Essays on Large Bayesian VARs
with COVID Volatility

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Abstract

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Chapter 1 introduces `covbayesvar`, a Python package for estimating large Bayesian Vector Autoregression (BVAR) models, that account for COVID-induced volatility. The package enables us to estimate the model with hierarchical prior selection when the parameters proliferate, accounting for structural shifts in macroeconomic and financial data during the pandemic. Incorporating various priors, it is versatile enough to answer wide-ranging policy-related questions. With detailed programming examples, I explain how to apply the functions on monthly and quarterly macro and financial data to construct unconditional and conditional forecasts, scenario analysis, assess joint predictive densities of variables, examine structural breaks during and after COVID, and how we can employ entropic tilting to modify the forecast distribution and construct forecasts conditional on long-term targets set by the Federal Reserve Bank. Accessible via PyPI, the package includes extensive documentation and code examples. `covbayesvar` advances the state-of-the-art in open-source econometric and statistical software, offering researchers a robust tool for analyzing large-scale systems under unprecedented uncertainty.

The remainder of the chapters in the dissertation employ the python package detailed in chapter 1 to answer a plethora of policy-making questions. For instance, chapter 2 examines the cyclicality of the financial intermediation variables before the 2008 Global Financial Crisis (GFC) using a large BVAR model with 43 variables. To establish stylized facts on the cyclical behavior, I construct reduced-form scenario analyses where unemployment rate rises by 1 pp, and illustrate the predictive densities at various quantiles. From the scenario analyses, we observe that M1 behaves counter-cyclically during downturns in business cycles

i.e. M1 rises when the real economy contracts such as when the industrial production declines and/ or the unemployment rate spikes. Measures of credit such as real estate loans, real commercial and industrial loans and consumer loans are procyclical. Leverage of securities brokers and dealers, and non-financial businesses are countercyclical in the short run, but procyclical in the medium and long run. On the other hand, tier 1 leverage capital, a measure of capital adequacy, is procyclical in the short run, but countercyclical in the medium and long run. A counterfactual analysis from 2008 to 2024 using a large BVAR with COVID volatility model reveals that financial intermediation variables significantly deviate from historical trends - most prominently evident for monetary aggregates, credit and loan supply, and interest rates.

Probing the cylicality of financial intermediary variables is crucial to understand how stress testing scenarios affect the trajectory of financial intermediation, and asses if the responses are consistent with the previously defined stylized facts. The Fed releases stress test projections every February, which contain the projected paths of macro and financial variables for the next 3 years in downturn and severely recessionary environments. Conditioning on these scenarios, they forecast disaggregated data for each bank separately, and sum the values to calibrate the system wide effects. This may miss general equilibrium, spillover and systemic effects. How can we condition the forecasts from a large BVAR on the stress test scenario values for multiple periods at the aggregated level? In chaptr 3, I employ a method known as entropic tilting to alter the forecast distribution to be as close as possible to the scenario paths. I also show how we can extend the entropic tilting method to condition the forecasts of macro and financial intermediary variables on the short and medium-run stress testing scenarios. Then, I show that the forecasts from this novel entropic-tilted approach are very close to the forecasts from the baseline stress testing scenario.

How do contractionary monetary policy shocks affect the financial intermediary variables? Answering this question is germane in today's environment, where the financial and macroeconomic variables are highly interdependent with some degree of uncertainty around monetary policy actions. Financial intermediaries serve as conduits to effectively transmit monetary policy to the broader economy by not only altering the supply of credit but also impacting asset prices, liquidity, and appetite for risk across sectors. Much of the Bayesian VAR literature has emphasized real macro aggregates such as output, inflation, and employment, overlooking balance sheet variables of financial intermediaries. When the Fed tightens monetary policy, adding the financial intermediary variables is crucial to extricate the elasticities of balance sheets such as loan volumes, leverage, and monetary aggregates. In chapter 4, I examine two scenarios. First, how does a surprise 100bps hike in monetary policy that is structurally recursively identified affect the flow of funds. Second, if agents expect that the Fed will hike the federal funds rate 100 bps 8-12 quarters into the future, how do the responses of the flow of funds compare?

Extending the closed-economy analysis of chapter 2, in chapter 5, I broaden the scope to an open-economic system. Now, what is the cyclicality of international economic indicators, and are there any structural breaks? This provides a quick overview of the correlations and co-movements of the international economic variables and sheds light on whether the 2008 GFC altered those patterns. I conclude that there are no structural breaks - treasury securities held by foreign investors and import price index are countercyclical; export price index, real exports and imports are procyclical. Then, with the recent developments in the trade war, I model a few scenarios: What are the implications of the Reverse Greenspan shocks: reduced foreign purchases of US Treasuries? Most importantly, how do the tariffs affect the US aggregate economy? I gauge the effects using a novel approach of changes in the import price index. A cost-push shock, this is a stagflationary scenario analogous to a recursively identified IRF with slow-moving macro and fast-moving financial variables, generating structurally interpretable responses. Then, I extend the analysis using finer-grained sector-specific disaggregated data to evaluate the impact of tariffs on various sectors of the US economy, such as the services, durables, non-durables, retail sector, etc, using a very large dataset of 127 variables.

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"Try and fail, but don't fail to try."

— *John Quincy Adams*

covbayesvar: A Python Package for Large Bayesian VAR Model with COVID Volatility

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1. Introduction

Macroeconometric forecasting often entails smaller time series of historical data, particularly, if we forecast using frequentist vector autoregressions (VARs) at the monthly frequency. Central banks and financial institutions employ vector autoregressions to forecast future economic conditions that assess the impact of monetary policy transmission mechanisms to understand how policy instruments such as interest rates affect the dynamic relationship between inflation, output, and unemployment. Among these are examining how fiscal stimulus or tax changes affect debt burden, can the US economy lands softly, and how high should the mortgage rates be to slow down the real estate market. This is critical in making decisions that have far-reaching consequences for the economy. Regulators and banks use these models to simulate adverse economic scenarios and analyze how banks will perform under stress such as severe recessions, rising defaults on loans, and diminished cash reserves.

Albeit these flexible time series models capture convoluted dynamic relationships among macro and financial variables, they become densely parametrized, yielding imprecise out-of-sample forecasts. Creating a problem of the "curse of dimensionality" where the number of observations exceeds the number of parameters to estimate, statisticians and economists have introduced Bayesian methods to address the problems of unstable and burgeoning parameters. Amongst those are BVARs with informative priors that shrink the overly parameterized models towards parsimonious models with sparse coefficients, developed by Giannone Lenza and Primiceri (2015). However, this methodology isn't necessarily most suitable to estimate a model on the pandemic-driven extreme observations, when key macro variables such as unemployment rate, oil prices, industrial production, and retail sales vary substantially. For instance, WTI oil prices nosedived to -53

[1] This package, accompanying research paper, codes and supplementary materials are not affiliated with, endorsed by, or sponsored by Amazon.com, its subsidiaries, or its employees. I independently wrote the functions of the package for research purposes prior to joining Amazon.com. Prior to my employment at Amazon, I had mapped the python functions one-to-one with the publicly-available MATLAB functions. I am solely responsible for any omissions or errors.

percent in March 2020 compared to one year ago, then skyrocketed to 272 percent in April 2021 when measured in year-over-year growth rates. Such extreme outliers warrant changing the estimation strategy to account for wider uncertainty when acutely large shocks propagate through the economy and skew the distribution of the time series data.

Owing to the contaminated data from the COVID outbreak, I forecast and estimate the responses to shocks when extreme observations such as those seen during the pandemic, starting from March 20, 2020, are present. Recognizing that the COVID-19 pandemic altered the statistical properties of a plethora of economic and financial variables, such as the moments, and autocorrelation, I employ a Bayesian inferential approach to combine standard prior beliefs with the information present in the data. Currently, there is no equivalent to the MATLAB estimation of BVAR models in Python that incorporates covid volatility in big data. Therefore, in Python, I forecast and estimate the responses to shocks when extreme observations such as those seen during the pandemic, starting from March 20, 2020, are present. Incorporating the Bayesian VAR developed by Primeceri and Lenza (2021), I first fit a Bayesian VAR model with covid volatility on medium-sized macro and financial variables data with the model specifications from Primiceri and Lenza (2022). Unlike their model with seven variables, I added numerous financial variables in a model typically used to analyze macro variables, showcasing use-cases with the monthly data to 28 variables, and a quarterly data of 29 variables. Macroeconomists often program their models in MATLAB. So, I first translated the MATLAB codes to Python, and built a Python package called `covbayesvar`, saving the functions in `large_bvar` module of the package. Users can install this package as it is available in the Python Package Index (PyPI), and can view the source code of the functions in the Github repository. It implements the modeling approach to prior selection and conditional forecasting as done in Giannone et. al (2015), Banbura, Giannone and Lenza (2015), Lenza and Primiceri (2022), and Crump et. al (2021). This package encompasses all the functions necessary to transform the data, estimate the model for inferences, calculate reduced-form impulse responses, construct beautiful unconditional (baseline) forecasts based on the historical correlations between variables, forecasts conditional on shocks on certain variables for given time horizons, plot scenario analysis of those shocks, plot joint distribution of forecasts, examine structural breaks, and employ entropic tilting to make projections conditional on long run targets set by the Federal Reserve Bank. To illustrate the usage of these functions, I've created and shared Google Colab Notebooks that showcase how to construct the model using macro and financial data and make forecasts. Furthermore, I published a separate documentation of all the functions along with examples in Github.

Several packages in R exist to estimate BVAR using varying estimation strategies. For instance, in the `bsvars` R package, Wozniak (2024) implemented the techniques in Lutkepohl, Shang and Wozniak (2024) to create an efficient procedure to estimate Structural BVAR model with homoskedastic, heteroskedastic, and non-normal specifications. Kruegar (2015) developed an R package called `bvarsv` to estimate Primiceri (2005)'s Time Varying Parameter VAR and construct impulse responses and posterior predictive distribution.

The bvartools R package contains algorithms for Bayesian inference of VAR and vector error correction models, leveraging functions from the introductory texts of Chan, Koop, Poirier and Tobias (2019) and Koop and Korobilis (2010) to simulate the posterior distributions, forecast, and create forecast error variance decomposition. Similarly, Kuschnig and Vashold (2021) developed the BVAR package to estimate the model with hierarchical prior selection, featuring structural analysis of forecasts and impulse responses using conjugate priors. The BayVAR_R package by Quilis (2022) models both classical and Bayesian versions, and the mfbvar package implements Bayesian mixed frequency VAR models. Complementing the structural VARs is the bsvarSIGNs package that constructs the structural BVAR model identified by zero, sign and narrative restrictions. Notwithstanding the plethora of R packages, none exists in python. covbayesvar is the first open-source python package to estimate the model with COVID-volatility as explained in Lenza and Primiceri (2022), and apply the method to a large number of variables as shown in Crump et. al (2021). Whilst researchers may drop the data seen in COVID months for estimation, disregarding the recent data is inappropriate to forecast the future trends of the economy as it underestimates uncertainty.

Next, I briefly introduce the BVAR model mathematically in Section 2 and elucidate the important estimation and forecasting functions in Section 3. Section 4 presents a simple Monte Carlo simulation of the constant volatility BVAR model to test its performance, where I evaluate how the simulated posterior estimates of the parameters fare relative to the true hypothesized values. Subsequently, in section 5, I discuss the monthly economic and financial data that the model estimates, present the forecasting results, a scenario analysis exercise, and a routine to condition the forecasts on Fed's long-run targets using entropic tilting. Section 6 demonstrates a diverse array of applications of the model using quarterly data. Section 7 replicates three figures from Lenza and Primiceri (2022) to juxtapose how the forecasts and impulse responses from the COVID-volatility model fare relative to those from the constant volatility model. Finally, section 8 concludes.

2. Model

Lenza and Primiceri's (2022) method explicitly models the changing volatilities in shocks and incorporates significant financial and macroeconomic innovations during the pandemic. Unlike other models that explain volatilities such as TVP-VAR, we know when the shock hit the economy, i.e., the variance of the innovations is known. So, I estimate the model and measure changes in the volatility, keeping in mind that the volatility can persist for several periods in the future. As the first extreme observation was in March 2020, I rescale the standard deviation of the shocks in March, April, and May to unknown parameters η_1, η_2, η_3, and estimate these parameters using Bayesian methods explained in Giannone et al. (2015).

Then, I estimate the variance of the residuals after March 2020, assuming that the volatility decays at a constant rate every month henceforth. The main model is a VAR(12):

$$y_t = \alpha + A_1 y_{t-1} + \cdots + A_{12} y_{t-12} + \eta_t \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma)$$

where $\eta_t = \eta_1$ before the pandemic began, and scales up the residual covariance matrix during the pandemic at time t^*.

$$\eta_t = \begin{cases} \eta_1 & t = t^* \\ \eta_2 & t = t^* + 1 \\ \eta_3 & t = t^* + 2 \\ \eta_{t+j} = 1 + (\eta_3 - 1)n_4^{-j/2} & \text{otherwise.} \end{cases}$$

The scaling factors take distinct values in the initial three periods after the pandemic began, before decaying at the rate η_4 henceforth. Since more lags proliferate the number of parameters in the model, we cannot feasibly estimate the model by OLS, especially when the "curse of dimensionality" precludes estimation in a richly parameterized model. Thus, I shrink the autoregressive parameter coefficients using the Minnesota prior. This prior presumes that the variables follow a random walk with drift, and shrink the coefficients of faraway lags. I also impose the natural conjugate prior, wherein I draw the elements of the variance-covariance matrix Σ from the inverse-Wishart distribution. Then, I obtain the posterior estimates of the parameters, fit generalized impulse responses, and forecast. More specifically, to estimate equation (1), if we assume that the scaling factor η_t is known, then we can rewrite equation (1) where I stack coefficients as:

$$y_t = X_t \Phi + \eta_t \epsilon_t,$$

where $X_t = I_k \otimes [1, y'_{t-1}, y'_{t-2}, \dots, y'_{t-12}]$ and $\Phi = \text{vec}([\alpha, A_1, A_2, \dots, A_{12}])$.

Normalizing the coefficients to account for the scaled idiosyncratic error, I divide equation (2) by f_t as:

$$\frac{y_t}{\eta_t} = \frac{X_t}{\eta_t} \Phi + \epsilon_t \quad \Rightarrow \quad \tilde{y_t} = \tilde{X}_t \Phi + \epsilon_t.$$

Using the transformed data to estimate the parameters $\tilde{y_t}$ and $\tilde{X}_t$, firstly, the prior distribution for the VAR error variance-covariance matrix Σ is the normal inverse-Wishart with the scale S and degrees of freedom $n + 2$. In other words, $\Sigma \sim IW(S, n + 2)$.

Secondly, the conditional distribution of the coefficient matrix Φ given the estimates of the variance-covariance matrix Σ is:

$$\Phi|\Sigma \sim N(\psi, \Sigma \otimes \Omega).$$

Thirdly, I characterize extreme values via the Pareto distribution, where the prior belief on all the scaling factors is the Pareto distribution with the unit values as the scale and shape parameters. To corroborate, the shape parameter connotes the speed at which the tail falls off, and the scale parameter regulates the threshold above which the distribution becomes conspicuously relevant. The unit values indicate that the Pareto distribution has a very long and flat tail, attributing that most of the probability mass is concentrated in lower values and the higher values occasionally occur. This is compatible with the belief that the variance of the errors is large during the pandemic:

$$\eta_t \sim Pareto(1, 1), \quad t = 0, 1, 2.$$

Fourthly, I impose a single unit root prior to reflect a belief with Bernoulli probability p that a series might be non-stationary or random walk. The single unit root prior reflects this persistence without strictly enforcing stationarity, unlike the Minnesota prior, which assumes stationarity. This Bernoulli probability p that a given series in unit root follows a Beta prior with the shape parameters (α, β) to determine how strongly we believe a series is likely non-stationary. Using a Beta distribution with a large mode of 0.8 and a standard deviation of 0.2 reflects a belief that we expect that series is highly persistent with some degree of uncertainty.

Finally, I employ another shrinkage prior, known as the sum of coefficients prior, to shrink the coefficients towards zero to preclude an overfit model. Conjecturing that a no-change forecast is a good forecast when the sample begins, it tapers the importance of deterministic components in a VAR estimated condition on initial observations. The deterministic element is:

$$E[y_t \,|\, Y_1, Y_2, ..., Y_{12}, \Phi].$$

Formulated using the Theil Mixed Estimation, it forms conjugate priors by constructing artificial data and appending them when the actual sample ends. Centering the prior belief that all the coefficients on their own lags sum to 1 in each equation:

$$(A_1 + A_2 + \cdots + A_{12})\,|\Sigma \sim N\left(I_k, V(\omega, \tilde{y}_0, \Sigma)\right),$$

where ω is the hyperparameter that regulates how dispersed the prior beliefs are. As $\omega \to \infty$, the prior is flat, and as $\omega \to 0$, the model has a unit root in each equation, ruling out cointegrated variables. It creates a sparse model as it restrains higher probability mass on smaller values of the coefficients, curtailing the number of parameters in the model. Whereas the Minnesota prior allows us to identify the important variables in the model, the sum of the coefficients prior identifies few important coefficients. Therefore, utilizing both the sum of coefficients and Minnesota priors in the same model additionally regularizes the model and allows the different types of priors to capture different features of the data. To estimate the posterior density of the parameters, I adopt a hierarchical technique of sampling using the Metropolis-Hastings algorithm defined by Primiceri and Lenza (2022). Briefly, first, I initialize the hyperparameters at their posterior mode; and draw the candidate values of these hyperparameters from the proposal distribution. Pre-specifying the acceptance rate at roughly 25 percent, I accept and reject the proposed draws of hyperparameters; then draw the coefficients Φ and variance-covariance matrix Σ from the normal-inverse Wishart density function.

3. Python Implementation: Main Functions

This section sheds light on four main functions in the `covbayesvar` package that are instrumental in defining the prior distributions, estimating the model to update the posterior distributions, and estimating and plotting the unconditional and conditional forecasts.

Priors and Hyperparameters

We assume external beliefs via additional inputs in the `set_priors_covid` function. Here, the priors enable us to regularize or shrink the parameter space that prevents overfitting when data is insufficient to estimate the parameters reliably, and the economy experiences sudden structural shifts.

The function returns a tuple with several dictionaries and lists, where each argument represents:

1. **`r` (Priors)**:

   A dictionary containing the priors for the BVAR model. This includes settings like `hyperpriors`, `Vc`, `pos`, and the hyperparameters for the Minnesota prior `MNalpha`, the time horizon for forecasts `hz`, and MCMC-related parameters such as the total number of draws in the MCMC simulation `Ndraws` and the initial number of draws burnt-in `Ndrawsdiscard`.

2. **`mode` (Hyperpriors' Mode Values)**:

   A dictionary containing the mode values for hyperpriors, such as:

   - **`lambda`**: The tightness of the prior for coefficients on own lags.
   - **`miu`**: A prior for the sum of coefficients.
   - **`theta`**: Controls the overall shrinkage.

- `eta`: Hyperparameters related to volatility changes due to the onset of COVID-19.

3. **`sd` (Standard Deviations for Hyperpriors)**:

   This dictionary contains the standard deviations for the hyperpriors `lambda`, `miu`, `theta`, `eta`, reflecting the uncertainty around their respective mode values.

4. **`priorcoef` (Priors' Coefficients)**:

   A dictionary of coefficients for the hyperpriors, calculated using functions like `gamma_coef()` for gamma priors and `beta_coef()` for beta priors. These coefficients are necessary for estimating the posterior distribution in the BVAR model.

5. **`MIN` and `MAX` (Bounds for Optimization)**:

   These dictionaries set lower and upper bounds for variables in the maximization process. For example, `MIN['lambda] = 0.0001` ensures that the prior's tightness cannot be smaller than 0.0001, and `MAX['lambda] = 5` prevents it from exceeding 5.

6. **`albet` and `mosd` (Beta Distribution Parameters)**:

   These are parameters related to the Beta distribution that affect volatility `eta`. The `alpha` and `beta` parameters describe the distribution of hyperparameters that govern the dynamics during COVID-19.

Estimating the BVAR

The function `bvarGLP_covid` estimates the Bayesian VAR model after considering changes in volatility due to the COVID-19 pandemic. Originally founded upon the model derived by Giannone, Lenza and Primiceri (2015) that utilizes Markov chain Monte Carlo (MCMC) methods, this function additionally captures volatile movements starting from March 2020 to estimate the posterior distribution of the model parameters.

Input Parameters

1. **`y`** : The matrix of economic time series data, where rows represent time periods and columns represent different variables.

2. **`lags`** : The number of lags to include in the VAR model.

3. **`kwargs`**: Additional arguments to specify the BVAR model settings, including:

   - **`mcmc`**: Indicator for running MCMC.
   - **`MCMCconst`**: MCMC constant.
   - **`MNpsi`** : Minnesota prior hyperparameter.
   - **`sur`**: Indicator for seemingly unrelated regressions in the model.

- `noc` : Indicator for no constant in the model.
- `Ndraws` : Number of MCMC draws.
- `hyperpriors` : Indicator for using hyperpriors.
- `Tcovid` : Time index that determines the onset of volatility due to COVID-19.

The function sets the priors using the `set_priors_covid` function which prepares various hyperparameters needed to estimate the model. Next, it prepares the input data matrix `y` by constructing lagged values as regressors. This involves creating a matrix `x` that includes a constant term and the lagged values of `y`. With the prepared inputs, it constructs the Minnesota prior mean vector `b` and defines the initial values for the key hyperparameters `lambda`, `theta`, `mu`, `alpha` that control the prior distributions. Later, it adjusts for volatility, particularly emphasizing changes post-COVID-19. To establish scaling factors, it compares the volatility before and after COVID-19. Fitting an AR(1) model to each variable, it estimates its residual variance and numerically optimizes over hyperparameters using the `csminwel` function to maximize the log marginal likelihood of the VAR model.

Unconditional and Conditional Forecasts

Crump et. al (2019) define unconditional predictive density as:

$$f\left(y_{T+1}, \ldots, y_{T+h} \mid y_{1:T}\right) = \int f\left(y_{T+1}, \ldots, y_{T+h} \mid y_{1:T}, \theta\right) f\left(\theta \mid y_{1:T}\right) d\theta$$

where, θ has all the coefficients of the model. Computing the predictive density requires iterating in two steps. First, we draw the coefficients from their posterior distribution. For instance, at the m-th draw, the posterior estimate is $\theta^{(m)}$. Then, given the posterior estimate, we sample from:

$$f\left(y_{T+1}, \ldots, y_{T+h} \mid y_{1:T}, \theta^{(m)}\right)$$

by drawing from the forecast errors $\epsilon_{T+1}, \epsilon_{T+2}, \ldots, \epsilon_{T+h}$ and iterating the model forward using the simulation smoother.

Using the VAR model estimates, the function `VARcf_DKcks` calculates the conditional forecasts by applying the Kalman filter and smoother. After reformulating the model in state-space form, we can either generate point forecasts using the Kalman filter or generate forecasts at various quantiles using the Durban-Koopman simulation smoother. Reflecting an uncertain future, the forecasts at various quantiles are forecast intervals that widen as the forecast horizon increases.

Input Parameters

1. **X**: A matrix of observable variables containing historical data of dimension $(T \times N)$, wherein T is the number of time series observations, and N is the number of variables in the model.

2. **p**: The number of lags in the VAR model.

3. **beta**: The VAR model's coefficient matrix of dimension $(Np + 1) \times N$, where the first Np rows are lagged coefficients and the last row represents the constant.

4. **Su**: The model's variance-covariance matrix of dimension $(N \times N)$.

5. **nDraws**: The number of draws to generate using the Durban-Koopman smoother. If `nDraws = 0`, the function performs a simple Kalman smoothing; otherwise, it performs simulation smoothing with `nDraws` samples.

Quantile Plots

Designing line charts with quantile bands to visualize forecast intervals and the historical data, the `quantile_plot` function plots the forecasts, sandwiched between the forecast bands. These bands represent different percentiles, where the inner band is the 25th to 75th percentile, and the outer band is the 5th to 95th band.

Input Parameters:

1. **time**: It denotes a sequence of dates on the x-axis.

2. **quantiles**: This is a matrix of quantile values to be plotted. It can either have 5 or 7 columns:

   - For a 5-column matrix, the columns represent the outer lower quantile, inner lower quantile, center (median or mean), inner upper quantile, and outer upper quantile.

   - For a 7-column matrix, the additional two columns represent middle-lower and middle-upper quantiles.

3. **base_color**: An RGB tuple that defines the base color for the quantile bands. If not provided, a default blue color is used.

4. **run_scenario_analysis**: If `True`, the plot will use a red color scheme to indicate a scenario analysis, which typically highlights a special case or alternative scenario. Otherwise, it uses a blue color scheme.

5. **show_plot**: If `True`, the function will display the plot immediately after creating it.

4. Monte Carlo Simulations

Through a simple simulation exercise in *MCMC Simulations* file, I evaluate and test the performance of the BVAR with a constant volatility model to assess how accurately the `bvarGLP` function estimates the parameters. So, we compare the true parameters of the simulated model with the estimated parameters drawn from the distribution and examine how far apart they are. For this, I randomly draw 500-time series of observations from a VAR(1) process:

$$Y_t = c + AY_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma)$$

Simulating randomly generated data from the aforementioned model, I run the BVAR model and plot the posterior distribution of each of the estimated parameters in Figure 1: β_{ij}, $\forall i = 1, 2, 3$; $j = 1, 2$, which are the coefficients of the matrix A and the constant vector of the model; σ_{ij}, $\forall i = 1, 2$, which are the variances and covariance terms of the errors in Σ; and λ, governing how the coefficients shrink in estimation.

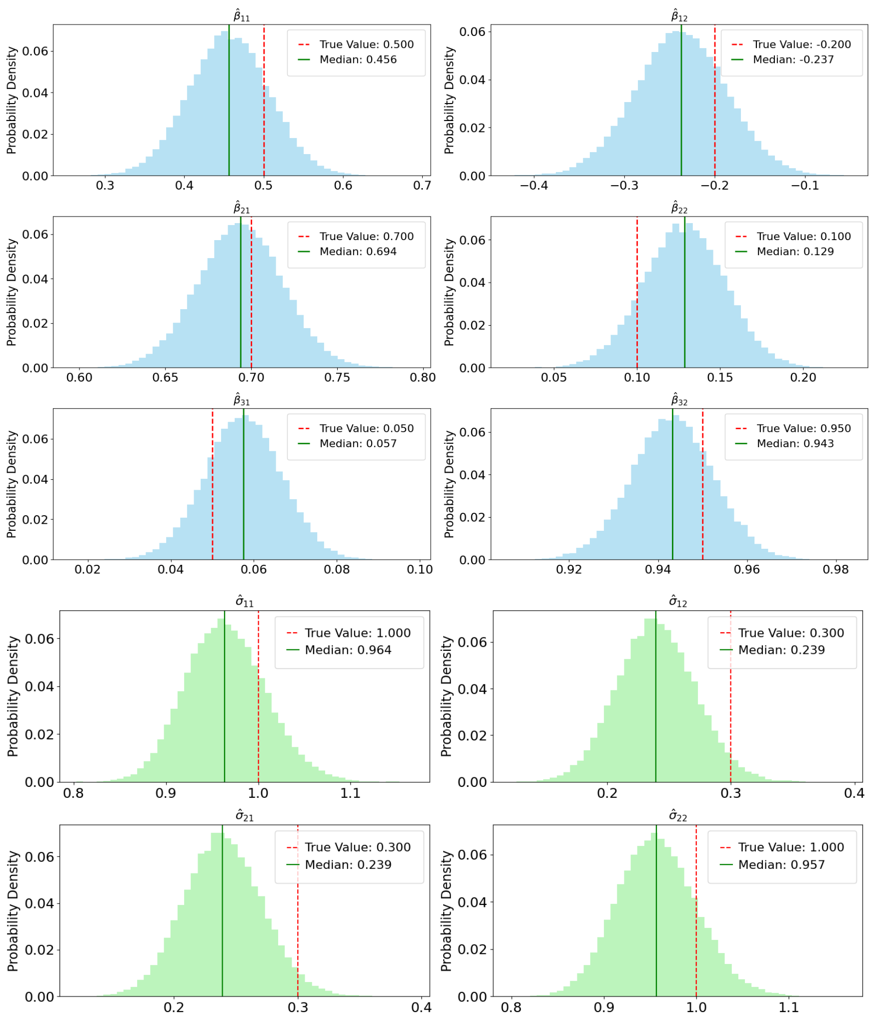

Figure 1: Posterior distribution of the coefficients of matrix A, and the variance and covariance terms of Σ from MCMC simulation with 100,000 draws where half of the draws were burnt-in, along with the true parameters.

