construction; all time variation in volatility is absorbed by $\boldsymbol{\Sigma}_t$. Crucially, \mathbf{B}_0 is left as a full, unrestricted nonsingular matrix—subject only to the normalisation that its diagonal elements equal one—rather than being constrained to a lower triangular form. This unrestricted specification is what delivers **order invariance**: because no zero restrictions are imposed on the off-diagonal elements of \mathbf{B}_0 , the estimation results are identical regardless of how variables are ordered in \mathbf{y}_t . The implications of this design choice—and why it is indispensable for a 43-variable system that mixes domestic and external series—are discussed in detail in subsection (1.3).

The structural heart of the model lies in the specification linking each variable’s log-volatility to the common uncertainty factors. Following Davidson, Hou and Koop (2025), the N variables in \mathbf{y}_t are partitioned into three blocks— n_m macroeconomic variables, n_f financial variables, and n_u unclassified variables, with $n_m + n_f + n_u = N$ —and the log conditional variance of variable i is decomposed into a **variable-specific idiosyncratic component** $\eta_{i,t}$ and a loading on the relevant common factor:

$$\log \sigma_{i,t}^2 = \begin{cases} \eta_{i,t}^m + h_{m,t} & \text{if variable } i \text{ is macroeconomic, } i = 1, \dots, n_m, \\ \eta_{i,t}^f + h_{f,t} & \text{if variable } i \text{ is financial, } i = 1, \dots, n_f, \\ \eta_{i,t}^u + h_{s_{i,t},t} & \text{if variable } i \text{ is unclassified, } i = 1, \dots, n_u. \end{cases} \quad (3)$$

The idiosyncratic terms $\eta_{i,t}^k$ ($k \in \{m, f, u\}$) capture variable-specific volatility movements that are orthogonal to the common factors, ensuring that the log-volatilities of variables within the same block are not forced into perfect collinearity. Each $\eta_{i,t}^k$ follows a stationary AR(1) process, so that idiosyncratic volatility shocks are mean-reverting while the common factors $h_{m,t}$ and $h_{f,t}$ can exhibit the persistent swings characteristic of aggregate uncertainty episodes. Variables pre-classified as macroeconomic load exclusively on $h_{m,t}$, so that their common volatility component rises and falls only with aggregate real-economy uncertainty. Variables pre-classified as financial load exclusively on $h_{f,t}$. For unclassified variables, however, the common factor is selected by a discrete latent state indicator $s_{i,t} \in \{m, f\}$: when $s_{i,t} = m$, the variable’s common volatility component is $h_{m,t}$; when $s_{i,t} = f$, it is $h_{f,t}$. This discrete switching mechanism—rather than a continuous blend of both factors—means that at each point in time the model assigns each unclassified variable entirely to one block, and the *posterior probability* of that assignment becomes the object of inferential interest. As we explain in subsection (1.2), this is the mechanism through which we identify whether a given external uncertainty source transmits to Taiwan through the macroeconomic channel or the financial channel.

The two common log-volatility factors evolve according to independent driftless random walks:

$$h_{k,t} = h_{k,t-1} + \zeta_{k,t}, \quad \zeta_{k,t} \sim \mathcal{N}(0, \sigma_{\zeta,k}^2), \quad k \in \{m, f\}, \quad (4)$$

where the innovation variance $\sigma_{\zeta,k}^2$ controls the degree of time variation in factor k . The random-walk specification permits persistent, unbounded movements in the log-volatility factors, consistent with the empirical evidence that uncertainty exhibits prolonged episodes of elevation—such as the 2008–2009 global financial crisis or the 2018–2019 U.S.–China trade war—followed by gradual mean reversion (Bloom, 2014). Moreover, the random walk nests the constant-volatility case as a limiting special case when $\sigma_{\zeta,k}^2 \rightarrow 0$, so that the degree of time variation is estimated from the data rather than imposed by assumption. Because $h_{m,t}$ and $h_{f,t}$ are defined in logs, the implied level of uncertainty $\exp(\frac{1}{2}h_{k,t})$ is guaranteed to be positive at all times.

The final component governs the time-varying classification of unclassified variables, which is the mechanism that transforms the statistical model into an economic identification device. For each unclassified variable i , the latent state indicator $s_{i,t} \in \{\text{macro}, \text{financial}\}$ in Equation (3) follows a first-order two-state **Markov chain** with transition probabilities $q_{mm}^{(i)} = P(s_{i,t} = m \mid s_{i,t-1} = m)$ and $q_{ff}^{(i)} = P(s_{i,t} = f \mid s_{i,t-1} = f)$. The posterior classification probability

$$\pi_{i,t} = P(s_{i,t} = \text{macro} \mid \mathcal{F}_t) \quad (5)$$

is the probability—conditional on the full information set \mathcal{F}_t —that unclassified variable i belongs to the macroeconomic block at time t , updated recursively using the Hamilton (1989) filter. This specification implies that a variable may be classified as macroeconomic during one episode and as financial during another, with the timing and persistence of regime switches determined entirely by the data. The transition probabilities $q_{mm}^{(i)}$ and $q_{ff}^{(i)}$ are estimated jointly with all other model parameters within the Bayesian MCMC framework, so that the persistence of each variable’s classification is itself a model output rather than a researcher-imposed restriction. In our application, the time path of $\pi_{i,t}$ for each external variable constitutes the primary object of interest: it reveals, at each point in the sample, whether the uncertainty associated with a given external driver transmits to Taiwan predominantly through the macroeconomic channel ($\pi_{i,t} \approx 1$) or through the financial channel ($\pi_{i,t} \approx 0$).

The full model—comprising Equations (1)–(5)—is estimated jointly in a single-step Bayesian Markov chain Monte Carlo (MCMC) procedure developed by Davidson, Hou and Koop (2025). The algorithm builds on the computationally efficient precision-based sampler of Cross et al. (2023), which exploits band and sparse matrix structures to draw the common log-volatilities in a single block, making estimation of very large SVMVARs feasible without resorting to dimensionality reduction techniques that would obscure the specific structural shocks we aim to identify. Davidson, Hou and Koop (2025) extend this approach with a novel parameter transformation for sampling the unrestricted \mathbf{B}_0 and with the Markov-switching classification mechanism described above. We do not derive the prior distributions or the posterior sampling steps here; the complete Bayesian implementation is detailed in the online appendix of Davidson, Hou and Koop (2025). All subsequent analysis in this project—time-varying classification probabilities, forecast error variance decompositions, and impulse response functions—is conducted on draws from the joint posterior distribution, ensuring that parameter uncertainty and classification uncertainty are fully propagated through to the final inferential objects.

1.2 Anticipated results and achievements

The Second Year

1.3 Methods, procedures, and implementation schedule

1.4 Anticipated results and achievements

2 Integrated research project

References

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