Furthermore, Table 1 displays the posterior mean or the average of the 50,000 saved posterior samples, the 95 percent credible interval of the parameter, and the mean square error (MSE) for each parameter, which measures how close the estimates are to the true values. The true values for all the parameters lie within the 95 percent credible interval, suggesting that the posterior distribution is capturing the true value well, albeit the posterior mean may be slightly off. Likewise, in nearly all estimates, the MSE is very low, indicating that the posterior samples are generally very close to the true values.

Parameter	True Value	Posterior Mean	95% Credible Interval	MSE
β_{11}	0.5	0.4564	(0.3582, 0.5553)	0.0044
β_{12}	-0.2	-0.2372	(-0.336, -0.1387)	0.0039
β_{21}	0.7	0.6938	(0.6455, 0.7419)	0.0006
β_{22}	0.1	0.1285	(0.0802, 0.1762)	0.0014
β_{31}	0.05	0.0574	(0.0394, 0.0753)	0.0001
β_{32}	0.95	0.9433	(0.9252, 0.9613)	0.0001
σ_{11}	1	0.9652	(0.8849, 1.0538)	0.0031
σ_{12}	0.3	0.2399	(0.1799, 0.303)	0.0046
σ_{21}	0.3	0.2399	(0.1799, 0.303)	0.0046
σ_{22}	1	0.958	(0.8774, 1.0458)	0.0036
λ	0.2	0.1971	(0.1971, 0.1971)	0

Table 1: Summary of Posterior distributions of all parameters, 95 percent credible intervals, and mean square error as a function of each MCMC sample of the parameter and the true value of the parameter.

Finally, I create trace plots to visualize if the MCMC chains have converged to the true posterior distribution. The trace plots of all the parameters depict stationary patterns as the values fluctuate around the mean without trending over time, implying that the chain has converged. In the next three sectionss, I explain how we can apply this model using time series data of monthly and quarterly macro and financial variables, referencing from the Google Colab notebooks.

5. Large BVAR Model with Covid-Volatility: Applied Examples Using Monthly Data

Data

First, I downloaded the monthly data of 28 variables with four macro and financial variables each from January 1962 to October 2024 from FRED-MD. The macro variables are the measures of the labor market such as the unemployment rate, output such as industrial production, housing starts, and prices measured via CPI. Financial variables such as the 10-year Treasury yields, yield, spreads, and the S&P 500 index. Keeping the rate, such as the unemployment rate and borrowing rates, in levels or percentage points, I transformed the remaining variables, such as CPI, and VIX into logged values, specifically, $100 \times$ log of the levels, and we interpret the transformed variables as year-over-year growth rates.

The Google Colab notebook named as *Descriptives.ipynb* procures this data, and transforms every column identified as "log" to 100 × log using the `transform_data` function to interpret them as percentage growth. Taking logs also helps in stabilizing the mean and variance of these non-stationary time series by compressing the spread of the data. This is particularly crucial when variables such as asset prices, volatility indexes, exhibit exponential growth rates, Without transforming them first will yield spurious correlations in VAR, and explode the forecasts. Lastly, I plot the time series of the original variable, and their transformation to detect the evolution of the variables and discern patterns or breaks (if any) in the data. The complete list of variables is in table A1 of the Appendix.

Applications of the Model

This section presents an example from *main* script, illustrating snippets of codes from the file. Open that file to review and run the code, and supplement it with guidelines from this section. To run the model from the *covbayesvar* package, install the package using the `pip` command and import the functions from the package's module known as `large_bvar` as:

```
!pip install covbayesvar
import covbayesvar.large_bvar as bvar
```

If we estimate the model and produce the forecasts using updated data for the first time, we set all the boolean flags to `True` so that the script runs the model and unconditional and conditional forecasts, and saves the estimates from the simulated draws in pickle files. Once we have already run the model first, if we would like to produce the conditional forecasts based on a different set of shocks, we can set each of the boolean flags of estimating the BVAR `estimateBVAR` and unconditional forecasts `runUNC` to `False`.

```
# Configuration settings
vis = True  # Set to False to hide figures
estimateBVAR = True
runUNC = True
plot_uncond_forecasts = True
plot_joint_uncond_forecasts = True
plot_scenario_analyses = True
runCF = True
lags = 12  # Number of lags in VAR, if monthly data
Ndraws = 40000  # Number of draws in MCMC simulation
discard = 20000  # Number of initial draws to discard (burn-in period)
vint = datetime(2024, 11, 1)  # The vintage date (forecasting start date)
```

Incorporating the COVID-related specifications, we determine the index when COVID began in March 2020, and the data from that date as a structural break, to ensure that the model accounts for the unprecedented volatility.

```
# COVID specific settings
if covid:
    # Index of start date of estimation
    T0 = 0
    # Index of end date of estimation (February 2020)
    TFeb2020 = np.where((dates.dt.year == 2020) & (dates.dt.month == 2))[0][0]
    # First time period of COVID (March 2020)
    Tcovid = TFeb2020 - T0 + 1
```

I establish the prior values in `prior_params` dictionary, which are the hyperparameters or the starting points of the parameters based on prior beliefs. These are the most likely value of each hyperparameter, measures of uncertainty or degree of spread around each parameter's mode, and the lower and upper bounds within which the estimated parameters must lie during Gibbs sampling.

- **`lambda_mode` (default: 0.2)**: Mode of the "tightness" parameter of the Minnesota prior, which controls the scale of all the variances and covariances. Lower values tighten the prior, reducing the influence of the data on the model parameters to prevent overfitting.
- **`miu_mode` (default: 1)**: Mode for the persistence (mean reversion) hyperparameter. It reflects the prior beliefs on how long the shocks persist or how slowly the shocks dissipate over time.
- **`theta_mode` (default: 1)**: Mode for the cross-variable shrinkage parameter. This parameter controls how strongly we expect the variables to interact in the model, i.e., if a shock to one variable significantly impacts others in the model. Collectively, `lambda_mode`, `miu_mode`, and `theta_mode` influence the spread of the inverse-Wishart prior Σ. Specifically, these hyperparameters configure the variance structure of Σ, determining how much weight is placed on the data (likelihood), and prior beliefs of the parameters to drive the mean of the posterior distribution.
- **`eta_mode` (default: [0, 0, 0, 0.8])**: Mode for the COVID-19 scaling factor's decay parameter, η_4, specifically applied to the first three months after the disease outbreak. Since the scaling factors $\eta_{t+j}, i = 0, 1, 2$ take fixed values in the first three periods and decay at a constant rate from the fourth

month, the vector `[0, 0, 0, 0.8]` controls the scaling factor for the residual covariance matrix for shocks in April, May, June 2020, and afterward. $\eta_4 \sim Beta(0.2, 0.8)$.

- **`eta_sd` (default: [0, 0, 0, 0.2])**: Standard deviation for the COVID-19 scaling factor. A low standard deviation (0.2) around the scaling factor indicates that we expect relatively small deviations from the central value of the scaling factor, reflecting a strong belief in the priors for the initial COVID-19 shock scaling.

- **`eta_min` (default: [1, 1, 1, 0.005])**: Minimum bounds for each element of the scaling factor during COVID. It ensures a minimum level of impact, particularly for the fourth element (0.005), which controls the decay of the impact of shocks after the initial COVID months.

- **`eta_max` (default: [500, 500, 500, 0.995])**: Maximum bound for each element of the COVID-19 scaling factor. High bounds on the first three elements (500) allow substantial impact from shocks in the first three COVID months. The fourth element (0.995) restricts the long-term effect slightly below 1, allowing for decay in the impact of shocks over time.

```
priors_params = {
    'lambda_mode': 0.2, #  "tightness" of the Minnesota prior: controls the scale of
        variances and covariances
    'miu_mode': 1, # mean reversion hyperparameter
    'theta_mode': 1, # mode of  cross-variable shrinkage
    'lambda_sd': 0.4, # standard deviation of the Minnesota tightness prior
    'miu_sd': 1, # standard deviation of the persistence prior
    'theta_sd': 1,
    'eta_mode': [0, 0, 0, 0.8], # mode of COVID-19 scaling factor, applied to first 3
        months of COVID-19 period
    'eta_sd': [0, 0, 0, 0.2], # standard deviation of the covid-19 scaling factor
    'lambda_min': 0.0001,
    'alpha_min': 0.1,
    'theta_min': 0.0001,
     'miu_min': 0.0001,
    'eta_min': [1, 1, 1, 0.005],
  'lambda_max': 5,
    'alpha_max': 5,
    'theta_max': 50,
    'miu_max': 50,
    'eta_max': [500, 500, 500, 0.995]

}
```

The code estimates the BVAR on the completed transformed dataset without any missing values with 12 lags (as the data is monthly) and initial parameters.

```
# Estimate on complete panel
# Find the last time period that does not have NaN values
Testim = np.nanmax(np.where(~np.isnan(data_transformed.sum(axis=1)))[0]) + 1
bvar_results = bvar.bvarGLP_covid(data_transformed[:Testim, :], lags=lags,
    priors_params=priors_params, mcmc=1,MCMCconst=1, MNpsi=1, sur=0, noc=0,
    Ndraws=Ndraws, Ndrawsdiscard=discard,hyperpriors=1, Tcovid=Tcovid)
```

The arguments of the function `bvarGLP_covid` are:

- **`lags`**: The number of lags (12, in this case, since the data is monthly).
- **`mcmc=1`**: This specifies that the BVAR estimation will use the Markov Chain Monte Carlo (MCMC) method.
- **`MCMCconst=1`**: This parameter controls a constant factor used in the MCMC algorithm.
- **`MNpsi=0`**: A hyperparameter for the Minnesota prior, often set to 0 to strongly shrink the coefficients towards 0.
- **`sur=0`**: This parameter specifies whether to use seemingly unrelated regressions (SUR). If set to 1, the model uses SUR, allowing for cross-equation error correlation.
- **`noc=0`**: A flag for including no constant in the model. If set to 0, the model includes a constant term.
- **`Ndraws and Ndrawsdiscard`**: These specify the number of total MCMC draws and the number of discarded draws (burn-in period), respectively.
- **`hyperpriors=1`**: Enables hyperpriors for regularization.

After estimating the model, I plot the distribution of the parameters across all 20,000 saved draws. Figure 2 illustrates the distribution of the standard deviation of the March shocks or the factors that scale the shocks in the BVAR model during and after COVID-19 and the volatility decay parameter η_4. The posterior distribution of the standard deviation of the Minnesota prior. Since the standard deviation of the Minnesota prior is tightly distributed, the coefficients in Φ are shrunk towards 0, yielding more precise estimates. However, if the distribution appears wider, the uncertainty about the true parameters in Φ rises.

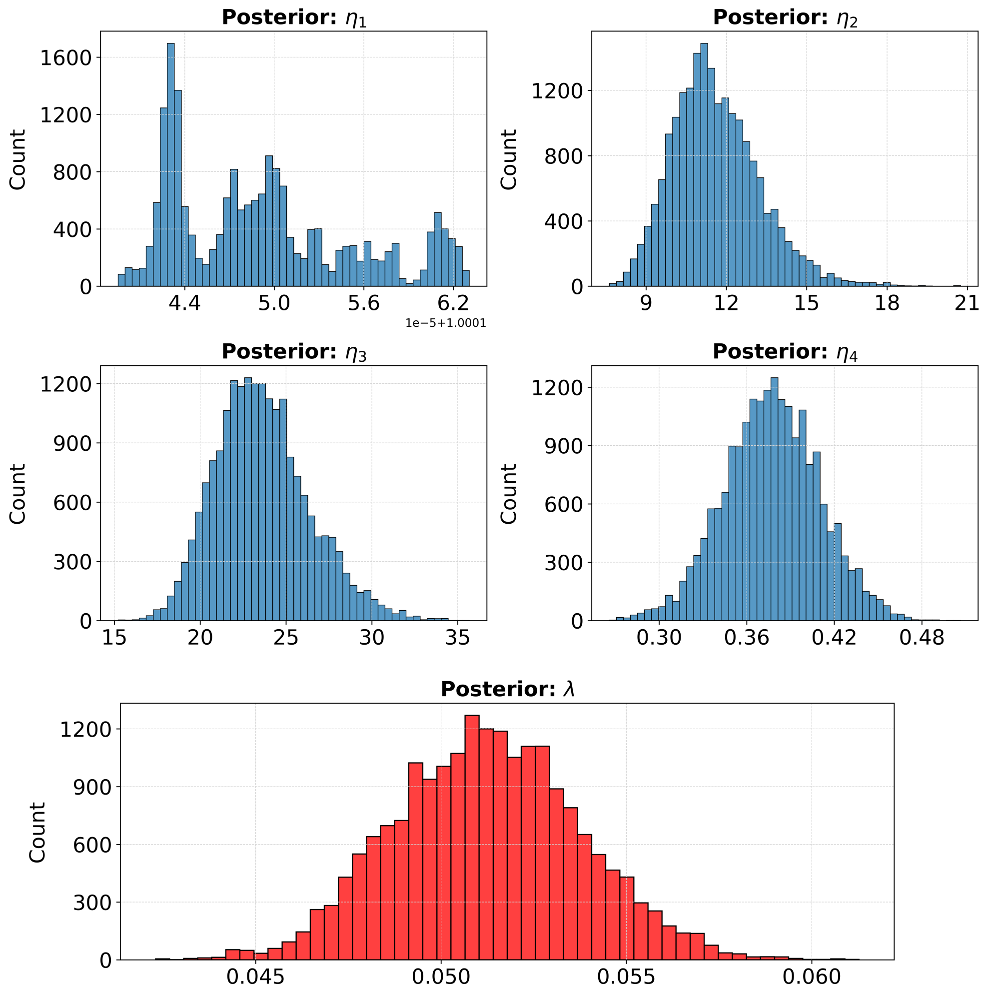

Figure 2. Posterior distribution of the Minnesota prior's standard deviation and the volatility scaling factors and the volatility decay parameter.

After estimating the parameters, I construct the unconditional forecasts for a forecast horizon of 36 months of all twenty-eight variables starting from October 2024. To accomplish that, I extract the saved parameter estimates from each of the $j = 1, \ldots, 20000$ draws from their posterior distribution. Then, I call the `VARcf_DKcks` function that generates the unconditional forecasts for j-th draw, which accumulates the forecast results for each draw across variables and months ahead in a 3D matrix called `PredY_unc`. In other words, the 3D array stores the forecasts at the h periods for n variables across all J draws.

```
for j in range(ndraws):  # Loop through the number of draws
    if (j % 10) == 0 or j == ndraws - 1:
        print(f"Generating unconditional forecasts: {j} of {ndraws} draws...")
        sys.stdout.flush()

```

```python
    # Extract the j-th draw for beta and sigma
    beta_j = bvar_results['mcmc']['beta'][:, :, j]
    Gamma_j = np.vstack((beta_j[1:, :], beta_j[0, :]))
    Su_j = bvar_results['mcmc']['sigma'][:, :, j]

    PredY_unc[:, :, j] = bvar.VARcf_DKcks(YFore, bvar_results['lags']['lags'],
        Gamma_j, Su_j, 1)
```

I plot the unconditional forecasts in various quantiles: $[0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8]$ along with the historical data. For instance, figure 3 portrays the historical data from January 2020 to October 2024, followed by the model-based "baseline" probabilistic forecasts in varying shades of blue. The dark blue line denotes the most likely "median" forecast or the forecast in the middle of the distribution. Half of the forecasted values lie above the forecast denoted by dark blue, and the other half lies below this point. Likewise, the forecasts in the quantiles 0.2 and 0.8 connote that 20 percent of the forecasts fall below this point, and 80 percent are above it, implying that these forecasts are closer to the tails of the distribution. Whilst figure 3 shows the forecasts only for four variables, the code generates similar graphs for all the variables and saves them individually as PNG files.

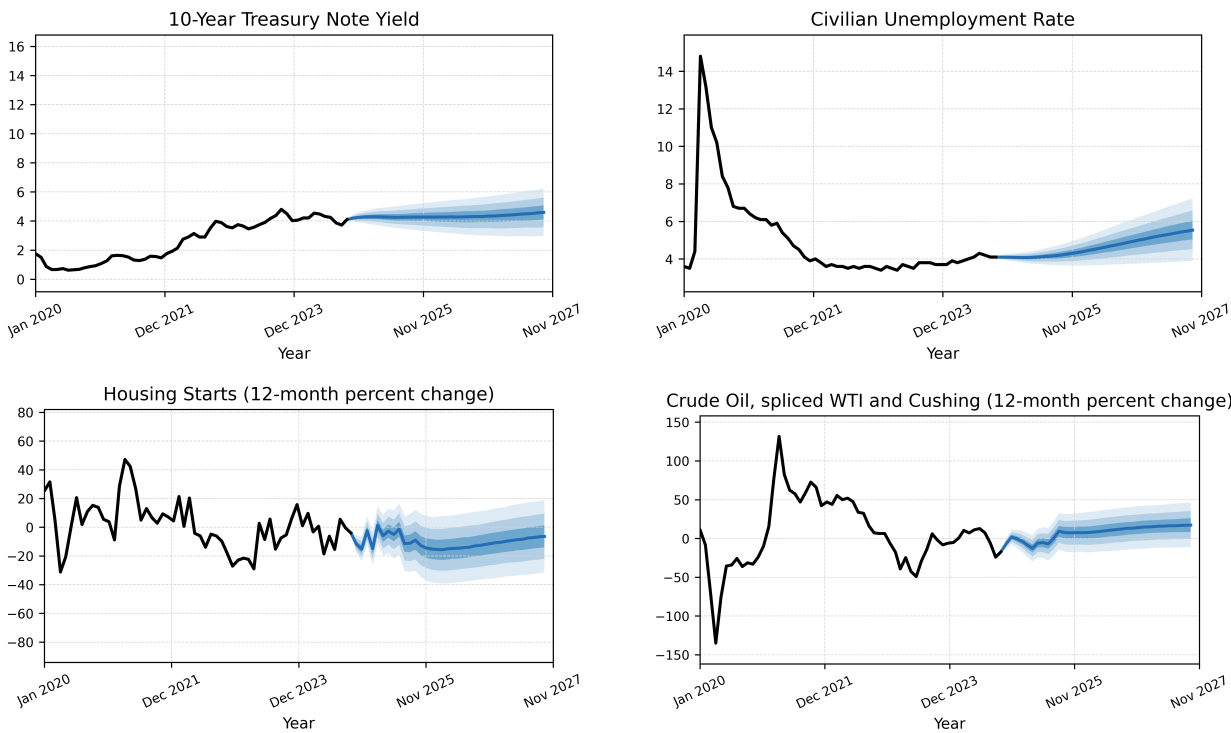

Figure 3. Actual values of the industrial production growth, unemployment rate, housing starts and oil prices (in black) till October 2024. Median forecasts for three years (in dark blue) and shaded regions represent forecast bands at 60, 70, and 80 percent coverage intervals.

Scenario Analysis

Further exploiting the versatile capabilities of the large BVAR model, we can employ the model to answer more policy-based questions, such as the impact of supply and demand shocks on predicted paths of key economic variables. I model a "forward-looking" scenario where tighter immigration rules such as mass deportations of undocumented workers and border controls shrink the labor force, constricting the supply of workers in the economy. Fewer workers can reduce the production of goods in the short run, especially those employed in construction, hospitality, and food services, weakening demand. This supply shock puts an upward pressure on wages as employees may compete more aggressively for a smaller pool of workers in the short run. To model this simple scenario, I assume that the total employees on non-farm payroll reduce by 5 percent 5-10 months into the future and the average hourly earnings of production and non-supervisory workers rise by 2 percent after labor supply shock hits the economy 7-10 months ahead.

Coupled with the supply shocks, the PCE inflation declines by 1 percent point in the short run: 3-5 months ahead. Leaving other variables unconstrained, figure 3 depicts the scenario analyses for different segments of the economy, with posterior median response surrounded by the 68 and 90 percent coverage intervals. Here, the conditional forecasts assume that the fixed paths of all employees in the nonfarm payroll and average hourly earnings may possess information about how other variables could react. These shocks in non-farm payroll employees and average hourly earnings define a scenario:

$$S_t = \{\alpha_{L_s}\epsilon_{l,T+s} + \alpha_{m_s}\epsilon_{m,T+s}, s = 1, 2, ...\},$$

where α_{L_s} and α_{m_s} are the coefficients associated with non-farm payroll employees, and average hourly earnings, respectively.

Similar to the unconditional predictive density, the conditional predictive densities additionally depend on a conditioning set C_t that contains scenarios or realized future paths of a set of variables:

$$f(y_{T+1}, ..., y_{T+h}|y_{1:T}, C_t) = \int f(y_{T+1}, ..., y_{T+h}|y_{1:T}, \theta, C_T)f(\theta|Y_{1:T})d\theta$$

Comparable to simulating from the unconditional predictive density, here we also iterate in two steps. First, we draw the coefficients $\theta^{(m)}$ at the m-th draw from their posterior distribution conditional on the scenario. Then, given the posterior estimate, we sample from $f(y_{T+1}, ..., y_{T+h}|y_{1:T}, \theta^{(m)}, C_T)$ using Kalman filter. Crump et. al (2021) apply the Kalman filter and simulation smoother derived in Banbura, Giannone and Lenza (2015) to make the model computationally feasible with a large dimension system.

In terms of code, the python function `VARcf_DKcks` generates and stores the conditional forecasts in a 3D matrix, just as the same function geneated the unconditional forecasts earlier. First, we define the indices of the variables on which we impose the shocks, then initialize a matrix of `NaN` values which will store the conditional forecasts. Next, we set the shocks for specified periods on the variables. Looping through the MCMC draws from the posterior distribution, we add the magnitude of the shock values to the unconditional forecasts and use the posterior estimate of the parameter from each draw to generate the conditional forecasts at each draw.

```
# Find indices of specific variables: All employees, total non farm
idxCV1 = Spec.index[Spec['SeriesID'] == 'PAYEMS'].tolist()[0]
# Average Hourly Earnings of Employees
idxCV2 = Spec.index[Spec['SeriesID'] == 'CES0600000008'].tolist()[0]
# Create a matrix of NaNs to store shocks
# n is the number of variables and T is the length of the initial data
Ycond = np.nan * np.ones((len(DateAll), n))

# Fill the initial part of Ycond with transformed data
Ycond[:T, :] = data_transformed
```

```
# Create a matrix for shocks
Shock = np.nan * np.ones((h_fore.sum(), n))  # h_fore is a boolean array indicating forecasts
Shock[5:10, idxCV1] = -5 # Apply shocks to % change in All Employees
Shock[7:10, idxCV2] = 2 # Apply shocks to % change in Average Hourly Earnings

# Initialize PredY_con for conditional density forecasts
PredY_con = np.nan * np.ones((len(DateAll), data_transformed.shape[1], ndraws))
for j in range(ndraws):  # Loop through the number of draws

    if (j % 10) == 0:
        print(f"Generating conditional forecasts: {j} of {ndraws} draws...")
        sys.stdout.flush()
    # Extract the j-th draw for beta and sigma
    Ycond[h_fore_1d, :] = PredY_unc[h_fore_1d, :, j] + Shock
    beta_j = bvar_results['mcmc']['beta'][:, :, j]
    Gamma = np.vstack((beta_j[1:, :], beta_j[0, :]))
    Su = bvar_results['mcmc']['sigma'][:, :, j]
    PredY_con[:, :, j] = bvar.VARcf_DKcks(Ycond, bvar_results['lags']['lags'], Gamma, Su, 0)


# Compute the difference between conditional and unconditional forecasts
dY = PredY_con - PredY_unc
```

The top graphs in Figure 4 a) and b) show the trajectory of all employees in the non-farm payroll and industrial production index after the former slumps by 5 percent points, respectively, from its benchmark forecasted paths. In contrast, the bottom graphs showcase the scenario, which is the difference between the forecasts conditional on the shocks on both variables, and the unconditional or baseline forecasts, which are devoid of any shocks. Mathematically,

$$D[y_{T+s}|y_{1:T}, C_T, \theta] = E[y_{T+s}|y_{1:T}, C_T, \theta] - E[y_{T+s}|Y_{1:T}, \theta]$$

$$\implies \int y_{T+s} f\left(y_{T+s}|y_{1:T}, \theta, C_T\right) dy_{T+s} - \int y_{T+s} f\left(y_{T+s}|y_{1:T}, \theta\right) dy_{T+s}$$

These forecasts are devoid of any structural identification schemes for the errors and are entirely based on past historical correlations among the variables in the system. Because the scenarios are derived from the reduced-form models, without identifying the structural shocks, I do not interpret them. In the Google Colab notebook, I use the `quantile_plot` function to generate these (2×1) subplots for all 28 variables and save each of them as PNG files.

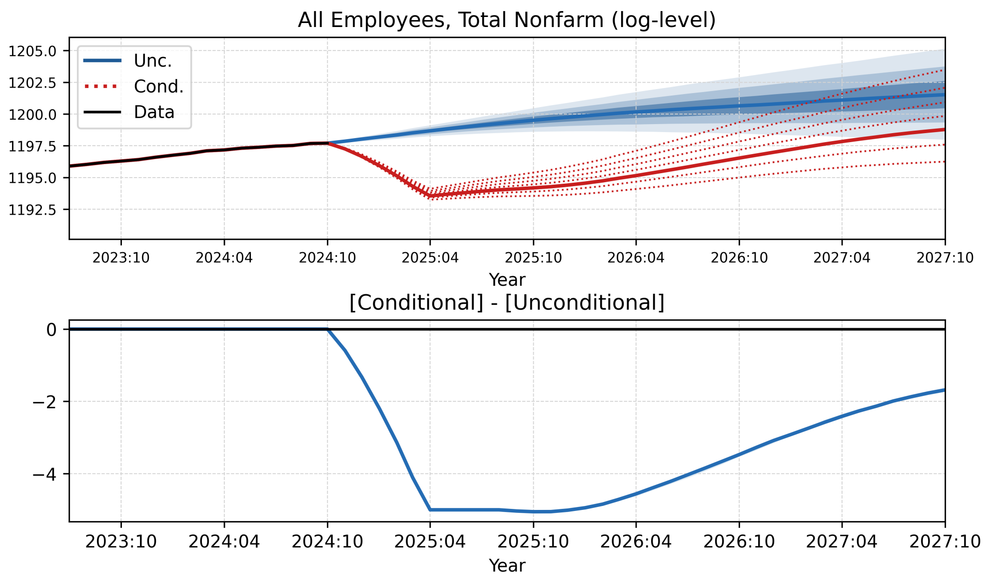

Figure 4a. Conditional forecasts (in red) and unconditional forecasts (in blue) of log-transformed data on all employees in non-farm payroll where the shaded areas are the 60, 70 and 80 percent forecast intervals. Lighter-shaded regions are forecasted paths that are less likely to occur. The forecast bands or credible intervals denoted by red dots result from the conditions that the number of employees in non-farm payroll falls by 5 percent, and wages rise by 2 percent.

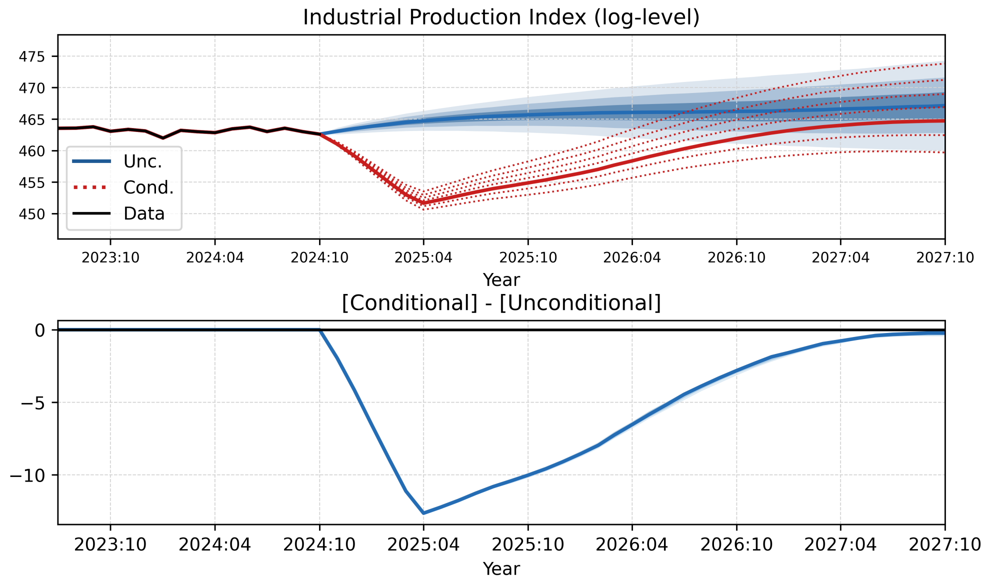

Figure 4b. Conditional forecasts (in red) and unconditional forecasts (in blue) of the log-transformed Industrial Production Index.

In the same spirit, the difference between conditional and unconditional forecasts is equivalent to the generalized impulse response functions to shocks in non-farm payroll employees and average hourly earnings. Formally, the impulse response function is the difference between the counterfactual and the baseline as:

$$\frac{\partial y_{i,T+h}}{\partial v_{j,T}} = \mathbb{E}\left[y_{i,T+h} \middle| y_{1:T-1}, v_{j,T} = 1, \gamma\right] - \mathbb{E}\left[y_{i,T+h} \middle| y_{1:T-1}, \gamma\right]$$

where, $v_{j,T}$ is the structural shock which is a linear combination of forecast errors, $v_{j,T} = \alpha' e_T$. In the above example, it is the linear combination of the forecast errors on non-farm payroll employees and average hourly earnings. Figure 5 displays the elasticities or responsiveness of all the variables to the persistent negative shocks on employees in the non-farm payroll and increasing hourly earnings.

Notably, we see that the measures of economic activity - capacity utilization, real manufacturing, and trade industrial sales decline by 10 percent from their baseline paths. Because of the relatively sudden shocks, firms cannot instantly replace or automate away the lost labor, slowing down output in the housing, construction, and manufacturing sectors, and spilling over into overall industrial production. The contracting economy dwindles the supply of goods and services, which also reduces the jobs available as the demand falls.

This spikes the unemployment rate as witnessed in the graph in the short run, immediately after the shock. A rise in the unemployment rate by 2.5 percent owing to lower output dips inflation if the negative output effect is larger than the cost-push effect from higher wages. But in the long run, if employers increasingly automate, offshore, or reorganize production, wage and price pressures dampen. In other words, they revert to their long-run means as evident in the scenario analysis in Figure 5.

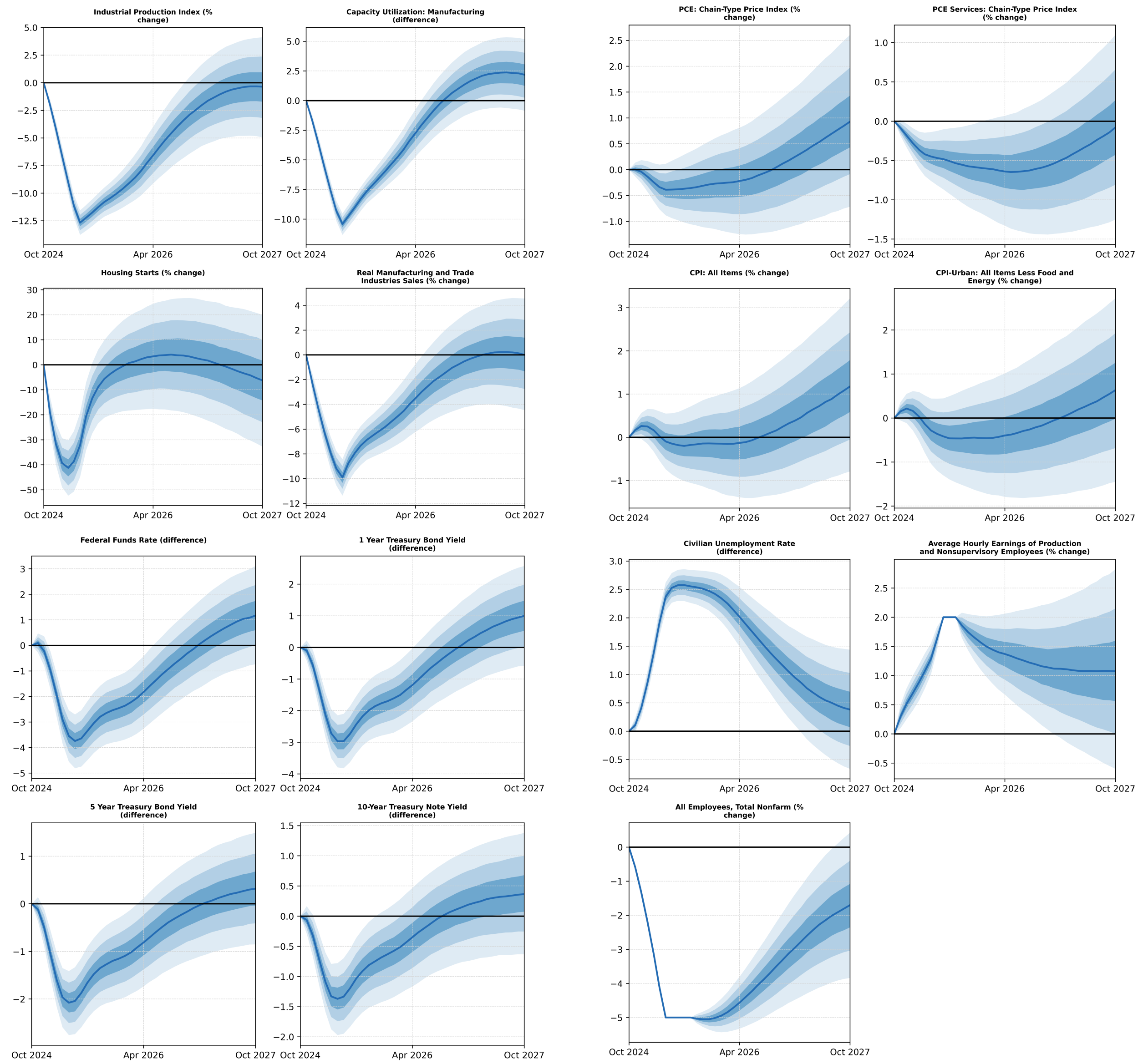

Figure 5. Response of all the variables when non-farm payroll employees persistently contract by 5 percent and average hourly earnings rise by 2 percent. The blue line connotes the median response, and the shaded regions indicate the 60, 70, and 80 percentile coverage intervals.

Joint Forecast Density: Unveiling Macro Risks, and Relationships

Until now, I had emphasized estimating the baseline and conditional forecasts of individual variables and computing the univariate densities of the forecasts. While this is useful to understand the expected path of the macro variables, we can also depict the entire plausible set of outcomes and demonstrate how two variables might co-move. For instance, with what probability does a high unemployment rate trigger a lower federal funds rate, or can both be high simultaneously? How does the predicted unemployment vary with monetary regime? How will the joint forecasts alter if the Fed targets lower inflation or unemployment? Are there potential trade-offs or correlations in the forecast period, and how uncertain are the forecasts?

To answer these kinds of questions, we can construct joint forecast density plots of any forecast horizon between two variables as exemplified in figure 6. The vertical dimension tells us the estimated joint probability of observing two macro variables one year ahead in October 2025, using the historical data till October 2024. Every point in the 2D plain is a possible combination, and the height denotes the likelihood of the combination from the predictive density. The grey dots, representing the cloud of points, are the posterior draws from the BVAR's predictive distribution. The side panes denote the marginal density plots, indicating the marginal distribution of forecasts. Showing a likelihood of various combinations, it helps to form internally consistent narratives under different scenarios. The tallest part of the surface is around the center of the dot cloud, implying the highest joint density or the "most typical" scenario occurs where the Fed Funds rate is around 4–5 percent and unemployment around 3.5–4 percent. A single peak in the graph connotes that the joint forecast distribution is unimodal. Predominantly, this occurs when the federal funds rate is approximately 5 percent. The joint density contours are concentrated in specific areas, suggesting a slight negative correlation between unemployment rate and the federal funds rate. Namely, lower unemployment (3–5%) is likely to coincide with either moderate (~5%) or significantly elevated (~12%) federal funds rate.

As dots heavily cluster when the unemployment rate is around 3–5 percent, the model expects a resilient labor market even in scenarios with aggressive monetary transmission (of ~12%). The latter can occur when inflation is out of control, raising the federal funds rate in response, but the economy is strong and lands softly. However, the right tail indicates that there are risks of elevated unemployment (~6–8%) in adverse economic conditions, albeit these are less likely. Another less likely scenario is stagflation, which marks periods of high unemployment and inflation mired with stagnant growth in output, triggering the Fed to reign in on spiralling prices by hiking the policy rates. This is because high unemployment clusters with lower federal funds rate in the left graph. The spread of the density contours signal uncertainty in forecasts where broader spread along the federal funds rate axis connotes higher uncertainty about the future path of the interest rates relative to those of unemployment rate.

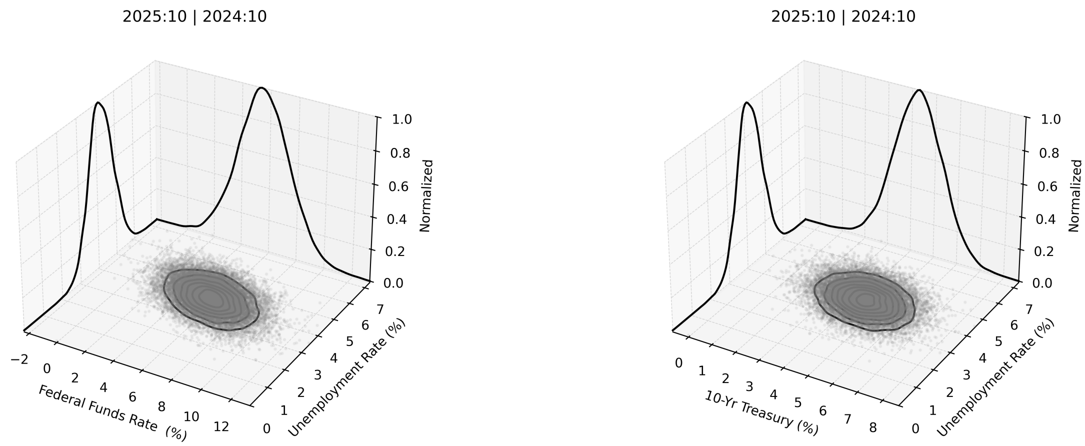

Figure 6. Joint forecasts of the variables for October 2025 using the historical data till October 2024. The grey cloud of the points in the center and the lightly visible contour line are the posterior predictive densities. The marginal densities of the forecasts are in the side panels.

Entropic Tilting: Softly Anchoring Forecasts to Long-Run Targets

Previously, I created baseline forecasts of all the variables without considering any targets, or long-run steady-state rates of variables set by the Federal Reserve. The BVAR model generates forecasts using MCMC simulations, assigning equal weights to each draw in the forecast distribution. Sometimes, central banks explicitly target variables such as inflation and unemployment rates, assuming that the inflation rate will converge to 2 percent in the long run. For instance, table 2 presents the central tendency of long-run projections of the FOMC released in the Summary of Economic Projections (SEP) in December 2024, capturing the middle-ground belief of policymakers regarding the long-run path of these variables. How can we adjust the forecasts to reflect these beliefs? The goal is to tilt the baseline distribution to reflect these beliefs while remaining as close to the original distribution. In this exercise, I employ the method of entropic tilting elucidated in Tallman and Zaman (2020) to modify the baseline distribution and refer to the *Entropic_Tilting* file in Google Colab and walk through the implementation procedure mathematically and programmatically. Unlike the scenario analyses above where I fixed the future paths of certain variables, also known as hard conditioning; I now relax that by allowing the conditioned future values of certain variables to lie within a certain range, also known as soft conditioning. Because we generally don't know the realized paths of endogenous variables in the long horizon, constraining the conditioned path of the variable within a certain range or an interval instead of an exact path is simpler. Furthermore, soft constraints recognize the uncertainty around the paths observed in the future.

Variable	Projection for 2026 (%)	Projection for 2027 (%)	Long run projection (%)
Unemployment rate	4.1 – 4.4	4 – 4.4	3.9 – 4.3
Real GDP	1.9 – 2.1	1.8 – 2	1.7 – 2
PCE inflation rate	2 – 2.2	2	2
Core PCE inflation rate	2 – 2.3	2	2
Federal funds rate	3.1 – 3.6	2.9 – 3.6	2.8 – 3.6

Table 2: Summary of Economic Projections released on December 18, 2024. These projections are central tendencies for change in the unemployment rate, real GDP, core PCE, PCE inflation rate, and the projected path of the federal funds rate. The central tendencies exclude the outlier projections (the three highest and lowest forecasts) and reflect FOMC's consensus view.

Let $y \in \mathbb{R}^n$ represent a vector of forecasts for n variables. If we run J draws from the MCMC simulations, then $y_j \; \forall \; j = 1, 2, \ldots, J$ is a forecast at the j^{th} draw. Initially, we assign equal weight to each draw, $w_j = \frac{1}{J}$. Now, we re-weight the baseline distribution $f(y)$ to a tilted distribution $\hat{f}(y)$ such that two conditions are met. Firstly, the reweighted distribution must satisfy specific moment conditions. Secondly, the tilted distribution must be as close to the original distribution.

The moment conditions are

$$E_{\hat{f}}[g(y)] = \bar{g},$$

where $g(y)$ is a set of m moment conditions, and $\bar{g} \in \mathbb{R}^m$ contains the target moments, which are the central tendency forecasts.

To determine the tilted distribution, we minimize the Kullback Leibler (KL) divergence between $f(y)$ and $\hat{f}(y)$:

$$\min_{w_j^*} KL(\hat{f}, f) = \sum_{j=1}^{J} w_j^* \log\left(J w_j^*\right) \text{ s.t. } \sum_{j=1}^{J} w_j^* = 1, \; \frac{1}{J} \sum_{j=1}^{J} w_j^* g(y_j) = \bar{g}.$$

The solution to find the optimal weights is

$$w_j^* = \frac{\exp(\gamma^\top g(y_j))}{\sum_{j=1}^{J} \exp(\gamma^\top g(y_j))}.$$

Here, γ is the Lagrange multiplier associated with the moment condition, and $g(y_j)$ is the moment function evaluated at j^{th} draw. We normalize so that the weights across all draws sum to 1. Before we can find the optimal weights, we optimize the Lagrange multiplier as

$$\gamma = \arg\min_{\gamma} \sum_{j=1}^{J} \exp(\gamma^\top g(y_j) - \gamma^\top \bar{g}).$$

Finally, the re-weighted (tilted) moments should match the target values $\bar{g}$ within a small tolerance:

$$E_{\hat{f}}[g(y)] = \frac{1}{J}\sum_{j=1}^{J} w_j^* g(y_j)$$

The code in *Entropic_Tilting* file implements "soft conditioning" by adjusting the baseline forecasts of key variables to reflect long-run projections from FOMC's SEP.

Below is the average of the range of the central tendency values.

```
# Conditioning assumptions: SEP released on Dec 2024 SEP for 2027
# Center of the central tendency: midpoint of the range
# find the index of the PCE inflation rate, Federal Funds Rate, and Unemployment Rate
    in the Spec DataFrame
idxCVPCE = Spec[Spec['SeriesName'] == 'PCE: Chain-Type Price Index'].index[0]
valCVPCE = (2 + 2) / 2

# Federal Funds Rate
idxCVFFR = Spec[Spec['SeriesName'] == 'Federal Funds Rate'].index[0]
valCVFFR = (2.9 + 3.6) / 2

# Unemployment Rate
idxCVLR = Spec[Spec['SeriesName'] == 'Civilian Unemployment Rate'].index[0]
valCVLR = (4 + 4.4) / 2
```

Using monthly data, I don't consider the average of the central tendency values of real GDP as that is available only in quarterly frequency, but I present another exercise using quarterly data in Appendix A.3 where I condition on real GDP, unemployment rate, PCE and core PCE inflation. Next, we procure the BVAR estimates `bvar_results` and distribution of unconditional forecasts `PredY_unc` computed and saved in pickle files in the *main* file. Then, we tilt the original forecast distribution to anchor the mean of the distribution to the midpoint of the central tendencies of SEP projections.

```
############################ Entropic Tilting: Shifting the mean
    ############################

n = PredY_unc.shape[1]  # Number of series (second dimension)
# 12-month change
dPredY_unc = np.vstack((
    np.full((12, n, ndraws), np.nan),  # Add NaNs at the beginning
```

```
    PredY_unc[12:, :, :] - PredY_unc[:-12, :, :]
))

# MCMC Draws for tilting variables (PCE inflation, unemployment rate, and federal funds rate) at forecast horizon
YYh = np.vstack((
    dPredY_unc[-1, idxCVPCE , :].T,  # Extract indices of federal funds rate and PCE inflation rate
    PredY_unc[-1, [idxCVLR, idxCVFFR], :]                  # Extract unemployment rate
)).T
# Target values: FOMC's centeral tendency projections for the targeted variables
target = np.array([valCVPCE, valCVLR, valCVFFR])

# Objective function to find the optimal lambda (Lagrange multiplier) values
def fun(gamma, YY, g0):
    return np.sum(np.exp((YY - g0) @ gamma))

# Optimization setup
opts = {'tol': 1e-20, 'options': {'maxiter': 1000}}
objective = lambda x: fun(x, YYh, target) # Objective function for optimization
gamma_init = np.ones(len(target)) # Initial guess for gamma
# Uses a quasi-Newton method for constrained optimization:
# minimizes the divergence between the original and tilted distribution while ensuring the mean of the tilted
# distribution satisfies the target constraints
res = minimize(objective, gamma_init, method='L-BFGS-B', **opts)
# optimal gamma values that adjust the weights of the forecast draws to align the distribution with the targets
gammaStarMean = res.x

# minimized objective function value (Kullback-Leibler divergence between the original and tilted distributions)
fStar = res.fun
# re-calculate weights for the forecast draws using the optimal gamma values
# normalize the weights to sum to 1
wStarMean = np.exp(YYh @ gammaStarMean) / np.sum(np.exp(YYh @ gammaStarMean))

# Verify moment condition
# check the mean of the re-weighted draws to ensure it aligns with the target values
```

```
print("Moment:")
# weighted average of the forecasted draws that must equalize the target values
print(np.mean(wStarMean[:, None] * YYh * 10000, axis=0))  # Scale by 10000
print("Target:")
print(target)
```

A disadvantage of tilting towards the mean is that the tilted forecasted distribution will be sensitive to outliers or extreme values, distorting results if outliers are unreliable. Skewing the forecasting distribution, the mean may not accurately represent the central tendency. On the other hand, extreme values don't affect the median, and central banks often focus on median forecasts while generating counterfactual forecasts. Therefore, I present an example where I tilt the forecast distribution so that the median of the forecast distribution matches the target values, ensuring that the tilted distribution stays as close as possible to the original distribution. I achieve this by minimizing the KL divergence:

$$\min_{w_j^*} KL(\hat{f}, f) = \sum_{j=1}^{J} w_j^* \log(J w_j^*) \text{ s.t. } \sum_{j=1}^{J} w_j^* = 1,\ \frac{1}{J}\sum_{j=1}^{J} w_j^* g(y_j) = 0.5$$

Now, the moment condition changes to:

$$E_{\hat{f}}[g(y)] = 0.5,\ \text{where } g(y_j) = 1\{y_j \leq \text{Target}\}$$

Therefore, 50 percent of the tilted distribution's mass should lie below the target $\bar{g}$.

```
############################ Entropic Tilting: Shifting the median
    ############################
# Create the indicator matrix to check if every value in the forecast matrix is less
    than or equal to the target value
YYhTemp = YYh <= target
YYhTemp = YYhTemp.astype(int)  # Convert the binary (True/False) to integer (1 and 0)

# Define the optimization objective
# find the optimal gamma that minimizes the Kullback-Leibler divergence between the
    original and tilted distributions
objective = lambda gamma: np.sum(np.exp((YYhTemp - 0.5) @ gamma))

# Perform optimization
gamma_init =  np.ones(len(target))  # Initial guess
```

```python
res = minimize(objective, gamma_init, method='L-BFGS-B', options=opts)
gammaStarMedian = res.x
fStar = res.fun

# Calculate weights for each forecast draw using the optimal gamma values
# Reweight the forecast draws (rows of YYh) using the optimized gamma values.
# Normalize the weights so they sum to 1.
wStarMedian = np.exp(YYhTemp @ gammaStarMedian) / np.sum(np.exp(YYhTemp @
    gammaStarMedian))

# Check that conditioning assumptions are satisfied
# Sort the forecast values (YYh) for each variable to compute the weighted median.
temp_s = np.sort(YYh, axis=0)  # Sorted values
idx = np.argsort(YYh, axis=0)  # Indices for sorting
cumsum_w = np.cumsum(wStarMedian[idx[:, 0]])  # Cumulative weights for the first
    column
j = np.argmin(np.abs(cumsum_w - 0.5))  # Find the index closest to 0.5
print("Value at median:", temp_s[j])  # Value corresponding to median
print("Target:")
print(target)

print("Median:")
median_values = np.array([
    bvar.wquantile(YYh[:, 0].reshape(1,-1), 0.5, wStarMedian),  # Weighted median for
        column 1
    bvar.wquantile(YYh[:, 1].reshape(1,-1), 0.5, wStarMedian),
    bvar.wquantile(YYh[:, 2].reshape(1,-1), 0.5, wStarMedian)
])
print(median_values)
```

Figure 7 illustrates the unconditional (baseline) forecast distribution from the BVAR model without imposing any external constraints or target (in shades of blue) and the conditional forecast distribution that considers long-run targets for PCE inflation rate, unemployment rate, and projected paths of the federal funds rate (in shades of red). Thereby, I introduce judgment by anchoring the median of the BVAR forecasts to the midpoint of the central tendency forecasts for the 2027 reference period. Upon tilting to the median, the red bands shift the forecast distribution such that 50 percent of the probability mass lies below their respective targets. Additionally, the median forecasts of PCE inflation, unemployment, and federal funds rate (denoted by dark red in the center of the conditional probabilistic distribution) converge to the stated targets of 2, 4.2, and 2.25 percent, respectively. This makes the forecasts more consistent with the consensus views of the FOMC, particularly in the medium to long run, where uncertainty might be higher, widening the forecast intervals.

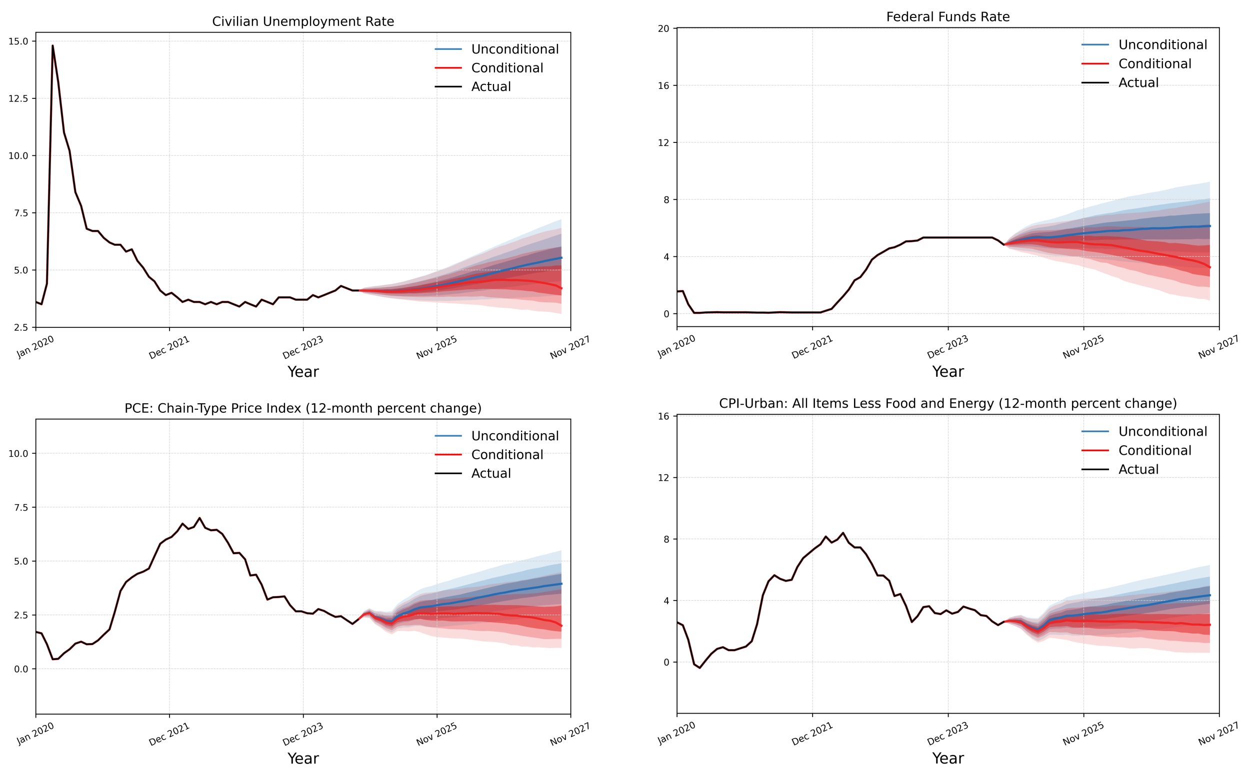

Figure 7. Unconditional forecasts and forecasts conditional on SEP projections of PCE inflation rate to 2 percent, unemployment rate to 4.2 percent, and federal funds rate to 3.25 percent 3 years into the future. These conditional forecasts are produced after tilting the forecast distribution such that the median of the forecast distribution anchors to the target SEP projections.

Figure 8 exhibits joint predictive densities of the unemployment and PCE inflation rates for 2 and 3 years into the future. The black lines are the unconditional joint predictive densities analogous to those in Figure 6. Alternatively, the red counterparts are the tilted distributions, matching the central tendencies of SEP projections for 2026 and 2027, respectively. The blue dots in the center of the red contours are the midpoint values of the central tendencies of the forecasts of a given year. These are the averages of the lower and upper range of the values in Table 2, yielding the midpoint forecast of 4.25 and 4.2 percent for the unemployment rate in 2026, and 2027, respectively. The unconditional and conditional marginal forecasts for densities for two years ahead (left) are comparable and unimodal, while those for three years ahead (right) are multi-modal.

Multiple peaks in the distribution can occur due to a few reasons. Firstly, as the forecast horizon extends further into the future, forecasts become more uncertain, amplifying the spread of the forecast distribution.

Secondly, the Federal Reserve's stated long-run targets (for example, 2 percent inflation) anchor for expectations. However, the path to reaching these targets may vary significantly depending on how the Fed reacts to economic developments. To elaborate, the joint predictive forecast density for November 2027 has three peaks. One occurs when the PCE inflation rate is approximately 2 percent, and the unemployment rate is approximately 4.2 percent. This peak corresponds to the Fed's long-run target where inflation stabilizes at 2 percent and the unemployment rate at 4.2 percent. The red-tilted density heavily weights this outcome, reflecting alignment with the SEP projections. In a stable and ideal economic scenario, the variables smoothly converge to the long-run equilibrium. Another peak occurs when the PCE inflation rate is approximately 3 percent, and the unemployment rate is approximately 5.5 percent. Signifying a stagflation-like scenario where inflation remains above target and unemployment is higher, a potential reason might be the wage-price spiral. Finally, a smaller peak occurs when inflation and unemployment rates are at approximately 1 and 3.5 percent, respectively. Whilst less likely, this optimistic outcome connotes a scenario where aggressive tightening of monetary policy can risk deflation and drive unemployment below long-run expectations.

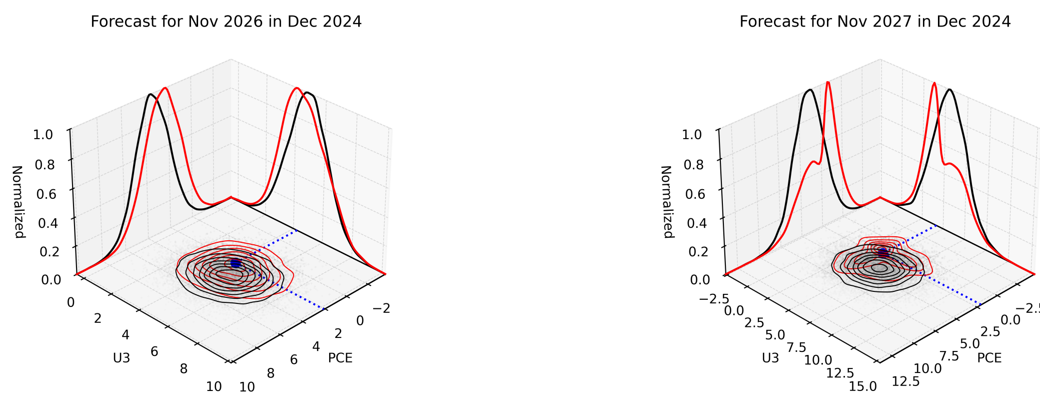

Figure 8. Joint forecast density functions of the forecast of the unemployment rate and PCE inflation rate for November 2026 (left), and November 2027 (right).

Thirdly, since entropic tilting modifies the posterior distribution by reweighting the MCMC draws to satisfy moment conditions, reweighting magnifies certain regions of the joint density (combination of unemployment and inflation rate) that aligns with the targets, and down-weights other regions. To elucidate, if the original posterior distribution already had higher density near the targets, tilting amplifies these regions, making the modes more pronounced. Moreover, if more draws from the less-dense regions are favored to satisfy the moments, tilting creates new modes. Relatedly, the scatterplot in Figure 9 visualizes the joint draws of inflation and unemployment rates for November 2027. Here, each point in the graph represents one MCMC draw from the posterior predictive distribution color-coded by the magnitude of the weights. For instance, MCMC draws (or points with darker colors) are weighted more than those with lighter colors. So, the blackcolored draws contribute most to the tilted distribution as they strongly align with the moment conditions ($U3 = 4.2\%$, $PCE = 2\%$). On the flip side, the yellow-colored draws are down-weighted as they are far from the moment conditions, contributing minimally to the tilted distribution.

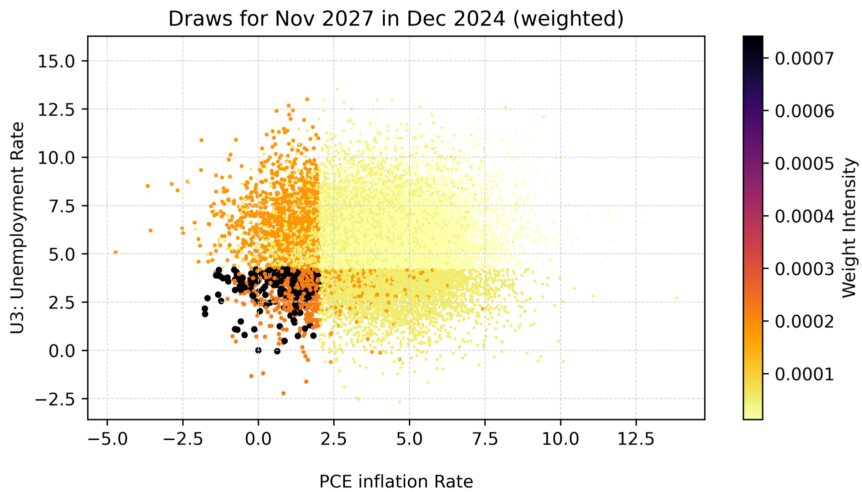

Figure 9: Joint MCMC draws of PCE inflation and unemployment rate for November 2027 in December 2024 categorized by weights. The size of each point proportionally changes with the weights optimized by entropic tilting so that the median of the tilted distribution anchors with the midpoint of the SEP's central tendencies.

6. BVAR with Covid Volatility on Quarterly Data

The BVAR model works with data of quarterly frequency as well. This is crucial because the components of the National Income Product Accounts such as Real Gross Domestic Product are measured only in quarterly frequency, enabling us to select a broader range of macroeconomic variables that organizations such as the Fed and Congressional Budget Office heavily incorporate in making forecasts. The baseline quarterly dataset contains 29 variables from FRED-QD to capture the macroeconomic and financial conditions employed in Crump et. al (2021) from Q1-1986 to Q3-2024. These include real indicators such as the real GDP, real federal government consumption; price indicators such as headline and core CPI, and PCE indices, GDP deflator; indicators on labor market, economic activity, Treasury yields and yield spreads and asset prices. The federal funds rate was near 0 during COVID from March 2020-2022 and during previous downturns, creating zero lower bound (ZLB), wherein interest rates cannot decline below in nominal terms. Since the Federal Reserve resorts to unconventional tools to stimulate the economy, the BVAR's linear equations cannot easily capture the effective "floor" at the zero. To avoid accounting for the non-linear and no variation when ZLB binds, I omit the federal funds rate in the model. Table A2 in the Appendix lists the quarterly variables and the transformations applied before estimating the model. Thereafter, I explore applications of how we can fit the model to quarterly data, construct scenario analyses, conditional and unconditional forecasts, gauge for structural breaks during the pandemic and build forecasts conditioned on long-term targets. The *Quarterly* folder saves all the scripts that plot the time series of the historical time series data in the *Descriptives* script and runs the model in other scripts.

Changes in Estimation of the Model with Quarterly Data

The codes in *main_quarterly* script show the minor adjustments made to account for the quarterly frequency of the data. Aggregating from monthly to quarterly reduces the time series by three-fold, making the model more susceptible to overfitting as it ingests fewer data points. Therefore, in the `prior_params` dictionary, I place more weight on the prior beliefs by changing `lambda_mode = 0.2` at a monthly frequency to `lambda_mode = 0.6`, tightening the prior. Now, the posterior estimates rely more heavily on the prior. Another change is in how the scaling factors evolve in each pandemic quarter. In the monthly setup, `eta_mode` and `eta_sd` capture how the model scales the variance of the shocks over the first three months of COVID (March, April, May 2020), and then gradually decays from June 2020. Beyond the initial shock months, `eta_mode = 0.8` is the starting guess for the scale factor, while `eta_sd` array indicates the degree of uncertainty allowed around each mode. In the quarterly setup of `prior_params`:

```
'eta_mode': [0, 0.8, 0.7, 0.6], # mode of COVID-19 scaling factor, applied to first 3 quarters of COVID-19 period
'eta_sd': [0, 0.2, 0.15, 0.1], # standard deviation of the covid-19 scaling factor
'eta_min': [0.0, 0.5, 0.5, 0.3]


'lambda_mode': 0.6, #  "tightness" of the Minnesota prior: controls the scale of variances and covariances
'lambda_sd': 0.3, # standard deviation of the Minnesota tightness prior
```

This implies that the COVID shock factor in Q1-2020 is entirely data-driven with uninformative prior. Subsequently, for Q2-Q4 2020, the declining prior values suggest subsiding volatility, capturing the time-varying nature of the pandemic shock. Apart from this, I run the model as usual on the quarterly data. As the model runs on fewer observations, it is computationally efficient reducing the time taken to estimate and generate forecasts.

Beyond the Boom: Increase in Real GDP

I analyze six scenarios using conditional forecasting beginning with one-time 1 percent increase in real GDP one quarter ahead relative to the unconditional forecasts. Analogous to the residual impulse response function from the traditional reduced form VAR with unorthogonalized innovations, I don't structurally identify the shocks.

```
# Find indices of specific variables
idxCV1 = Spec.index[Spec['SeriesID'] == 'GDPC1'].tolist()[0]  # real GDP
# Create a matrix of NaNs to store shocks
# n is the number of variables and T is the length of the initial data
Shock = np.nan * np.ones((h_fore.sum(), n))  # h_fore is a boolean array indicating forecasts
Shock[0, idxCV1] = 1 # Apply shocks to % change in real GDP
```

Figure 10 demonstrates the responses of metrics pertaining to the labor market, real economic activity, prices, asset prices and interest rates. All the real macro variables such as personal consumption expenditure, investment, and income rise as GDP rises. Over time, these cascading effects taper as the the model's dynamics move the system back toward equilibrium. Measures of prices, Treasury yields, real exports and imports rise.

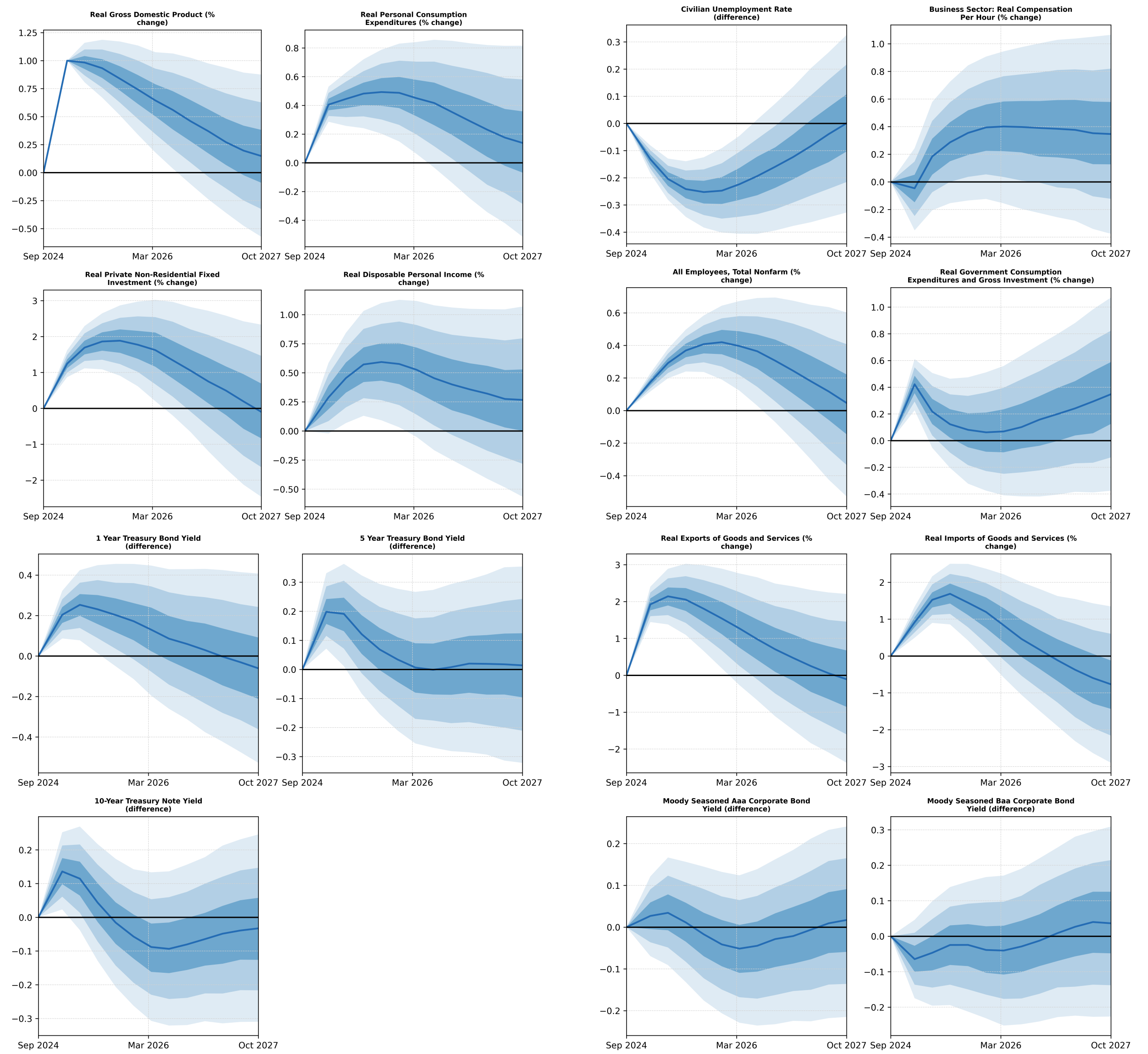

Figure 10. Response of 1 percent increase in real GDP one quarter ahead over a period of 3 years where the dark blue lines are the posterior median values.

In contrast to the short-term one time shock, figure 11 illustrates the responses of the variables when GDP increases 1 percent 8–12 quarters ahead, without affecting other variables. I model this scenario in *increaseGDP_longRun* script, by adjusting the index of shocks in the `Shock` numpy array as follows:

```
idxCV1 = Spec.index[Spec['SeriesID'] == 'GDPC1'].tolist()[0]   # real GDP
Shock = np.nan * np.ones((h_fore.sum(), n))
Shock[7:12, idxCV1] = 1 # Apply shocks to % change in real GDP
```

As Crump et. al (2021) state, this "medium-run" scenario conditions on a combination of reduced-form shocks that lifts real GDP by 1 percent in two years. In the reduced-form model, the historical relationships among variables determine the combination of shocks that produce the desired path where real GDP is elevated by 1 percent from the baseline path. Unlike structural impulse responses that utilize Cholesky or sign restrictions to isolate each shock, I construct generalized impulse response functions (where the shocks are not orthogonal) as the difference between the conditional and unconditional forecasts presented in figure 12.

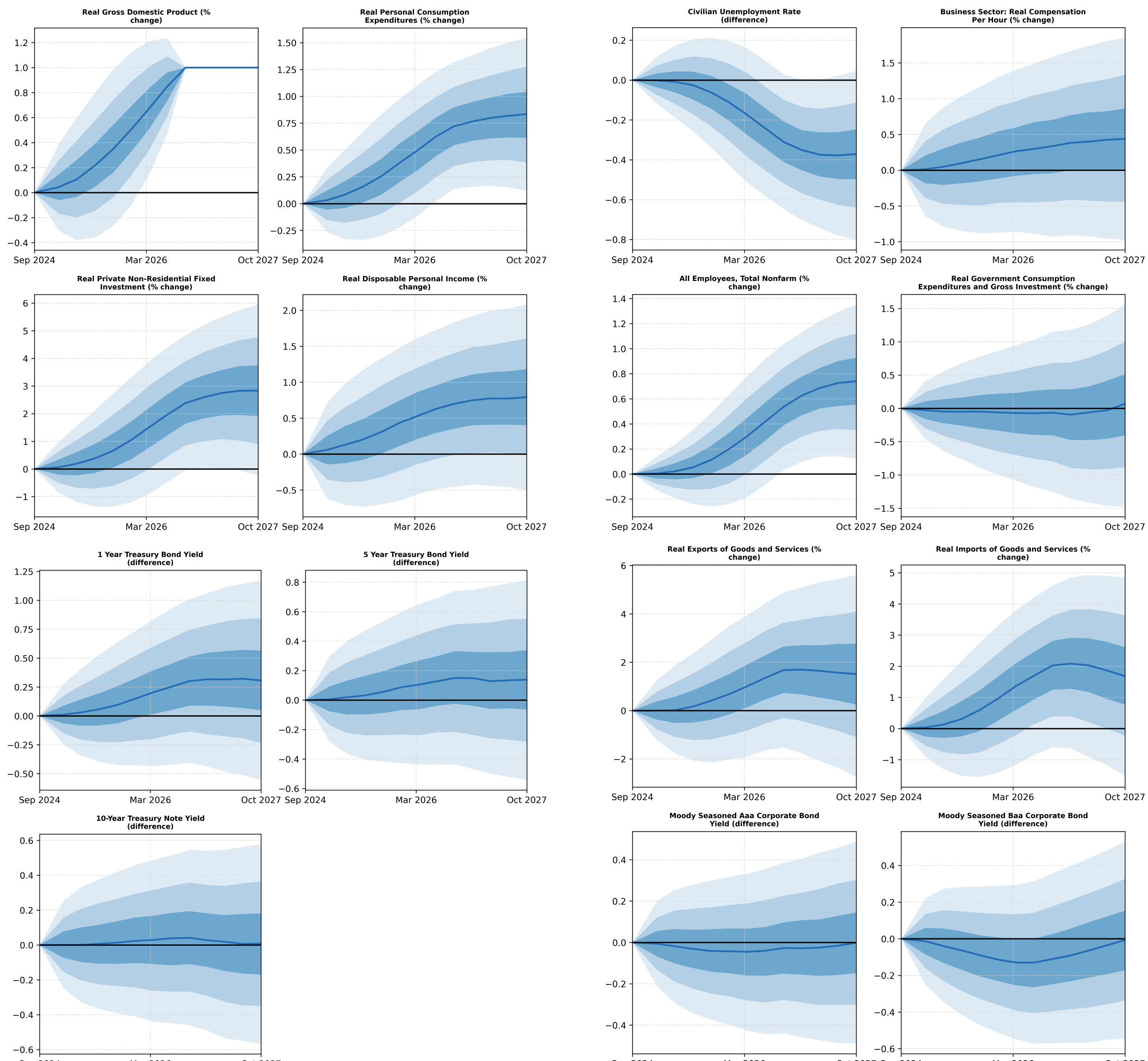

Figure 11. Response of 1 percent increase in real GDP 8-12 quarters ahead over a period of 3 years where the dark blue lines are the posterior median values.

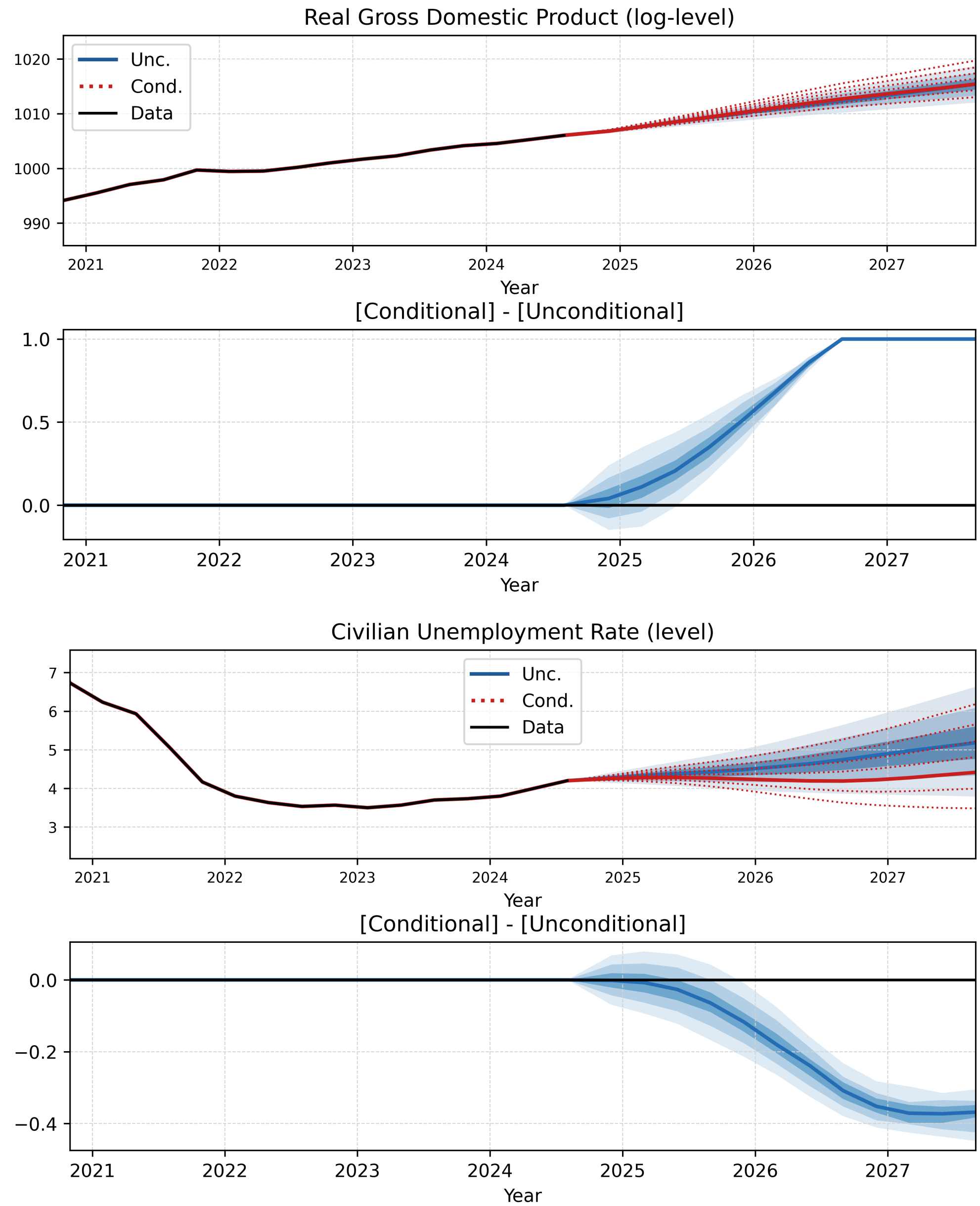

Figure 12a. Baseline (unconditional) forecasts (blue bands) and forecasts conditional on 1 percent increase in GDP 8-12 quarters ahead. The shaded bands are 60, 70, and 80 percent coverage intervals. The bottom row presents the plot of the log-level difference between the unconditional and conditional forecasts, which is equivalent to a generalized impulse response function to GDP.

Riding The Yield Curve: Increase in 1-Year Treasury Rate

Short and medium-term Treasury yields influence borrowing costs for households and business, impacting interest rates on car loans, student loans, corporate financing, etc. Changes in these yields ripple quickly through financial asset prices, namely equity valuations, risk premiums and exchange rates. Moreover, 1-year

Treasury yield is very sensitive to changes in the federal funds rate or investors' expectations about the how the Fed will alter monetary policy in the short-run. Given its importance, I examine two scenarios. First, in *increase1Y_unrestricted* script, I construct unorthogonalized impulse responses and scenario analyses to 75 basis points increase in 1-year Treasury yield one quarter ahead, leaving other variables unconstrained. Effectively, this imposes a scenario where the short-term rates jump above model's baseline predictions. Viewed as sudden tightening of financial conditions, this can happen for a number of reasons. Namely, when markets expect the policy rate to hike; the US Department of Treasury issues shorter-maturity Treasury bills to fulfill the escalating debt burden which drops prices and pushes yields upwards; tapered demand from large buyers of Treasuries; and perceived risk that inflation may run hotter than expected causing the buyers to demand higher yield to compensate for eroding purchasing power. Because the residuals in the reduced-form model are correlated, a shock to the 1-year rate implicitly moves other variables in the system based on historical correlations.

```
idxCV = Spec.index[Spec['SeriesID'] == 'GS1'].tolist()[0]  # 1-Year Treasury Yield
Shock = np.nan * np.ones((h_fore.sum(), n))
Shock[0, idxCV] = 0.75  # 75 bps increase in 1-Year Treasury Yield
```

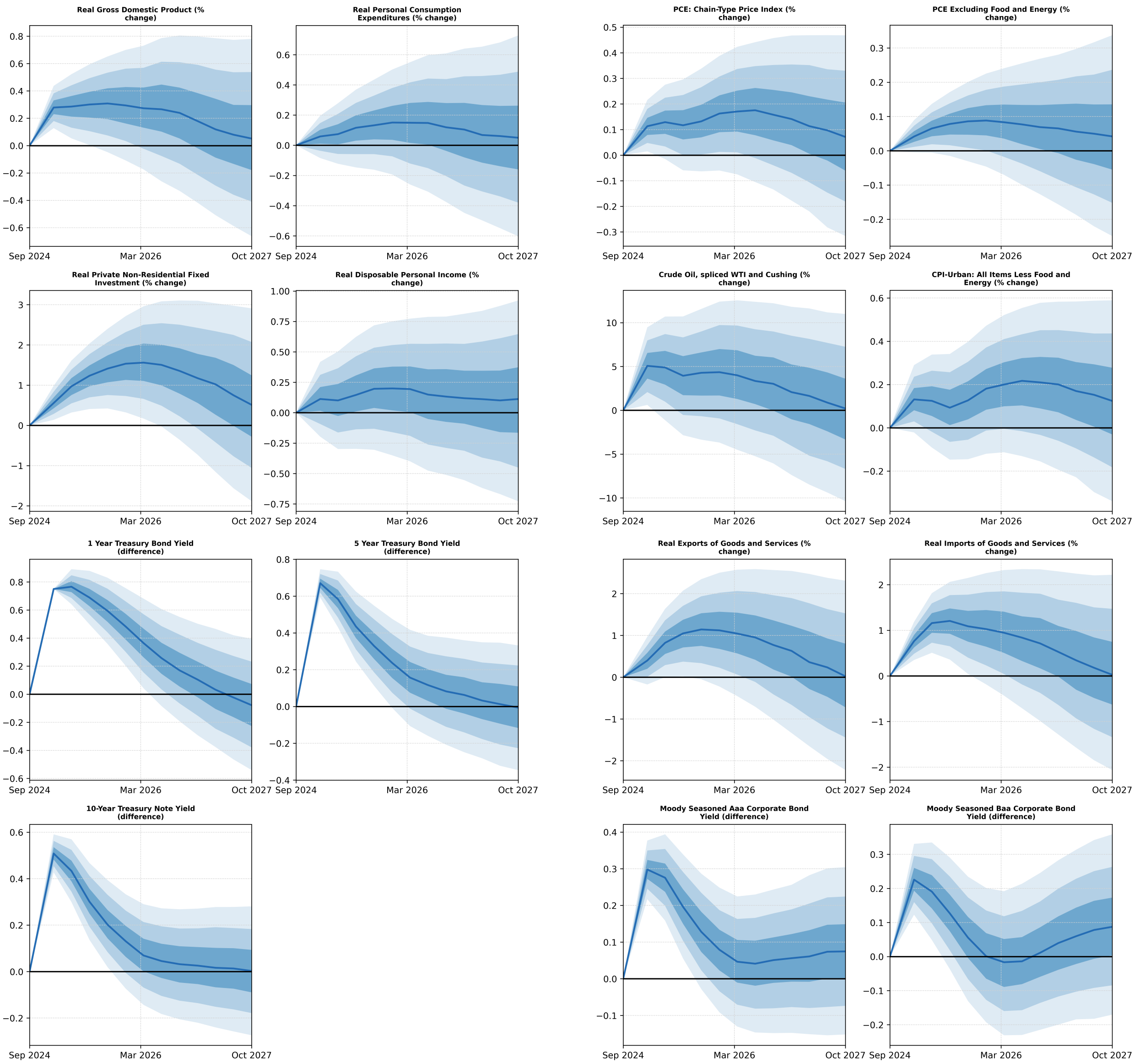

Figure 13: Response of a 75 bps increase in 1-year Treasury yield one quarter ahead over a period of 3 years where the dark blue lines are the posterior median values. All variables respond to the unrestricted shock endogenously.

Second, in *increase1Y_Cholesky* script, I impose a restricted scenario where I not only raise the 1-year Treasury rate by 75 basis points one quarter ahead, but also fix the near-term forecasts for real macroeconomic indicators (such as GDP, unemployment, prices, etc) to remain at their unconditional baseline for that same quarter.

```
idxGS1 = Spec.index[Spec['SeriesID'] == 'GS1'].tolist()[0]  # 1-Year Treasury Yield
# List of indices for macro variables
idxMacro = Spec.index[(Spec['isFinancial'] == 0)].tolist()
```

```python
# Create a boolean array indicating variables used for plotting
idxCV = np.isin(range(n), idxMacro + [idxGS1])
Shock = np.nan * np.ones((h_fore.sum(), n))
Shock[0, idxMacro] = 0  # Set macro variables to unconditional forecast (0 shock)
Shock[0, idxGS1] = 0.75  # 75 bps (basis points) increase from the baseline forecast
```

In other words, albeit the Treasury rate hikes, the macro variables aren't immediately affected by the shock. This mimics a recursive or Cholesky identification scheme where "fast-moving" financial variables react contemporaneously to changes in the real-economy, but "slow-moving" macro variables adjust with a lag, analogous to tightening of monetary policy. For instance, a surprise hike of the policy rates may lift the short end of the yield curve instantaneously, but will not move real GDP in the same quarter.

Figure 13 and 14 depict the elasticities in the unconstrained and constrained scenarios, respectively. Juxtaposing the results, we can attribute the movement of the elasticities in the unconstrained scenario to all historical reasons for heightened Treasury yield, including those endogenously related to stronger economic conditions. By restricting the response of the macro variables immediately when Treasuries hike, the second restricted scenario filters out those "endogenous" components and isolates a pure (exogenous) monetary policy shock. Yet, the responses don't exactly align with the theoretically expected results where rate hikes decelerates real GDP shortly after the initial impact, and unemployment rises. Rather, real GDP, investment and government spending boost initially, unemployment falls as employees in non-farm payroll rises and wages decline *initially*, before reversing directions in the medium run. While this may contradict the theoretical underpinnings of Cholesky-identified VAR models, these patterns emerge from the BVAR model as the recent post-COVID data show a positive correlation between interest rates and real activity in the short-run. For instance, after the pandemic the economy rebounded strongly during 2021-2022 when the Fed signaled hiking rates. Unlike Crump et. al (2021), this model spans periods when the Fed raised the federal funds rate from ZLB in March 2022 to 5.25-5.5 percent points in July 2023, the highest since 1980s and demand surged after the pandemic slump and supply chain disruptions healed. Rate hikes co-existed with robust output growth and tight labor market – quite different from the pre-pandemic historical trends. Observing these atypical episodes wherein expansions coincide with or follow higher rates, the scenario analyses from BVAR with COVID volatility model extrapolate and depict the stated trends for the first two years after the shock. Afterward, in the third year, economic activity becomes sluggish, unemployment rises, consumer sentiments worsen, volatility measured by the VIX index clambers, imports and exports decline, and Moody's seasoned corporate bond yields drop. So, even with the "exogenous" shock, recent swings in pandemic data can cause the subsequent few quarters to show GDP mildly rise in the very short-run, but the downturn from the third year surfaces once the model's dynamics override the short-term historical patterns of tight labor markets.

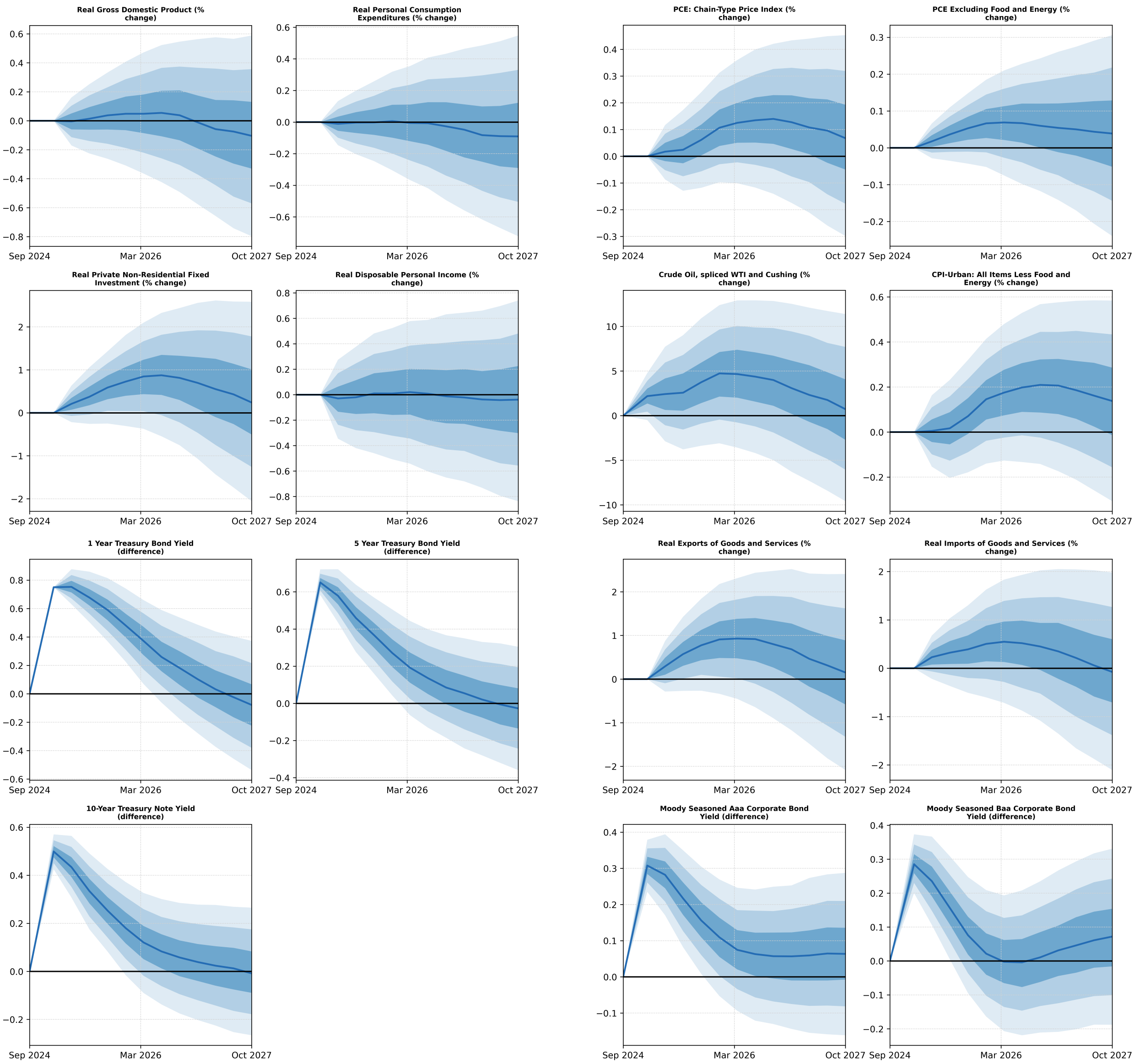

Figure 14: Response of a 75 bps increase in 1-year Treasury yield one quarter ahead over a period of 3 years where the dark blue lines are the posterior median values. This scenario affixes the macro variables to their unconditional forecasts when the Treasury yield hikes, but reacts endogenously next period onwards with a lag.

Financial Turmoil - Disentagling the Effects of Supply and Demand Shocks

Financial turbulence characterized 2015 – commodity and oil prices depressed, hitting a lowest of $30.31 since 2009, stock volatility spiked, major stock indices plunged, yields rose as investor demanded higher return for holding risky assets, US dollar appreciated as growing expectations of Fed rate hikes makes the dollar-denominated assets more attractive to global investor offering higher returns. Tighter financial conditions created a demand shock as borrowing rates rise, reducing consumer and business spending. Alternatively, falling oil and commodity prices comprise of supply shocks which lower input costs for production. To analyze the effects of the 2015 financial turmoil, I first forecast all the variables in the system as if no financial turmoil occurred. In other words, I only use data until 2015-Q2 and construct baseline forecasts thereafter. Then I construct two scenarios - financial turmoil, and no-supply shock scenarios. The "financial turmoil" scenario conditions on the the observed financial market outcomes outcomes in 2015-Q3, such as Treasury and corporate bond yields, stock index, and volatility index. Figure 15 illustrates the responses of the variables. Notably, real GDP declines by 0.4 percent, unemployment rate rises by 0.1 percent at its peak, fully recovering after two years, corporate bond yields rise, headline and core inflation drop by around 0.2 and 0.3 percent respectively, recovering after three years. Most notably, the WTI crude oil price plunges by 22 percent before reverting to the baseline levels in three years. Moreover, VIX index spikes by around 20 percent, also diminishing consumer confidence as evident by nearly 3 percent drop in the University of Michigan Consumer Sentiment Index. The "financial turmoil" scenario shows that a combination of firm financial conditions (negative demand shock) and falling commodity prices (positive supply shock) diminished output and prices over the horizon.

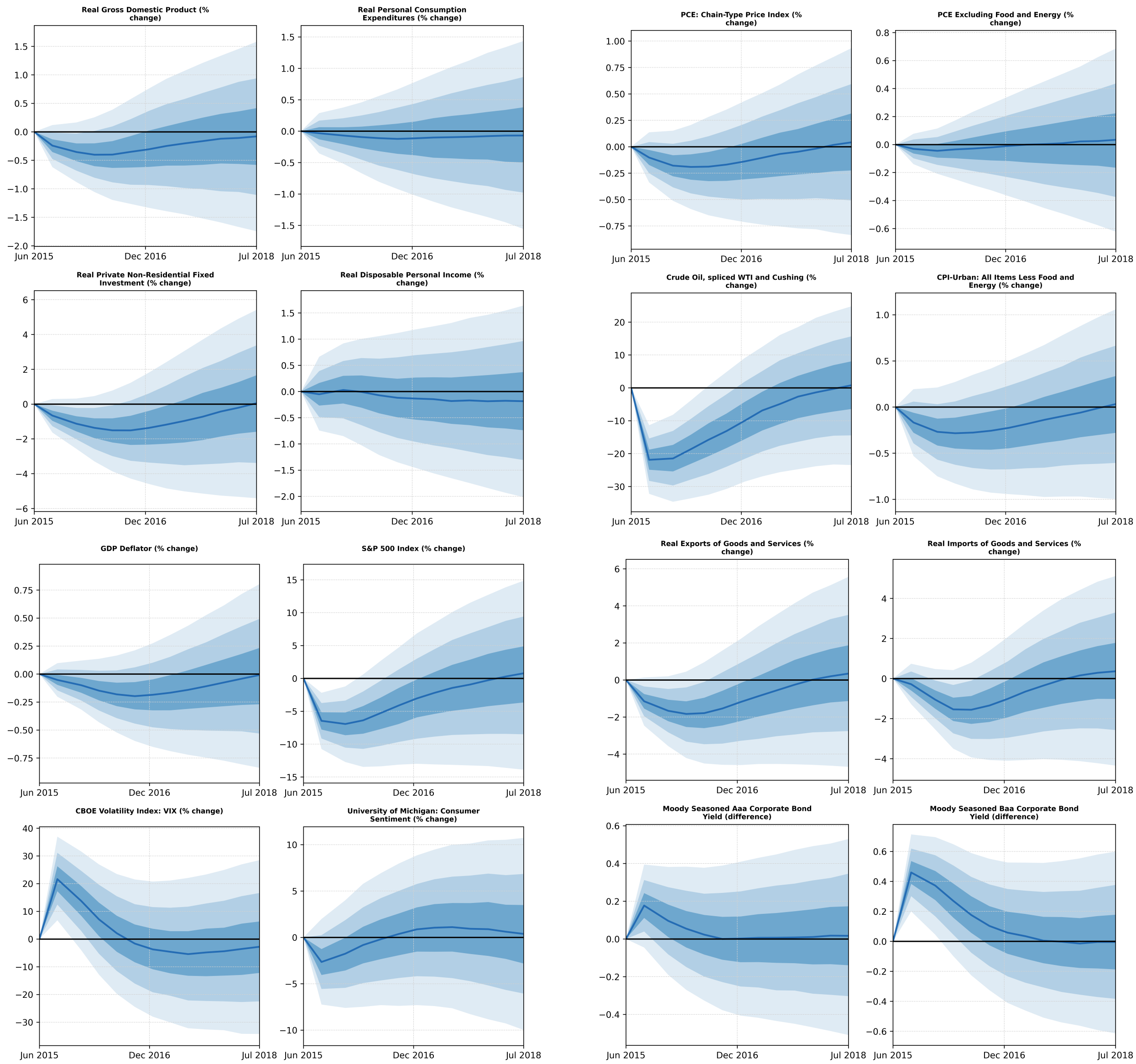

Figure 15: Financial turmoil scenario – the responses conditioned on the known paths of the financial variables in 2015-Q3.

To disentagle the elasticities of demand shock only, isolating the effects of supply shock, the second scenario is the "no-supply shock". Similar to the above scenario wherein I condition on the observed paths of financial variables, I exclude the WTI crude oil price from the list of conditioning variables and plot the elasticities in figure 16. Juxtaposing the elasticities of figure 16 with those in 15, the demand shock alone causes a deeper and prolonged decline in output as GDP and investment fall by 0.5 and 2 percent, respectively; and unemployment rate rises by 0.2 percent. Devoid of the positive supply shock, prices decline by lesser magnitude than in the first scenario. On the other hand, including the oil prices (first scenario) lowers the prices further as input costs slump. Furthermore, output grows as supply shock offsets some of the effects of the demand shocks.

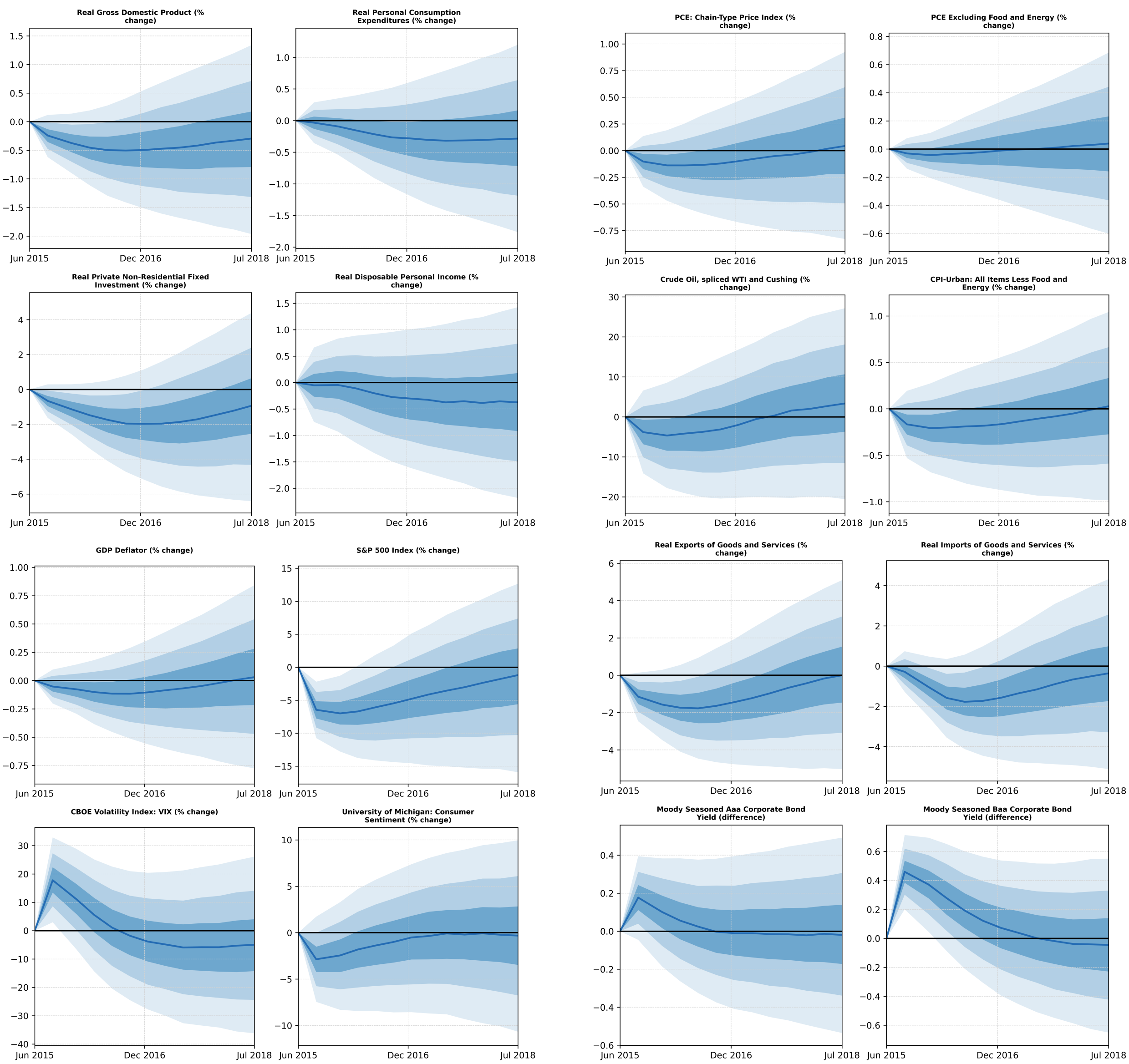

Figure 16: Financial turmoil excluding oil prices – conditioned on the observed values of all financial variables in 2015-Q3 except for WTI crude oil prices.

Pandemic Aftershocks: Detecting Structural Breaks During COVID and Why Inflation Defied Expectations

In addition to the examining the forecasts and impact of shocks, the model can detect structural breaks that occur when properties such as the mean, variance and covariances of variables significantly change over time. For instance, Furlanetto and Lepetit (2024) and Stock and Watson (2021) provide empirical evidence and theoretical reasons that the Phillips curve flattened in the pre-pandemic period. In early 2020, unemployment rate skyrocketed from 3.5 percent in February 20 to 15.8 percent in April 2020, while inflation remained subdued as core PCE inflation fell to 1 percent. Starting June 2020, inflationary pressures picked up as supply-chains were disrupted (due to congested ports and dearth of semiconductor), commodity prices rose, fiscal stimulus boosted demand despite falling yet sky high unemployment of 11 percent. Inflation continued to accelerate while unemployment crept downwards, raising questions if the Phillips curve has steeped. Separately, from the policy front, the COVID-related Tax Relief Act of 2020 was enacted in late December 2020, authorizing additional Economic Impact Payments of up to $600 per eligible adult and $600 per qualifying child under the age of 17. While the quarterly growth rate of real GDP rebounded to 33.4 percent in Q3 after the economy reopened from the pandemic slump, it grew at 4 percent Q4 – a rate that aligns more closely with historical data. Likewise, consumer spending followed a similar trajectory – growing at a substantially lower pace 2.5 percent Q4 than in 41 percent in the prior quarter. These developments underscore the dynamic policy responses boosted by fiscal and monetary support and a rapid recovery in activity – whereas real GDP fell steeply and abruptly, it was temporary.

In light of the developments, I evaluate the structural changes in the dynamic system by first estimating the model in the entire dataset till Q3-2024, then I re-estimate the model till the break period of Q3-2020 in the *structuralBreak* file. With the BVAR estimates fitted in the entire data, I construct in-sample (IS) conditional forecasts from Q4-2020 till the end of the information set. Using the second model fitted till the break, I construct out-of-sample (OOS) conditional forecasts from Q4-2020 till Q3-2024 and let the historical correlations between variables in the data dictate the forecasts. In both cases, I build two types of conditional forecasts. First, I condition the out-of-sample forecasts on thirteen real activity variables, whose realized paths are known for the remainder for the information set after the break, Second, I again condition the forecasts given the realized paths of unemployment rate and real GDP only.

```
# List of real activity variables
realActivityVars = [
    'GDPC1',  # Real GDP
    'PCECC96', # Personal Consumption Expenditures
    'PRFIx',  # Real Private Residential Fixed Investment
    'PNFIx', # Real Private Non-Residential Fixed Investment
    'EXPGSC1',  # Real Exports of Goods and Services,
    'IMPGSC1',  # Real Imports of Goods and Services,
    'GCEC1',  # Real Government Consumption Expenditures and Gross Investment
    'INDPRO',  # Industrial Production Index
    'CUMFNS',  # Capacity Utilization: Manufacturing
    'UNRATE',  # Civilian Unemployment Rate
```

```python
    'RCPHBS',  # Business Sector: Real Compensation Per Hour
    'HOUST',  # Housing Starts
    'DPIC96'  # Real Disposable Personal Income
]

# Settings for two conditioning schemes
Settings = [
    {
        'idxCond': Spec.index[Spec['SeriesID'].isin(realActivityVars)].tolist(),
        'labCond': 'real activity'  # Condition on real activity
    },
    {
        'idxCond': Spec.index[Spec['SeriesID'].isin(['GDPC1', 'UNRATE'])].tolist(),
        'labCond': 'GDP and unemployment rate'  # Condition on GDP and unemployment rate
    }
]

jBreak = np.where((dates.dt.year == 2020) & (dates.dt.month == 9))[0][0]  # Date of break
heff = T - jBreak  # Number of periods being forecasted

# Out of sample: model estimated through the break
# These results are out-of-sample in the sense that forecasts are generated for dates beyond the break
bvar_results_OOS = bvar.bvarGLP_covid(data_transformed[:jBreak, :], lags=lags,
    priors_params=priors_params, mcmc=1, MCMCconst=1, MNpsi=1, sur=0, noc=0,
    Ndraws=Ndraws, Ndrawsdiscard=discard, hyperpriors=1, Tcovid=Tcovid)

# In-sample: model estimated on full date
# These results are in-sample in the sense that forecasts are generated for the dates contained in this sample
Testim = np.nanmax(np.where(~np.isnan(data_transformed.sum(axis=1)))[0]) + 1
bvar_results_IS = bvar.bvarGLP_covid(data_transformed[:Testim, :], lags=lags,
    priors_params=priors_params, mcmc=1, MCMCconst=1, MNpsi=1, sur=0, noc=0,
    Ndraws=Ndraws, Ndrawsdiscard=discard, hyperpriors=1, Tcovid=Tcovid)

# Determine the number of draws in the MCMC simulation
ndraws = bvar_results_IS['mcmc']['beta'].shape[2]
```

```
############################ Get unconditional forecasts ############################

for setting in Settings:
    idxCond = setting['idxCond']
    labCond = setting['labCond']

    # Generate conditional forecasts
    YCond = np.nan * np.ones((T, n))
    YCond[:jBreak, :] = data_transformed[:jBreak, :] # fill historical data up to the
        break for non-conditioning variables
    YCond[:, idxCond] = data_transformed[:, idxCond] # fill paths of conditioning
        variables for all time period

    # Initialize storage for conditional forecasts
    PredYIS = np.nan * np.ones((T, n, Ndraws - discard))
    PredYOOS = np.nan * np.ones((T, n, Ndraws - discard))

    for j in range(Ndraws - discard):  # Loop through the number of draws
        if (j % 1000) == 0 or j == Ndraws - 1:
            print(f"Processing draw {j} of {Ndraws - discard}...")
            sys.stdout.flush()


        # In-Sample (IS) forecasts
        beta_j = bvar_results_IS['mcmc']['beta'][:, :, j]
        Gamma_j = np.vstack((beta_j[1:, :], beta_j[0, :]))
        Su_j = bvar_results_IS['mcmc']['sigma'][:, :, j]
        PredYIS[:, :, j] = bvar.VARcf_DKcks(YCond, bvar_results_IS['lags']['lags'],
            Gamma_j, Su_j, 1)

        # In-Sample (IS) forecasts
        beta_j = bvar_results_OOS['mcmc']['beta'][:, :, j]
        Gamma_j = np.vstack((beta_j[1:, :], beta_j[0, :]))
        Su_j = bvar_results_OOS['mcmc']['sigma'][:, :, j]
        PredYOOS[:, :, j] = bvar.VARcf_DKcks(YCond, bvar_results_OOS['lags']['lags'],
            Gamma_j, Su_j, 1)

    # Growth rates (quarterly growth, annualized)
```

```
    dPredYIS = np.concatenate((np.nan * np.ones((1, n, Ndraws - discard)),
        (PredYIS[1:, :, :] - PredYIS[:-1, :, :]) * 4), axis=0)

    dPredYOOS = np.concatenate((np.nan * np.ones((1, n, Ndraws - discard)),
        (PredYOOS[1:, :, :] - PredYOOS[:-1, :, :]) * 4), axis=0)
```

I assess the magnitude of the difference in the in-sample and out-of-sample forecasts to examine if the pre-break model can accurately forecast post-break dynamics. In other words, do the economic and structural changes from before and after the COVID Tax Relief Act was enacted, affect economic and financial relationships? If the OOS forecasts deviate significantly from the observed data and IS forecasts, this indicates that the relationships estimated pre-break no longer hold, implying a structural break. Alternatively, if they are consistent, the relationships across the periods are stable.

The first panel of figure 17 depicts the trajectory of Core CPI inflation conditioned on GDP and unemployment rate, whereas that in the second panel conditions on thirteen real economic activity variables. The OOS forecasts are slightly closer to the actual data when conditioned on the thirteen real economic activity variables than when conditioned on only two of them. However, the OOS forecasts deviate significantly from from the IS forecasts, pointing evidence to structural breaks in CPI inflation rate. Furthermore, the OOS forecasts in both panels underestimate the inflationary pressures that brewed after the expansionary fiscal programs of the government pumped in stimulus checks and tax breaks to households and firms. The COVID–Related Tax Relief Act of 2020 is one prominent example that contributed to the demand-side factors fueling inflation. The BVAR model estimated up to Q3-2020 (before the break) is based on historical correlations, placing more weight on the past behavior of inflation, particularly when inflation expectations were stable, low and generally well-anchored. So, it's information set is devoid of the period when the the law was passed and the macro-financial relationships changed post-COVID, showing pronounced structural breaks in inflation forecasts. Likewise, the OOS conditional forecasts of Treasury yields and corporate bonds (not shown here) are lower than their actual counterparts, and the structural breaks are more pronounced. This is because Treasury yields and corporate bonds reflect expectations of inflation and monetary policy. Albeit, pre-COVID, these interest rates were low, the Fed aggressively pivoted in 2022-2023 by hiking rates to curb inflation. This structural shift was not embedded in the model estimated till the break.

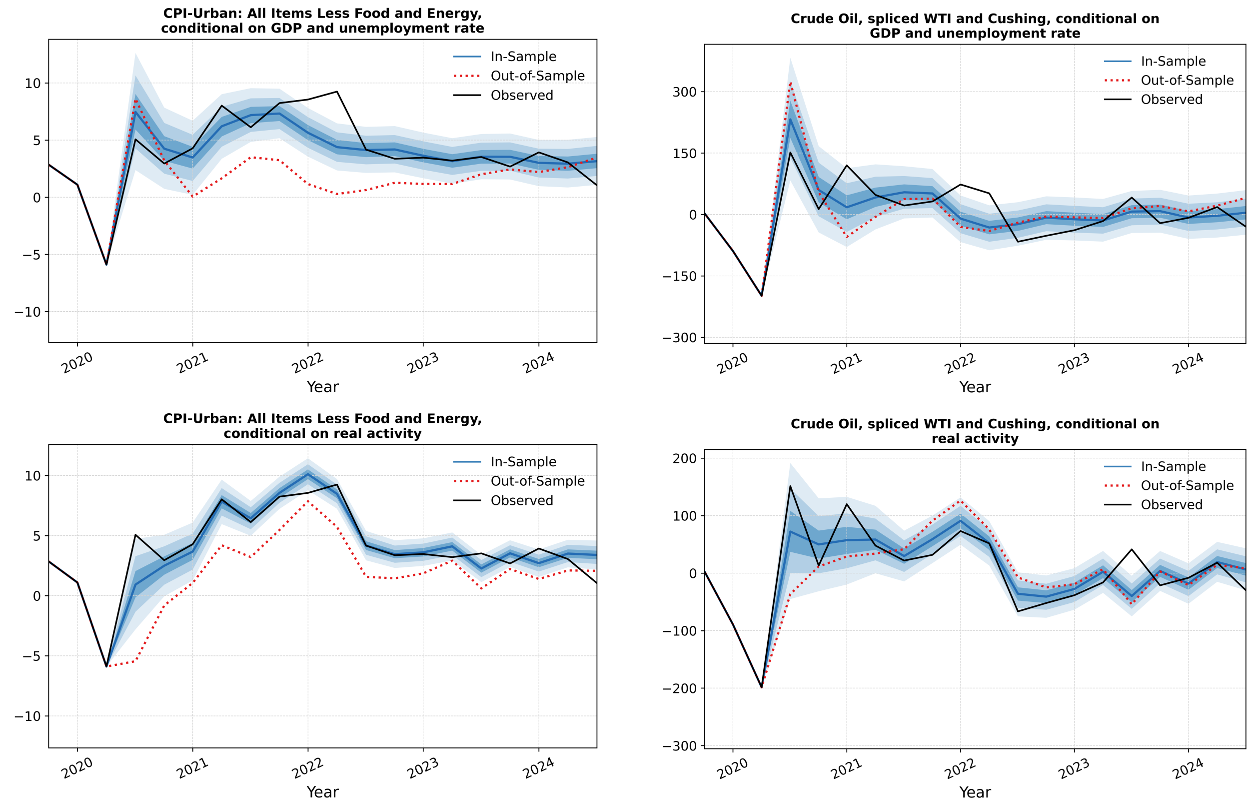

Figure 17: In-sample (IS) and out-of-sample (OOS) forecasts of core CPI and WTI oil prices are conditioned on the known paths of real GDP and unemployment rate in the top row, and conditioned on the known paths of thirteen real activity variables in the bottom row. The black lines are the historical values of core CPI and oil prices, whereas the blue shades depict the 60, 70 and 80 percent bands for the in-sample forecasts. The dark blue lines represent the median in-sample forecasts constructed using the model estimated till Q3-2024.The red dotted lines are the in-sample forecasts constructed using the model estimated till the break, Q3-2020.

Yet, the structural breaks aren't visually conspicuous in the forecasts of other macro and financial variables as evident in figure 18. These variables include crude oil prices, volatility index, residential and non-residential investment, and hourly compensation to name a few. As "fast-moving" variables, financial metrics adapt quicker to the new economic environment relative to the "slow-moving" macro variables, and tend to revert to the means after extreme events (for example, VIX spikes then collapses, stock indices drop then rally). Given that the pre-2020 data contains other crises periods such as the 2008 Global Financial Crisis, the BVAR with covid volatility model captures these dynamics, reducing the forecast errors between OOS conditional forecasts and realize data, and between OOS and IS forecasts.

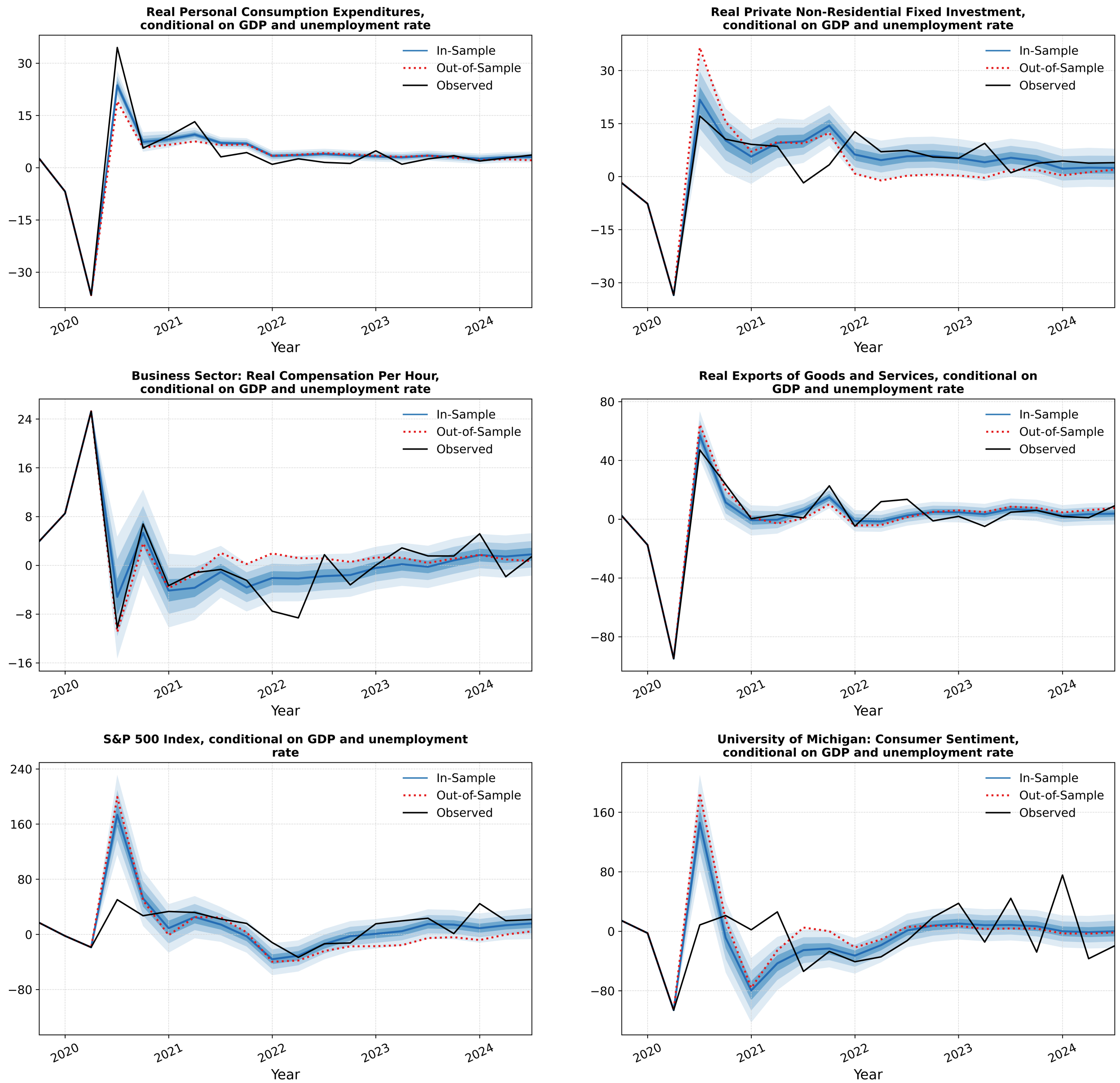

Figure 18: In-sample (IS) and out-of-sample (OOS) forecasts of macro-financial variables, conditional on the known paths of real GDP and unemployment rate. The black lines are the historical values of the variables, whereas the blue shades depict the 60, 70 and 80 percent bands for the in-sample forecasts.The dark blue lines represent the median in-sample forecasts constructed using the model estimated till Q3-2024.The red dotted lines are the in-sample forecasts constructed using the model estimated till the break, Q3-2020.

7. Replication Figures from Lenza and Primiceri (2022): How to Estimate a VAR after March 2020?

Lenza and Primiceri (2022) examine how the impulse responses functions, and conditional forecasts of variables change when we estimate the model with and without COVID-volatility. Their dataset comprises of unemployment rate, employment measured via total number of employees in non-farm payroll, and five pricing variables such as PCE Services and Core PCE. I attempt to replicate figures 2,3 and 4 of their paper using the functions in `covbayesvar` package and the python scripts. Whilst I used the exact dataset they employed for their analysis, we can also obtain the updated data directly from the FRED Economic Data repository, operated by St. Louis Fed. The *Data/LP Data Collection and Cleaning* has a short script to easily retrieve the data automatically from their website using an API, rather than manually downloading data separately.

```
from fredapi import Fred

fred = Fred(api_key='write_your_API_here')
file_name = 'LP_data.xlsx'


# monthly data from FRED-MD
series_list = [
    'CPIAUCSL',  # Consumer Price Index for All Urban Consumers: All Items
    'DDURRG3M086SBEA',  # Personal consumption expenditures: Durable goods (chain-type
        price index)
    'DGDSRG3M086SBEA',  # Personal consumption expenditures: goods (chain-type price
        index)
    'DNDGRG3M086SBEA',  # Personal consumption expenditures: Non-durable goods
        (chain-type price index)
    'DPCCRC1M027SBEA',  # Personal consumption expenditures excluding food and energy
        (Billions of dollars)
    'DSERRG3M086SBEA',  # Personal consumption expenditures: Services (chain-type
        price index)
    'INDPRO',  # Industrial Production Index, Index 2017=100
    'PAYEMS',  # All employees, total nonfarm, Thousands of Persons
    'PCE',  # Personal consumption expenditures, Billions of dollars
    'PCEDG',  # Personal Consumption Expenditures: Durable Goods
    'PCEND',  # Personal Consumption Expenditures: Non-Durable Goods
    'PCEPI',  # Personal consumption expenditures: Chain-type price index
```

```
    'PCEPILFE',  # Personal consumption expenditures: Chain-type price index excluding food and energy
    'PCES',  # Personal Consumption Expenditures: Services, Billions of Dollars
    'UNRATE',  # Civilian Unemployment Rate

]
data = DataReader(series_list, "fred" ,start=datetime(1947, 1, 1), end=datetime(2025, 2, 1))
```

Figure 19 presents the generalized impulse responses for key pricing and labor variables when unemployment rate hikes by 1 percentage point and when we place the unemployment rate first in the Cholesky identification scheme. In the top left panel, the unemployment rate jumps due to the shock, but gradually declines returning to its baseline level. The red solid line depicts the posterior median responses when the model accounts for heightened volatility during the COVID months. These contrast with the grey dashed line, generated after estimating the model with constant volatility in the full sample till May 2021. Accounting for the COVID volatility, the responses of unemployment (top-left panel) decline shower relative to the responses from the constant volatility estimated estimated both till full-sample of May 2021 (grey dotted line) and the pre-pandemic sample February 2020 (blue dotted line). Therefore, the COVID volatility model suggests that the macro variables drop deeper for longer duration than those from the constant volatility model. Likewise, prices decline, indicating a persistent downward pressure on inflation. The COVID volatility model predicts a weaker decline than that from the conventional model. Although the responses are consistent with the notion that disruptions in the labor market lower demand and prices, the responses from the constant volatility model appear unrealistic, showing erratic movements that differ from the historical relationships. Hence, including the post-pandemic data without adjusting for time-varying volatility yields biased and unstable estimates, which juxtaposes with the more robust and credible estimates from the COVID-volatility model.

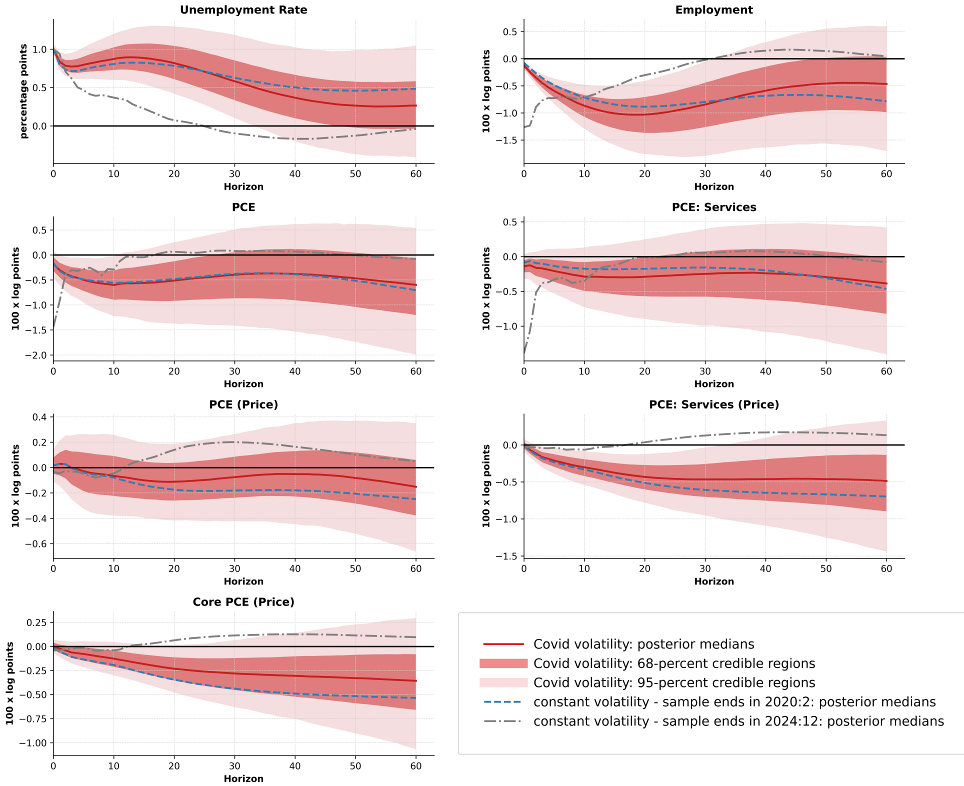

Figure 19: Generalized impulse responses of all macro variables when the unemployment rate rises by 1 percentage point. To identify the structural shocks using Cholesky decomposition, we order the unemployment rate first.

To generate the graphs in figure 19, refer to the scripts in *LP 2021* folder named *Baseline_May2021*, *CV_May2021*, *CV_Feb2020_May2021*, and *generate_figures*. For instance, first I load the data, and define the dates up to which we estimate the model, forecast horizons, and apply other transformations in the data as follows:

```
data['UNRATE'] = np.exp(data['UNRATE'] / 100)
# Real PCE: nominal PCE / PCE deflator
data['PCE_real'] = data['PCE'] / data['PCEPI']
# Real PCE services: nominal PCE services / PCE services deflator
data['PCE_services_real'] = data['PCES'] / data['DSERRG3M086SBEA']
# Selecting variables in the baseline model
indmacro = ['UNRATE', 'PAYEMS', 'PCE_real', 'PCE_services_real', 'PCEPI',
    'DSERRG3M086SBEA', 'PCEPILFE']
# Y-axis labels for IRF and Forecast plots
YLABELirf = ["percentage points", "100 x log points", "100 x log points", "100 x log
    points", "100 x log points",
           "100 x log points", "100 x log points"]
```

```python
YLABELfcst = ["percentage points", "index", "index", "index", "index", "index",
    "index"]

# Choice of estimation sample, constant or varying volatility, and forecasting period
T0 = data.index[(data['DATE'].dt.year == 1988) & (data['DATE'].dt.month == 12)][0]
        # beginning of estimation sample
T1estim = data.index[(data['DATE'].dt.year == 2021) & (data['DATE'].dt.month ==
    5)][0]    # end of estimation sample

T1av = T1estim       # date of last available data for forecasting
Tend = T1estim       # date of last available data in the dataset

# Position of the Feb 2020 observation
Tfeb2020 = data.index[(data['DATE'].dt.year == 2020) & (data['DATE'].dt.month ==
    2)][0]
Tcovid = Tfeb2020 - T0 + 1           # first time period of COVID (March 2020; set to
    "None" if constant volatility)

Tjan2019 = Tfeb2020 - 13    # initial date for conditional forecast plots
TendFcst = Tfeb2020 + 22 + 6
# TendFcst = Tfeb2020 + 71   # end date for projections (June 2022)
hmax = TendFcst - T1av    # corresponding maximum forecasting horizon

# Monthly VAR estimation
Ylev = data.loc[T0:T1estim, indmacro]
Ylog_df = 100 * np.log(Ylev)
Ylog = Ylog_df.to_numpy()
Time = data['DATE'].iloc[T0:]
T, n = Ylog.shape
```

Then, I estimate the model using the `bvarGLP_covid` function as shown previously, and estimate the generalized impulse response functions (GIRFs) to shock to the unemployment rate using the `bvarIrfs` function. The `bvarIrfs` computes the GIRFs using the Cholesky identification scheme to identify structural shocks, allowing us to analyze how a shock to one variables propagates through the system over time.

```python

########################## generalized IRFs to an "unemployment" shock
    ############################
# Compute the IRFs
```

```
H = 60
M = bvar_results['mcmc']['beta'].shape[2]
Dirf1 = np.zeros((H+1, Ylog.shape[1], M))

for jg in range(M):
    Dirf1[:, :, jg] = bvar.bvarIrfs(bvar_results['mcmc']['beta'][:, :, jg],
        bvar_results['mcmc']['sigma'][:, :, jg], 1, H+1)
sIRF1 = np.sort(Dirf1, axis=2)
```

Figure 20 presents conditional forecasts under two different estimation methods: COVID volatility model till June 2020 in the left panel, and constant-volatility model using data up to February 2020 in the right panel. In other words, as of June 2020, these forecasts simulate the predictions for employment, and varying measures of prices, given the observed paths of unemployment rate (top row), including actual realizations from July 2020 - May 2021, and projections from the Blue Chip Consensus Forecasts for unemployment rate after June 2021. The shaded regions are the 68 and 95 percent credible intervals in both figures. These intervals are wider when we account for COVID volatility (left panel), indicating that the COVID-volatility model accounts for increased uncertainty during the pandemic. On the other hand, the forecast intervals from the constant-volatility model are narrower, implying more confidence in the forecasts and less uncertainty. Moreover, the realized data (black crosses) often fall outside or near the edges of the blue credible regions, connoting that the model underestimated the true variance of economic fluctuations. This contrasts with the wider forecast distributions of the COVID-volatility model that encompasses the realized data as they mostly fall inside the red shaded regions. Therefore, the COVID-volatility model provides more accurate probabilistic forecasts.

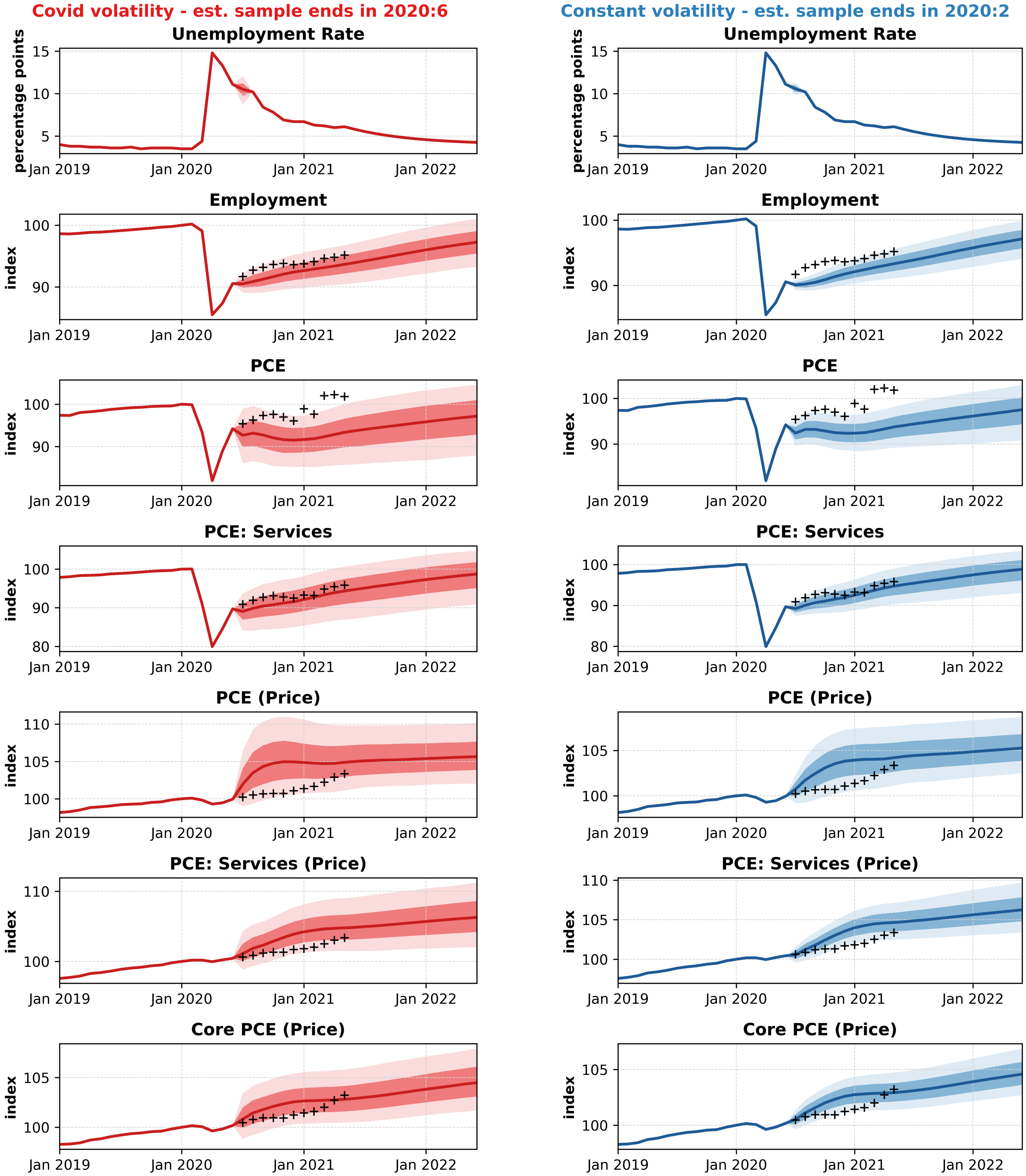

Figure 20: Conditional forecasts as of June 2020 given the realized paths of unemployment rate from June 2020 - May 2021 (black crosses), and the Blue Chip Consensus projections of unemployment rate from June 2021. The dark red and blue lines are the posterior median forecasts, and the shaded regions are the 68 and 95 percent credible posterior distributions.

```
############# conditional forecasts ################

# Create a matrix to store historical data (Jan 2019-May2021) and store future prokections
YYfcst = np.vstack([100 * np.log(data.loc[Tjan2019:T1av, indmacro].to_numpy()),
   np.full((hmax, n), np.nan)
])

# Condition on the Blue Chip forecasts of unemployment rate after July 2021
# start at the last known value of 5.8% and converge to 4% at an exponential decay of 0.85 per month
YYfcst[-hmax:, 0] = 4 + (5.8 - 4) * (0.85 ** np.arange(hmax))
TTfcst = YYfcst.shape[0] # Total time periods for forecasting
M = bvar_results['mcmc']['beta'].shape[2] # Number of MCMC samples (posterior draws)
DRAWSY = np.full((n, TTfcst, M), np.nan)

# Forecasts: Loop Over MCMC Posterior Samples
for i in range(M):
   betadraw = bvar_results['mcmc']['beta'][:, :, i]
   G = np.linalg.cholesky(bvar_results['mcmc']['sigma'][:, :, i]).T


    # Handling Time-Varying Volatility
   if Tcovid is None:
       etapar = [1, 1, 1, 1] # Constant volatility case
       tstar = 1000000  # arbitrary large value to avoid COVID adjustment
   else:
       etapar = bvar_results['mcmc']['eta'][i, :]
       tstar = TTfcst - hmax + Tcovid - T # First period of COVID shocks
   varc, varZ, varG, varC, varT, varH = bvar.form_companion_matrices_covid(betadraw, G.T, etapar, tstar, n, lags,
                                                                           TTfcst)
   s00 = np.flip(YYfcst[:lags, :], axis=0).T.flatten().reshape(-1, 1)
   P00 = np.zeros((n * lags, n * lags))
   DrawStates, shocks = bvar.disturbance_smoother_var(
       YYfcst, varc, varZ, varG, varC, varT, varH, s00, P00, TTfcst, n, n * lags, n, 'kalman'
   )
   DRAWSY[:, :, i] = DrawStates[:n, :]
```

```

IRFA = DRAWSY[:n, :, :]
IRFAsorted = np.sort(IRFA, axis=2)
```

Finally, figure 21 illustrates conditional forecast, conditioning on the Blue Chip Consensus Forecasts of unemployment released in June 2021. The left panel accounts for time varying volatility, implying that shocks were more extreme at the onset of the pandemic, but gradually decay over time. The right panel excludes all the data after February 2020, disregarding the unique patterns in the shocks observed during the pandemic, and assuming that the pandemic doesn't affect the volatility. Despite the differences in the modeling assumptions, the forecast distribution gauging uncertainty around the median forecasts are similar across both models. This is because the estimated volatility decay parameter is 0.8, tapering the shock volatility over time which returns to pre-pandemic levels. Thus, by May 2021, the differences in volatility, reflected in the forecast intervals, have narrowed, yielding similar levels of forecast dispersion.

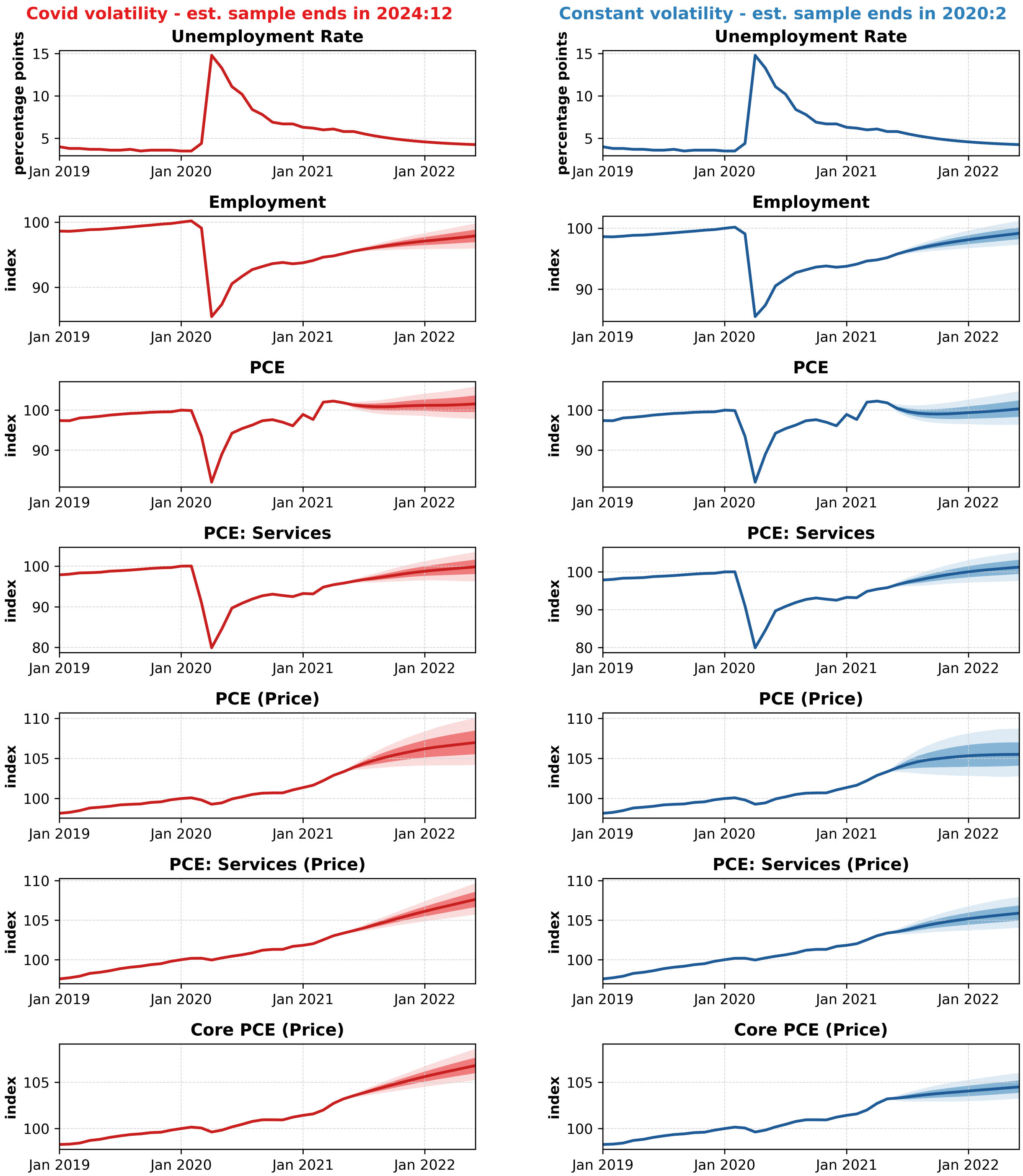

Figure 20: Conditional forecasts as of May 2021 given the realized paths of unemployment rate from June 2020 - May 2021, and the Blue Chip Consensus projections of unemployment rate from June 2021. The dark red and blue lines are the posterior median forecasts, and the shaded regions are the 68 and 95 percent credible posterior distributions.

8. Summary and Discussion

In this paper, I detailed the procedure to implement a large BVAR model with COVID volatility using the novel python's `covbayesvar` package, which is an amalgamation of the works of Giannone Lenza and Primiceri (2015), Banbura, Giannone and Lenza (2015), Crump et. al (2021), and Lenza and Primiceri (2021). I applied the model to the monthly and quarterly frequency medium-sized datasets, explained the functionalities of the most crucial Python functions, and conducted a Markov chain simulation exercise. Then, I presented use cases using both monthly and quarterly frequency data. Additionally, I replicated the figures from Lenza and Primiceri (2022) to demonstrate the distinguishing features of the forecasting the variables in the system with and without COVID volatility, and underscore that the model without COVID volatility underestimates the degree of uncertainty around the forecasts during COVID. To the best of my knowledge, this is the first open-source package which can estimate the model with COVID volatility and is versatile as it answers a breadth of policy questions via a reduced-form approach using a large number of variables.

Nevertheless, we can extend it to solve a diverse array of questions. A simple extension is to use a similar BVAR with COVID volatility to construct an exchange rate index for the US (similar to a trade-weighted US dollar index), which, to my knowledge, no one has constructed before using a BVAR model. That entails gathering a larger set of international-oriented data on bilateral exchange rates, import and export price indices, trade balance of goods on a balance of payment basis, and trade data on US imports and exports of goods. Although I run the model for the US only, we can apply this model for more than one country, and enhance the efficiency by parallelizing the code using the `joblib` package, exploiting all CPU cores. This is feasible and will drastically reduce the time to run the model, and produce and store the results. An alternative is to deploy a cluster of computers to radically speed up the estimation process, such as SageMaker Studio instances in Amazon Web Services.

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Appendix

A1. Description of Monthly Macro and Financial Variables

Series Name	Units	Transformation	isFinancial	Prior
Industrial Production Index	Index 2017=100	100×log	0	RW
Capacity Utilization: Manufacturing	Percent of Capacity	Raw	0	RW
Housing Starts	Thousands of Units	100×log	0	RW
Real Personal Income ex. Transfer Receipts	Billions of Chained 2012 Dollars	100×log	0	RW
Real Personal Consumption Expenditure	Index 2017=100	100×log	0	RW
Real Manufacturing and Trade Industries Sales	Millions of Chained 2017 Dollars	100×log	0	RW
All Employees, Total Nonfarm	Thousands of Persons	100×log	0	RW
Civilian Unemployment Rate	Percent	Raw	0	RW
Average Hourly Earnings of Production and Non-supervisory Employees	Dollars per Hour, Monthly	100×log	0	RW
Initial Claims		100×log	0	RW
CPI: All Items	Index 1982–1984=100	100×log	0	RW
CPI-Urban: All Items Less Food and Energy	Index	100×log	0	RW
PCE: Chain-Type Price Index	Index 2017=100	100×log	0	RW
PCE Services: Chain-Type Price Index	Index	100×log	0	RW
PPI by Commodity: Metals and Metal Products	Index	100×log	1	RW
Crude Oil, spliced WTI and Cushing	Dollars per Barrel	100×log	1	RW
10-Year Treasury Note Yield	Percent	Raw	1	RW
1 Year Treasury Bond Yield	Percent	Raw	1	RW
5 Year Treasury Bond Yield	Percent	Raw	1	RW
Federal Funds Rate	Percent	Raw	0	RW
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw	1	RW
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw	1	RW
M2 Money Stock	Billions of Dollars	100×log	1	RW
S&P 500 Index	Index	100×log	1	RW
CBOE Volatility Index: VIX	Index	100×log	1	WN
Japan / U.S. Foreign Exchange Rate		100×log	1	RW
U.S. / U.K. Foreign Exchange Rate		100×log	1	RW
Canada / U.S. Foreign Exchange Rate		100×log	1	RW

A2. Description of Quarterly Macro and Financial Variables

Series Name	Units	Transformation	isFinancial	Prior
Real Gross Domestic Product	Billions of Chained 2017 Dollars	100×log	0	RW
Real Personal Consumption Expenditures	Billions of Chained 2017 Dollars	100×log	0	RW
Real Disposable Personal Income	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Non-Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Government Consumption Expenditures and Gross Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Industrial Production Index	Index 2017=100	100×log	0	RW
Capacity Utilization: Manufacturing	Percent of Capacity	Raw	0	RW
Housing Starts	Thousands of Units	100×log	0	RW
All Employees, Total Nonfarm	Thousands of Persons	100×log	0	RW
Civilian Unemployment Rate	Percent	Raw	0	RW
Business Sector: Real Compensation Per Hour	Index 2017=100	100×log	0	RW
GDP Deflator	Index 2017=100	100×log	0	RW
PCE: Chain-Type Price Index	Index 2017=100	100×log	0	RW
PCE Excluding Food and Energy	Index 2017=100	100×log	0	RW
CPI: All Items	Index 1982–1984=100	100×log	0	RW
CPI-Urban: All Items Less Food and Energy	Index	100×log	0	RW
Crude Oil, spliced WTI and Cushing	Dollars per Barrel	100×log	1	RW
10-Year Treasury Note Yield	Percent	Raw	1	RW
1-Year Treasury Bond Yield	Percent	Raw	1	RW
5-Year Treasury Bond Yield	Percent	Raw	1	RW
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw	1	RW
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw	1	RW
Real Exports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
Real Imports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
S&P 500 Index	Index	100×log	1	RW
CBOE Volatility Index: VIX	Index	100×log	1	WN
University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	100×log	0	RW

A3. Entropic Tilting: Conditional Forecasts of Quarterly Data Anchored to Long Term Expectations

Section 6 introduced the framework of deploying entropic tilting to anchor the unconditional forecasts to long-term targets as defined in the Summary of economic Projections. Though I use monthly data in that example, we can apply the same method on quarterly data as well. This is crucial for mainly two reasons. Firstly, the FOMC reports projections in quarterly or annual terms, particularly for longer horizons spanning more than one year into the future. Using quarterly forecasts data ensures that the forecasts align with the policy horizon and the frequency at which the Fed communicates its targets. Secondly, it allows us to capture the most important metric of economic activity, real GDP, which is inherently a quarterly measure. Thirdly, monthly data can be volatile due to seasonal effects, measurement errors or short-term shocks, breeding noise that can distort long-run trends. Alternatively, quarterly data aggregates monthly observations, smooths out short-term fluctuations and provides a clearer signal of the underlying economic trends. This is advantageous if we condition on long-run targets where the emphasis is to capture persistent trends rather than transient movements. Therefore, *entropicTilting* file exemplifies how to generate the forecasts given the long-term targets and evaluate the joint predictive "tilted" distributions of such forecasts.

```python
# Conditioning assumptions: SEP released on Dec 2024 SEP for 2027
# Center of the central tendency: midpoint of the range
# find the index of the PCE inflation rate, Federal Funds Rate, and Unemployment Rate
    in the Spec DataFrame
idxCVPCE = Spec[Spec['SeriesName'] == 'PCE: Chain-Type Price Index'].index[0]
valCVPCE = (2 + 2) / 2

# Core PCE
idxCVPCEcore = Spec[Spec['SeriesName'] == 'PCE Excluding Food and Energy'].index[0]
valCVPCEcore = (2 + 2) / 2

# Unemployment Rate
idxCVLR = Spec[Spec['SeriesName'] == 'Civilian Unemployment Rate'].index[0]
valCVLR = (4 + 4.4) / 2

# Real GDP
idxCVGDP = Spec[Spec['SeriesName'] == 'Real Gross Domestic Product'].index[0]
valCVGDP = (1.8 + 2) / 2
```

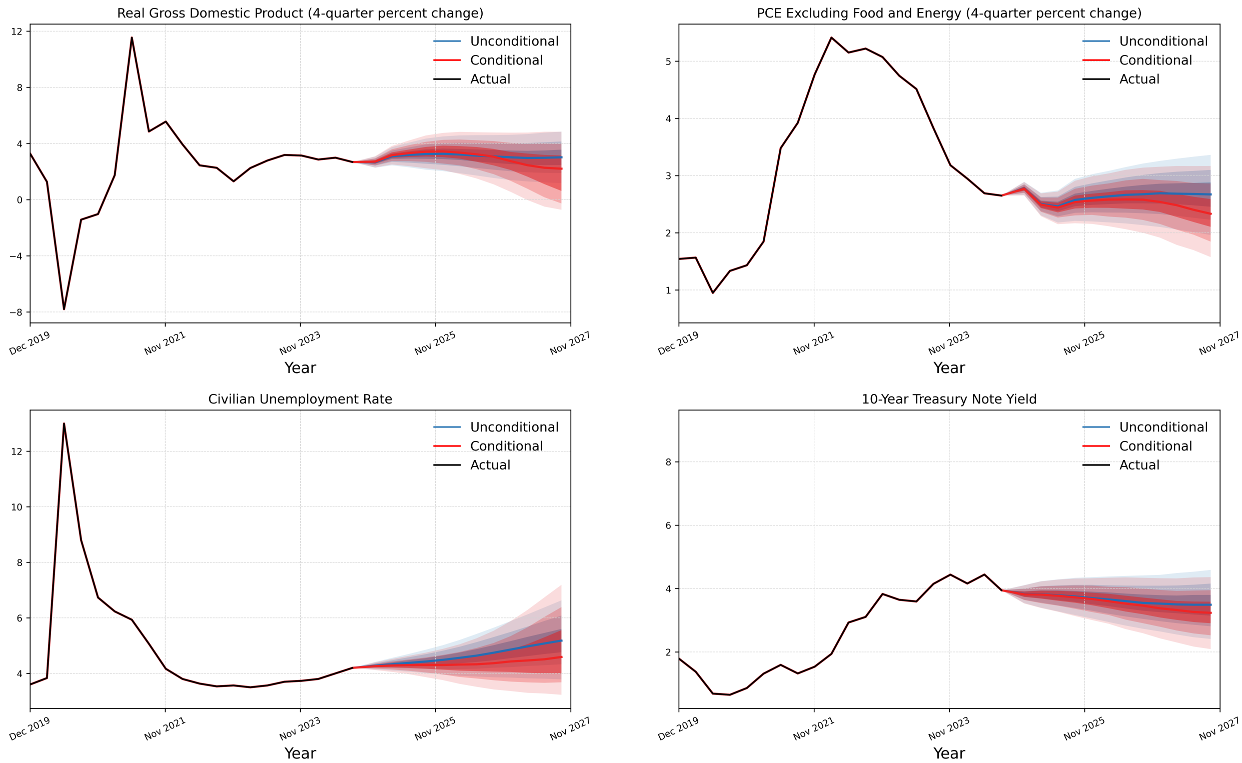

Figure A1: Unconditional forecasts and forecasts conditional on SEP projections of PCE inflation and core PCE inflation rate to 2 percent, unemployment rate to 4.2 percent, and real GDP growth rate to 1.9 percent 3 years into the future. These conditional forecasts are produced after tilting the forecast distribution such that the median of the forecast distribution anchors to the target SEP projections.

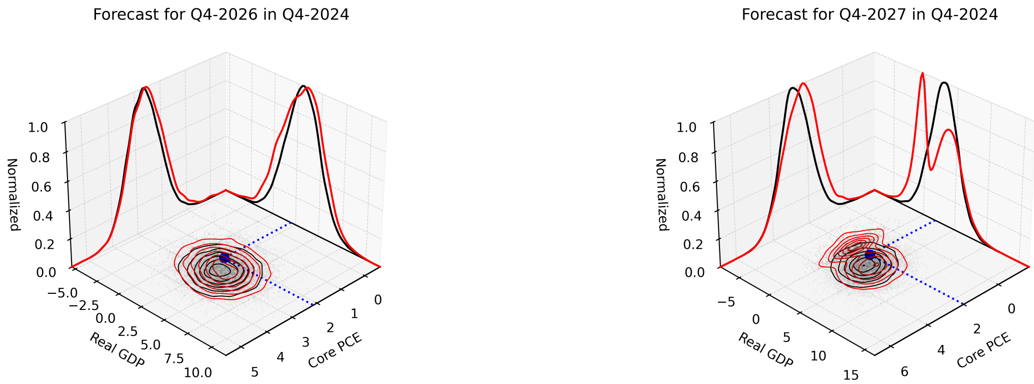

Figure A2: Joint forecast density functions of the forecast of the YoY growth rate of real GDP and PCE inflation for Q4-2026 (left), and Q4-2027 (right). The black lines are the unconditional (baseline) forecast distribution, where the contours in the centers represent the joint distribution, and those on the side panes are the marginal distributions. The red curves are the "tilted" distributions obtained after adjusting the original forecast distribution to anchor to the long-run targets - these are the average of the central tendency values present in the Summary of Economic Projections released on December 18, 2024. The blue dot in the surfaces are the midpoint of the central tendency values: real GDP growth and PCE inflation rate are 2 and 2.15 percent, respectively in 2026. Likewise, they are 1.9 and 2 percent, respectively in 2027.

From Boom-Bust to COVID: Revisiting the Cyclicality of Financial Intermediation Before and After 2008

1. Introduction

The global financial crisis (GFC) of 2008 froze interbank lending, dried up credit to consumers and businesses, and tightened lending conditions as banks lost money on mortgage defaults, which ultimately spawned new financial stability and macro-prudential regulations embedded in the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Excess build-up of leverage, both on and off balance sheets, made the financial system very fragile, erupting the GFC (Financial Stability Forum (2009)). I examine the stylized facts that link a rich tapestry of financial, macro, and monetary conditions, and check if this relationship before the 2008 GFC has altered since then. In particular, I examine if the crisis caused a structural break in the relationship between financial intermediation variables such as lending rates and loans, and the remainder of the US economy. The Federal Reserve's Flow of Funds Accounts tracks how the funds flow across the various sectors - households and non-profit organizations, non-financial business sectors, financial sector, government, rest of the world and the Federal Reserve. Within the financial sector, funds flow through financial intermediaries such as banks, pensions, insurance companies, and mutual funds. Documenting economic trends, the financial intermediation metrics gauge how debt and credit in each sector - ranging from households to corporate sectors, evolve. Specifically, they track the financial assets and liabilities such as savings and time deposits, mortgages, corporate bonds, equity valuations, mutual funds, and bank loans held by various entities in each sector.

Crucially, it's important to understand the cyclicality of the financial intermediation metrics - bank loans, lending rates, leverage, and monetary aggregates - for a few reasons. Financial intermediaries are conduits or channels that transmit changes in monetary policies. In other words, any time the Fed adjusts the federal funds rate, purchases assets in large scale or resorts to other unconventional monetary policy, its effectiveness depends on how financial and non-financial institutions change their lending behavior. If intermediation variables such as loans are very procyclical, an ease in monetary policy may amplify booms, while a tightening cycle may exacerbate recession. Adrian and Shin (2010), and Adrian, Boyarchenko and Shin (2016) document that leverage of intermediaries, in particular security brokers and dealers is highly procyclical - financial intermediaries actively adjust their balance sheets such that leverage soars during booms and falls during busts. Consequently, when intermediaries expand their balance sheets by borrowing more, their risk appetite increases, lowering risk premium and VIX. They lend more, amplifying the financial cycle. Conversely, intermediaries delever in downturns, demanding higher compensation for bearing risk and VIX rises. Selloff of assets during downturns depress prices, reduce collateral values and restrict credit. Moreover, they show that the cyclical nature of borrowing and lending predicts changes in risk appetite and fear or expected future volatility in the stock market. Related research by Ariccia, Laeven and Marquez (2014) conclude that leverage fuels in low interest rate environment when banks bear more risk. Since banks are heavily interconnected, even a small proportion of banks with procyclical leverage can have a large systemic impact, exacerbating a supply side financial accelerator (Beccalli et al. (2015)).

Besides leverage, a related widely-gauged barometer for the health of the financial system is the leverage ratio, which is the ratio of tier 1 capital and total assets, that may or may not be weighted by their risk profile. A leverage ratio serves as a backstop or a brake to counterbalance the growth of excessive credit lending in booms. In the burgeoning literature to verify pro-cyclicality in various ways, Kalmemi-Ozcan et al. (2012) report that leverage ratio is procyclical for US investment banks and large commercial banks between 2000 and 2009 using micro firm and bank-level data from several countries. The leverage ratios and off-balance sheet exposure of commercial banks in the US signal that they didn't accumulate high risk before the 2008 sub-prime mortgage crisis. However, large investment banks in the US and Europe aggressively leveraged, particularly after the SEC relaxed capital requirements for investment banks in 2004. Using a large data spanning 1995-2012 for 14 advanced economies, Brei and Gambacorta (2014) discover that the Basel III leverage ratio is substantially more countercyclical than the risk-weighted regulatory capital ratio. In other words, leverage ratio tightens or reduces in booms, and rises in busts.

Additionally, uncovering cyclical patterns of intermediation variables aids policy makers in identifying systemic vulnerabilities and calibrating appropriate macroprudential policies such as countercyclical capital buffers. Notably, if the financial system is fragile during downturns and a bank reduces leverage by selling assets at depressed price, this distressed fire sale of assets can trigger mark-to-market losses across the financial system, spawning a contagion effect (Greenwood, Landier Thesmar (2015)). When leverage, credit growth and lending spreads behave procyclically, systemic risk silently builds during booms in the form of inflated asset prices, lax lending standards and excess leverage. Conversely, they amplify downturns when credit tightens, firms deleverage, and asset prices sink. In these phases of business cycles, macroprudential tools - countercyclical capital buffers, operate to raise capital buffers to inhibit excess credit lending and risk taking; and release capital buffers in bust so that banks can absorb losses, continue lending and allow banks to remain viable.

Extensive literature in this field uses firm-level micro and aggregate macro data. Prominently, Adrian, Etul, and Moench (2010) probe how changes in the balance sheet aggregates strongly influence excess returns on equities, corporate, and Treasury bond portfolios. Adrian, Colla, and Shin (2012) review micro and aggregate data to examine how the financial crisis changed the composition between loans and bonds, and while banks reduced lending to firms, bond financing rose to make up for the deficit. Adrian and Boyarchenko (2015) document the cyclical features of the balance sheets of various intermediaries, concluding that the banking sector's leverage is highly procyclical as opposed to the acyclical nature of leverage in the nonbank financial sector. Specifically, leverage of non-bank financial sector doesn't expand when the financial sector grows or contracts. Based on these observations, they propose a theory of a two-agent financial intermediary sector within a dynamic model in continuous time, infinite horizon economy. Their conclusion starkly contrasts with those of He and Krishnamurthy (2013), who find that market leverage of the fund sector is countercyclical. Miranda-Agrippino and Ray (2010) show how a tight monetary policy in the US significantly deleverages the global financial intermediaries, worsens foreign financial conditions, and shrinks the international flow of credit. They use a rich-information VAR with international and domestic variables to analyze how monetary policy transmits across the border. Likewise, Giannone, Lenza, and Reichlin (2019) probe the relationship between business cycles and financial intermediation in the Euro Area, inspiring the analysis of this paper. To characterize the business cycle features of financial intermediary variables, they produce impulse response functions to a "cyclical shock", which is a shock that accounts for majority of the fluctuations in business cycles. This cyclical shock is a linear combination of independent shocks that explains most of the variance of industrial production at business cycle frequencies.

To establish the stylized facts using the pre-crisis data, I employ a time-invariant BVAR model with COVID-volatility because it alleviates the problem of the curse of dimensionality. This problem aggravates when we fit a TVP-SV-BVAR model as a model becomes densely over-parameterized and computationally expensive. The primary purpose of this paper is not to introduce a novel BVAR estimation strategy, or to identify breaks over the US sample, but to deploy and extend existing methods from Banbura, Giannone, and Lenza (2015), Crump et al. (2021), and Lenza and Primiceri (2022) to answer empirical questions using my own python package. Unlike the marginal approach, which entails constructing a small system and adding variables incrementally (Christiano, Eichenbaum, and Evans (1996), den Haan, Sumner and Yamashiro (2007)), this method analyzes the joint dynamics of 43 time series variables. The marginal approach of adding one variable at a time omits relevant variables, particularly in the interconnected system where macro and financial variables are linked to one another. Also, while much of the empirical work in this topic has employed smaller-scale VAR models (e.g., Christiano, Eichenbaum and Evans (1996)), and fitted panel regressions and examined correlations through scatterplots (e.g., Adrian and Shin (2010), and Adrian, Boyarchenko and Shin (2016)), the large BVAR approach is advantageous because it accounts for leads, lags, trends and uncertainty.

I study the cyclical characteristics of the variables by fitting a large BVAR on the historical data before the inception of the 2008 financial crisis and construct scenario analysis wherein I study how variables respond to a hike in the unemployment rate. Empirical findings connote the nature of elasticities of the financial intermediation and macro variables variables, i.e. the rate with which they change to shocks, and how persistent these effects are. From the scenario analyses, we observe that M1 behaves counter-cyclically during downturns in business cycles i.e. M1 rises when the real economy contracts such as when the industrial production declines and/ or the unemployment rate spikes. M1 serves as a haven for liquidity as people develop precautionary motives, reflecting the flight-to-liquidity mode of people in uncertain times. Measures of credit such as real estate loans, real commercial and industrial loans and consumer loans are procyclical. Leverage of securities brokers and dealers, and non-financial businesses are countercyclical in the short run, but procyclical in the medium and long run. On the other hand, tier 1 leverage capital, a measure of capital adequacy, is procyclical in the short run, but countercyclical in the medium and long run.

After establishing the stylized facts in the pre-GFC data, I assess if these facts or historical regularities still hold after the 2008 subprime mortgage crisis ended, particularly after the pandemic. Any evidence of striking differences in the responses of the financial intermediation and macro variables will indicate that a structural break has occurred, prompting us to re-evaluate the stylized facts. To that end, I construct counterfactual paths ranging from December 2008 to December 2024 using the BVAR estimates obtained from the pre-crisis data, and condition these forecasts on the known paths of the real activity variables during 2008-2024. These counterfactuals are based on the belief that the variables in the system follow historical trends. Importantly, the historical data used to determine the pre-crisis regularities comprise only two recessions - the early 1990s and 2000s. These recessions don't constitute episodes of major disruptions in the financial markets to the extent that manifested in the 2008 subprime crisis, generating a global financial meltdown. If the actual data deviates significantly from the counterfactuals, the crisis breaks down the normal transmission mechanisms and reveals structural changes in how the financial intermediation interacts with the business cycle.

The structure of the paper is as follows. Section 2 describes the main variables that enter the system and section 3 outlines the the BVAR with the COVID-volatility model. Section 4 presents an empirical scenario analyses of a unemployment shock using pre-crisis data to establish stylized facts. Section 5 illustrates counterfactuals to elucidate how the financial crisis broke the historical regularities, paying special attention to divergence seen during the pandemic.

2. Data

Inspired by the works of Crump et al. (2021), I gather quarterly data for 43 variables from March 1986 to December 2024 from FRED-QD, covering the period of the "Great Moderation" when the market-based financial system was formed (Adrian and Shin (2010)). The set of variables also encompasses data from the Federal Reserve Board of Governer's Tealbook A Greensheets. Spanning a breadth of key US financial and macroeconomic conditions, the Greensheets contain projections of these indicators created before every FOMC meeting and guide policymakers at the Federal Reserve Board of Governors. Additionally, I added variables that reflect the financial intermediary balance sheet from the Federal Reserve's Flow of Funds accounts. Incorporating a comprehensive set of financial intermediation variables is crucial to accurately assess the resilience of financial institutions and how they interplay with the broader economy. As highlighted in the Federal Reserve's 2025 Supervisory Stress Testing methodology, these encompass various aspects of banks' balance sheets, income statements, loan portfolios, capital adequacy, and liquidity positions.

The macro variables include metrics on real activity such as real GDP, industrial production, and capacity utilization; labor market variables such as unemployment rate, number of employees in the non-farm payroll, and real compensation per hour in the business sector; various metrics for inflation including PCE and CPI, and core PCE and core CPI, WTI crude oil, a measure of confidence captured in the University of Michigan Consumer Sentiment, the crude oil price in the US; Treasury securities of varying maturities ranging from short 1 year to long term 10 years. Reflecting the long-term borrowing costs, I include Moody's seasoned corporate bonds of the highest quality (Aaa) and those with medium credit rating (Baa).

From the asset side, I include bank loans and credit supply variables as also used by Correia, Kiernan, Seay and Vojtech (2020). These are real commercial and industrial loans that measure how much credit is available to businesses and tend to behave procyclically; real consumer loans at all commercial banks that measure the amount of inflation-adjusted consumer loans (such as student loans, auto loans, personal loans, credit-card debt) provided by commercial banks only and affect household spending; real estate loans that track credit in the mortgage and housing market and are essential for borrowing for the long term; total consumer credit outstanding that includes all forms of consumer credit lent from all types of lenders - banks, credit unions, fintech companies, federal governments, etc; total real non-revolving credit that measures longer-term fixed payment loans; total real revolving credit that captures credit card borrowing, which is a key indicator of household liquidity; and consumer loans and leases securitized by finance companies. Nonbanking institutions - finance companies, pool loans to asset-backed securities and sell to investors in the shadow banking sector. This variable tracks how much credit is funneled through capital markets rather than traditional banks. Prior to the 2008 GFC, financial innovation and lax underwriting practices rapidly grew volumes of consumer loans, making it easier to pool and sell the loans. Doing so, the finance companies could transfer some of the credit risk to investors, fueling lending. The volume of securitized consumer loans peaked in February 2008 at $900,060.16 millions, and plummeted to $644,680.18 million in November 2010, falling 28.3 percent over the years. During and after the crisis, the securitization market dried as investors became highly risk-averse, sharply reducing the demand for asset-backed securities. This led to a liquidity crisis as finance companies couldn't securitize new or refinance exisiting loans. Furthermore, regulators tightened lending standards, and underwriting standards became stricter, reducing exposure to credit risks.

The various kinds of loans such as real estate loans, revolving and non-revolving credit gauge how much credit is available to households as it drives consumption, whereas total outstanding credit reflects the overall debt burden. Moreover, they constitute a significant portion of banks' asset portfolios, which are directly impacted by macro conditions. For instance, fluctuations in output or other cyclical shocks can hinder a borrower from repaying loans, dampening the quality of assets. Crucially, intermediaries manage bank lines of credit, or revolving credit facilities during bouts of financial stress ((Sufi (2009)). Relatedly, Reich et al. (2020) draw insights from loan-level data to show that small and medium-sized enterprises (SMEs) obtain much shorter credit lines, pay higher interest rates on loans, post more collateral on their credit lines and loan terms as they pose higher credit risks relative to large firms. Also, they tend to utilize their credit lines fully, signaling tighter liquidity conditions.

Additionally, I incorporate two monetary aggregates from most to least liquid - M1 and M2, as those are key components of liabilities in the balance sheets of financial intermediaries (Adrian and Shin (2010)). Highly liquid, M1 includes currency and demand deposits that respond to changes in monetary policy. Serving as a broader classification than M1, M2 encompasses M1 plus savings deposits, and time deposits that are less liquid but crucial for households and businesses.

Similar to the works of Kollmann and Zeugner (2012) and Adrian, Boyarchenko and Shin (2016), I incorporate book value of leverage of sectors - non-financial corporations, non-financial non-corporation businesses, securities brokers and dealers, commercial banks, and life insurance companies. Leverage is the ratio of total assets and equity, where equity or net worth is the difference between assets and financial liabilities of the specific sector. Acquired from FRED, financial liabilities comprise of debt securities and loans. Historically, debt securities and loans of securities, dealers and brokers, and non-financial corporations have grown at a slower pace than the total assets have grown, burgeoning net worth. Leverage indicates how many dollars of assets are financed by every dollar of equity, capturing the amount of debt used to finance assets. Equity represents a sector's cushion or safety net that it can utilize to cover its losses. If a sector has small equity cushion relative to its assets, even a small loss can wipe out that buffer, raising the risk of insolvency. The Basel bank capital regulations and stress testing scenarios are centered on the book value of leverage.

Likewise, I add Balance Sheet Tier 1 Leverage Capital (PCA framework), measuring the core capital of banks - common equity, retained earnings, disclosed reserves, preferred stocks and other instruments that are high-quality. There are different ways to measure bank capital adequacy - risk-based capital ratios stipulated in Basel III regulations and non-risk based leverage ratios stipulated under the Prompt Corrective Action (PCA) framework by the FDIC. While the Basel III accord requires banks to possess at least 6 percent of tier 1 capital out of its total risk-weighted assets, the PCA framework states that a bank is considered adequately capital if its tier 1 leverage ratio is at least 4 percent, regardless of the risk level of assets. A higher tier 1 leverage capital suggests that banks are more capitalized to absorb losses and resilient to weather shocks, which is crucial to assess whether banks can continue lending during downturns. If tier 1 leverage is low, as it fell during the 2008 GFC and 2020 pandemic, banks may be undercapitalized and may restrict lending, affecting credit flows to households and businesses.

Finally, I add data on interest rates that influence the cost of credit, such as the short-term federal funds rate, and the long-term 30-year average fixed mortgage. The latter gives insight into the cost of borrowing for home buyers. Before fitting the non-stationary model, the variables in rates enter as levels, and most other variables are transformed to log levels. Table A.1 in the appendix lists all the 43 variables and the transformations applied to each variable before estimating the model.

3. Model

To establish the stylized facts for the US, I construct a non-stationary linear Bayesian VAR(4) model with features of COVID volatility described in Primiceri and Lenza (2022) where the main idea is that the volatility can persist for several periods in the future. As the first extreme observation was in March 2020, I rescale the standard deviation of the shocks in first, second and third quarters of 2020 to unknown parameters η_1, η_2, η_3, and estimate these parameters using Bayesian methods explained in Giannone et al. (2015).

The non-stationary model is a BVAR(p):

$$y_t = \alpha + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \eta_t \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma)$$

where $\eta_t = \eta_1$ before the pandemic began, and scales up the residual covariance matrix during the pandemic at time t^*.

$$\eta_t = \begin{cases} \eta_1 & t = t^* \\ \eta_2 & t = t^* + 1 \\ \eta_3 & t = t^* + 2 \\ \eta_{t+j} = 1 + (\eta_3 - 1) n_4^{-j/2} & \text{otherwise.} \end{cases}$$

More succinctly, I form prior beliefs of the parameters having the following prior distributions: sum of coefficients, single unit root, and Pareto prior distributions. To estimate the posterior density of the parameters, I adopt a hierarchical technique of sampling using the Metropolis-Hastings algorithm defined by Primiceri and Lenza (2022). Briefly, first I initialize the hyperparameters at their posterior mode; draw the candidate values of these hyperparameters from the proposal distribution.

I present the conditional, unconditional forecasts, and the scenario analyses from the model, where the time horizon for the forecasts and impulse responses is 3 years. Contingent on the known paths of the future values of some of the variables in the dynamic system, I recursively estimate the conditional forecasts and scenarios using the algorithm elucidated in Giannone, Banbura, and Lenza (2015) adding COVID volatility. After casting the $VAR(p)$ in the state space form, this algorithm is computationally feasible in large models. Formally, a scenario analysis is the difference between the expectation under the conditional and the baseline forecasts:

$$D[y_{T+h} \mid C_T, \theta] = E[y_{T+h} \mid y_{1:T}, C_T, \theta] \; - \; E[y_{T+h} \mid y_{1:T}, \theta]$$

$$= \int y_{T+h} \, f(y_{T+h} \mid y_{1:T}, C_T, \theta) \, dy_{T+h} \; - \; \int y_{T+h} \, f(y_{T+h} \mid y_{1:T}, \theta) \, dy_{T+h}$$

where C_T is a conditioning set containing scenarios on future realized values of observable(s), and θ has all the coefficients of the model.

Next, I apply the model to inspect the responses of the variables in a scenario where unemployment rate rises by 1 pp. I fit the model on data before the 2008 Global Financial Crisis, and deduce the stylized facts based on the cyclical characteristics of the responses. The conditional forecast approach to generate the scenario analysis uncovers the most likely sequence of shocks that constraint the unemployment to follow a specified path. So, we interpret the responses from the scenario analysis differently relative to those obtained from orthogonalized impulse response functions (IRFs). This is because in an IRF, one shock perturbs the economy at horizon 0, allowing us attribute the responses to a singular shock rather than a multitude of shocks of different nature.

4. Stylized Facts from Pre-GFC Sample: 1986-03-01 to 2008-09-01

Slack in the Labor Market: Strains in the Economy When Unemployment Rises

Estimating the model till September 2008 - when the Lehman Brothers collapsed, I analyze a scenario that shows how variables respond in the future when the unemployment rate rises by 1 percentage point relative to the unconditional forecasts, leaving other variables unchanged. Analogous to residual impulse response functions with unorthogonalized shocks, this approach does not structurally identify the shocks as the responses are based on historical correlations among the variables. So, this scenario captures a multiplicity of structural shocks that transmits in the model to shift the unemployment rate upwards. In other words, it represents a linear combination of structural disturbances that drive the forecast error in unemployment one-quarter ahead. This combination of structural disturbances also accounts for the majority of the business cycle fluctuations in real activity, but disregards other sources of macroeconomic variations (Del Negro, Lenza, Primiceri, Tambalotti (2020)). They also show that the responses from this approach is nearly identical to those produced from a business cycle shock (from Giannone, Lenza, Reichlin (2019)) defined in a frequency domain to explain the bulk of variance in unemployment at 2-8 year cycles. So, it coincides with downturns seen in business cycles where output falls, and number of employees in non-farm payroll declines. Note that we cannot necessarily pinpoint the responses of variable to one specific shock, like a monetary policy shock as a blend of structural disturbances jointly drive the responses. This is because I didn't impose any theory-based restrictions or assumptions to fully recover all the structural shocks, but let the data determine the direction of responses of the variables.

Figures 1 and 2 present the scenario analysis where the dark blue lines are the median elasticities. The shaded blue regions are the 60, 70 and 80-percentile coverage intervals around the median responses. They measure a range of uncertainty around the central projected elasticities, derived from the quantiles of the predictive distribution. Various measures of output such as industrial production and capacity utilization decline by roughly 1.5 percent, real GDP by 1.2 percent, and housing starts plummet by nearly 10 percent at their nadir. This indicates a narrative typically observed in recessions as the number of non-farm payroll employees also drop by 0.5 percent. Observing a positive correlation between economic activity and interest rates, as both dwindle when the economy contracts, this matches empirical results in the literature. Both the real disposable income and business sector hourly compensation fall, and the consumer confidence measured by the University of Michigan: Consumer Sentiment slumps by 7 percent on impact. WTI crude oil price declines with a lag of two quarters.

While it's curious to see PCE and core CPI move in the opposite direction, this is not the price puzzle famously discussed in the literature. They rise on impact but decline subsequently, without reverting to their long-run steady-state levels, still departing from the inverse relationship between prices and unemployment as posited by the conventional Philips Curve in the short-run. This suggests that they respond with a lag when unemployment spikes and output falls. As real personal consumption spending contracts, the downward pricing pressures intensify, steadily deflating prices.

The short and long-term Treasury yields fall together, keeping the yield curve stable. Regarding responses of monetary aggregates, the real stock M1 adjusted for inflation rises by 2 percent at its peak in two years before gradually declining. Signally economic weakness, a rise in unemployment increases the households' and businesses' demand for cash and liquid deposits (M1) in uncertain times. Changing liquidity preferences, consumers hold more money in liquid (cash, checking accounts) instead of investing in risky assets such as stocks, increasing the precautionary savings of consumers. Thus, M1 behaves countercyclically, boosting in recessionary times when output tumbles. Moreover, declining prices enhance the purchasing power of M1 in real terms as the deflationary effect reinforces increases in real M1. Once the economy stabilizes, the demand for liquid cash diminishes, and M1 reverts downwards as exemplified in the scenario analysis. Households and firms reallocate funds into interest-bearing assets, making investment and savings accounts more attractive. Similarly, M2 remains unchanged for a quarter, rises briefly for a quarter, and then drops, implying that the short-term liquidity preferences temporarily spill over into the broader monetary aggregates. In other words, economic agents deposit money in less liquid savings accounts and time deposits to hold precautionary savings. As the downturn deepens, agents reallocate portfolios from less liquid (M2) towards liquid assets (M1), causing M2 to decline eventually. M2 is weakly correlated with business cycle, behaving countercyclically in the short run, and pro-cyclically in the medium run.

Also, consumer credit and various loans such as real commercial and industrial, real estate loans slump by nearly 4, and 1.2 percent, respectively at the nadir. This occurs when banks tighten lending standards, making it harder for agents to access new credit for over three years. Facing greater risks of bankruptcy, commercial loans to firms shrink, just as consumer loans decline when the probability of defaulting on loans rises as unemployment rises. Not only do the supply-side effects of tight lending standards prevail, but also the demand-side effects of lower borrowing ensue as disposable income reduces. So, loans behave procyclically, as they are positively correlated with output. Berger and Udell (2022) study the procyclicality of bank lending, noting that banks lend more during expansionary phases than during recessionary phases when a “credit crunch” follows. Introducing the “institutional memory hypothesis”, they suggest that banks may ease credit lending standards during prolonged expansions as memories of past defaults fade, raising loans. Conversely, banks tighten lending standards during downturns when credit risks soar, shrinking the number of loans issued. As procyclical variables, loans move in the direction of business cycles and respond by greater magnitude to shifts in real variables such as unemployment rate and industrial production than changes in lending rates. Additionally, loans are sticky or more persistent as opposed to lending rates.

Both tier 1 leverage capital and leverages of financial intermediaries portray asymmetric cyclical patterns. In the short run, leverage of all sectors rise heterogeneously - securities and broker dealers, non-financial corporate and non-corporate businesses by 0.75, 0.6, and 0.2 percent, respectively. Prior to the GFC, real GDP was very weakly negatively correlated with leverage of non-financial non-corporation businesses (-0.048), and moderately negative correlated with non-financial corporations (-0.566), but moderately positively correlated with the leverage of securities brokers and dealers (0.418). So, the balance sheet variables respond mechanically (net worth shrink faster than book assets during downturns to raise the ratio). The brief rise in leverage on impact coincides with the period when borrowing costs are cheaper - Treasury yields of varying maturities and federal funds rate decline. Yet, over a full cycle (medium and long term), leverage reduces across the sectors as firms shrink debt burden, implying that in medium and longer horizon, leverage is procyclical. Adrian and Shin (2010) delineate the consequences of procyclical leverage - in contractionary phases of business cycles when the demand of assets lowers, the asset prices also falls, diminishing net worth. Financial intermediaries reduce their balance sheets, borrow less to buy fewer assets, and sell risky assets, shrinking leverage. This feedback loop is true in the reverse direction in the expansionary phase of the business cycle.

In contrast, Tier 1 leverage capital is procyclical in the short run and countercyclical in the medium and long term. Initially, it declines by about 2 percent - deteriorating the core equity buffer of the banking system, but banks recoup the lost capital buffer within a year, recapitalize and grow positively after two years. Historically, tier 1 leverage capital occurs when banks' profits drop, and banks may mark down certain assets, which reduces capital. After a quarter of drop, capital buffer rises again when leverage falls, signaling a less fragile system. If, however, leverage rises and tier 1 capital falls in the long term, then it would imply banks have less buffer to absorb future shocks, worsening systemic vulnerabilities in the financial system. So, the cyclicality of leverage and tier 1 capital provides an early warning signal of how much stress transmits through the financial intermediaries' balance sheets over time.

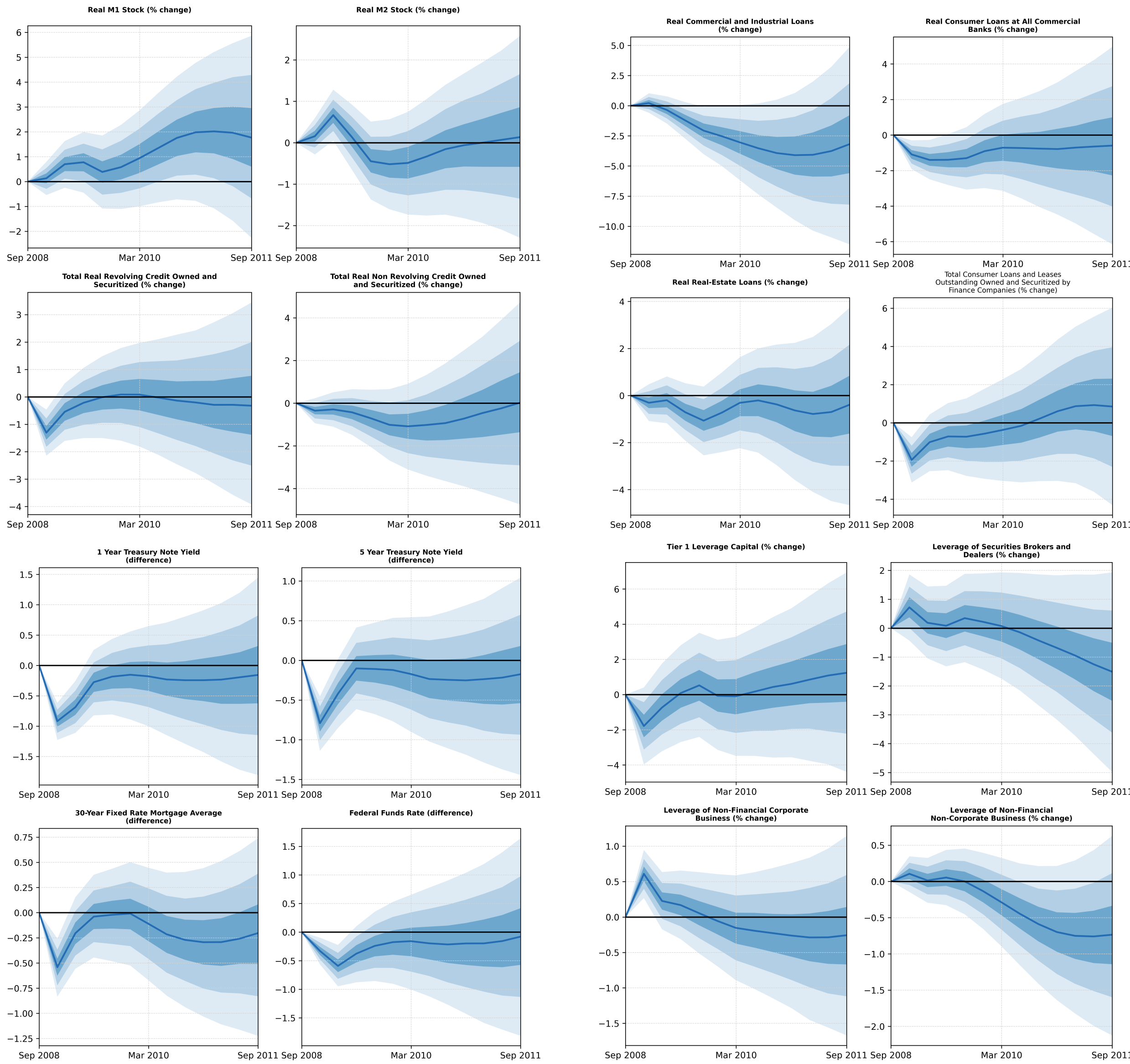

Figure 1. Responses when unemployment rate rises by 1 percentage point in a model estimated till September 2008. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

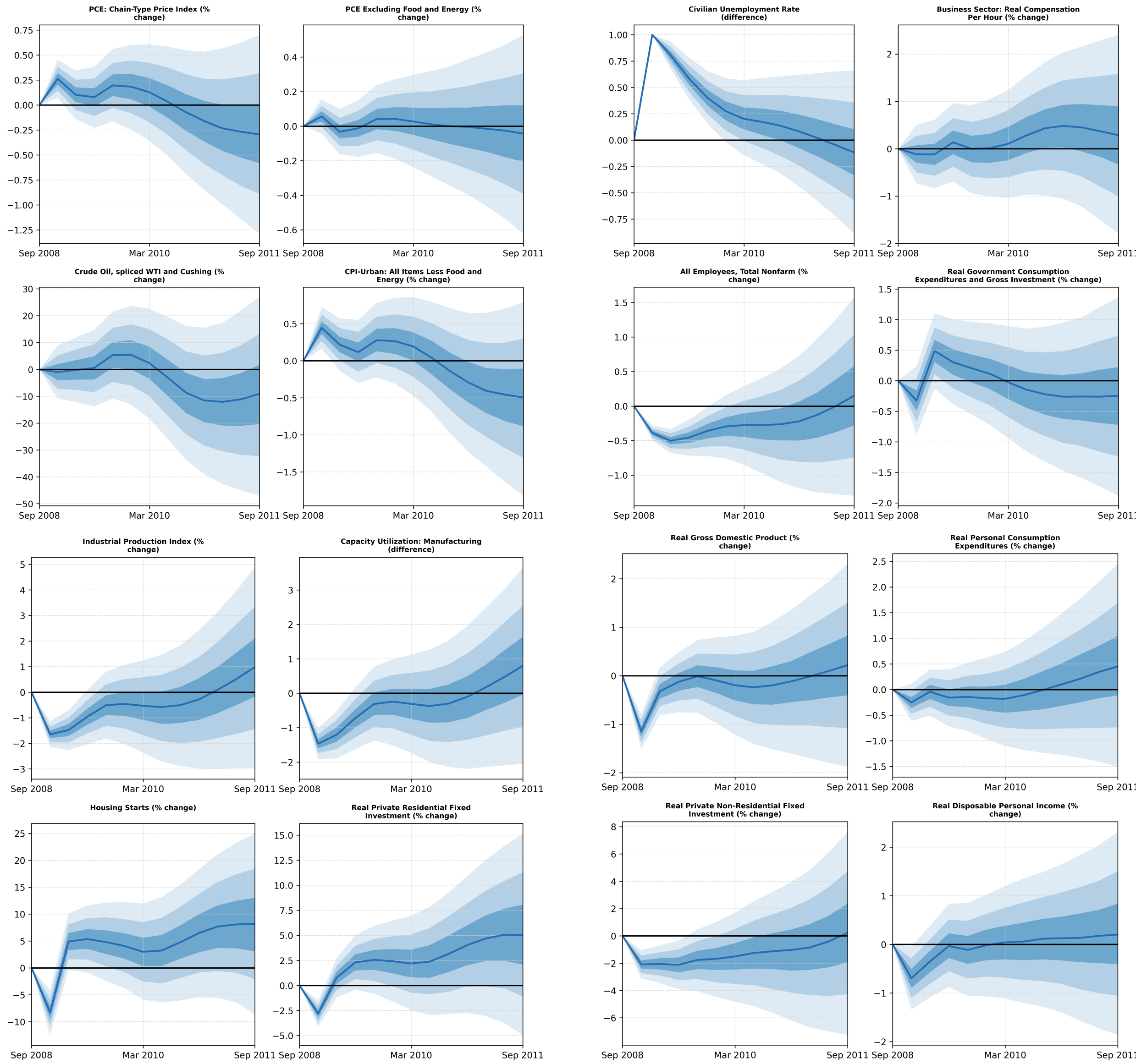

Figure 2. Responses when unemployment rate by 1 percentage point.

5. Structural Breaks: Deviations from the Financial Regularities?

Now, I check if the responses alter after 2008; in other words, do the historical regularities or stylized facts for the US economy established using the pre-crisis data hold during and after the subprime mortgage crisis? To answer this question, I further investigate if the dynamic relationship between the financial intermediation and the remaining economy alters by creating counterfactual forecasts of monetary aggregates, loans, lending rates, assets, and other economic variables. First, I estimate the BVAR(4) till September 2008 and forecast the variables after the estimation period (from December 2008), known as the out-of-sample (OOS) forecasts.

Then, knowing the realized values of the thirteen macroeconomic variables in the data for the remainder of the information set after the break, I fit the model in the entire sample till December 2024 with COVID volatility, allowing the historical correlations between variables in the data to dictate the conditional forecasts. The counterfactual paths, or the OOS forecasts portray the forecasts we would have seen given the pre-crisis regularities (or stylized facts) in the US and known behavior of real activity aforementioned in periods December 2008 to September 2024. By conditioning on the actual realized paths of the real activity variable, the model isolates real shocks from financial shocks. They show how the financial intermediary variables respond to an actual economic environment, such as a deep recession. If real-side shocks, such as sharp decline in GDP or spike in unemployment, are historically correlated with changes in credit or interest rates, the large BVAR conditional forecasts incorporate those correlations in the forecasts directly. If, however, the GFC introduced unprecedented financial shocks, the conditional forecasts will not reflect those. In other words, if the counterfactual paths substantially differ from the realized values, we may attribute those to peculiar transmission mechanisms or structural changes in the estimates due to the financial crisis. Without conditioning on the real activity variables, we cannot disentangle whether the discrepancies are because of unusual behavior in the real side of the economy or because the pre-crisis relationships changed.

The graphs in Figures 3 and 4 illustrate the in-sample and out-of-sample forecasts along with the historical data of the financial intermediation variables. The OOS forecasts of the year-over-year growth of M1 align closely with the actual data and the IS forecasts for most years, except at the beginning of the GFC (September - December 2008), and during COVID-19 in 2020. In the former, the OOS forecasts of M1 declined whereas the IS forecasts and actual M1 rose. Since the Fed trimmed interest rates aggressively and the TARP bailout injected liquidity into the banking system, the actual M1 spiked as banks increased their reserves and consumers and firms held more liquid assets. However, as the BVAR model is trained on pre-crisis data, and as prior recessions did not feature such a severe financial shock, the BVAR model doesn't capture the enhanced liquidity of the banking system. Therefore, the OOS forecasts move in the opposite direction in the aftermath of the crisis. During the pandemic, the actual M1 skyrocketed by more than three-fold, growing at an astonishing rate of more than 500 percent in March 2020, before progressing at historical trends in 2021 and beyond. This massive divergence between the counterfactuals and actual data coincides with the Fed's swift unconventional monetary responses, stimulus checks from the government, and other pandemic-related fiscal interventions. The outbreak of COVID-19 led to dysfunction in the Treasury and mortgage-backed securities market. As these markets serve a critical role in flowing credit to the broader economy, and act as benchmarks for other lending rates, the Fed initiated quantitative easing, purchasing billions of Treasury securities in the coming months to bolster the faltering economy. Although the OOS and IS forecasts of M1 during the COVID months rose, they matched nowhere near the extraordinary scale seen in the actual data.

Likewise, the OOS forecasts of the growth of M2 deviate from mid-2009 till mid-2014, and again between

2022 and 2024, showing evidence of structural breaks post-GFC and the COVID pandemic. Before 2008, money supply (M2) was tightly linked to bank lending, adhering to the classical money multiplier framework - when the Fed injected reserves into the banking system, banks lent out most of these reserves, creating new deposits, which expanded M2. After the 2008 crisis when the Fed increased reserves via QE, banks held onto those reserves, instead of lending them and Basel III regulations enabled banks to meet stricter capital requirements. Notably, Ivashina and Scharfstein (2009) report that new loans to large borrowers tumbled by 47 percent in Q4-2008 relative to Q3-2008, and by 79 percent relative to the peak of the housing boom in Q2-2007. Accumulating the reserves broke down the pre-crisis relationship between reserves and M2, collapsing the money multiplier. As the model is trained on pre-crisis data where M2 growth is closely tied to expanding credit, the model underestimated M2's rise.

Similar to the widening gap in M1 and M2 after COVID, the OOS forecasts expected mortgage rates, and Treasury notes to decline post-2022. Presumably, this is because previous historical correlations captured from the BVAR model estimated till September 2008 suggested that inflation would subside faster than it did, or that the economy would enter a deeper recession, lowering long-term yields. Yet, sticky inflation forced the Fed to keep rates elevated for longer, pushing up the long-term yields as markets re-calibrated their expectations of Fed cuts.

Unlike the monetary aggregates, real consumer loans, real commercial and industrial loans, and outstanding consumer loans and leases decline but don't show conspicuous structural breaks after the GFC, and closely track their actual values, implying stable dynamics. However, the OOS and IS forecasts of total consumer loans outstanding plummeted during the onset of the pandemic, diverging from the actual data, which evolved at levels consistent with historical data in 2020. But actual consumer loans spiked by more than 50 percent in 2021. Statistical properties attribute to the model's forecasts of collapsing consumer loans in 2020. During the GFC, consumer credit slumped as lending standards tightened, household balance sheets deteriorated, and demand for credit declined. The pre-crisis data supports the pro-cyclical nature of lending, as credit lending and business cycles are positively correlated. Alternatively, the Fed and the Congress dealt the pandemic-induced recession with unprecedented easing monetary and fiscal stimulus that propped up household incomes, allowing consumers and businesses to borrow and lend better than the model expected. Instead of a credit crunch, households accumulated excess savings as they reduced spending on travel, dining, and entertainment. When the economy reopened in 2021, pent-up demand spiked borrowing for auto loans, credit cards, and mortgages, which the forecasts correctly capture.

In the aftermath of the pandemic, all measures of loans such C&I loans, consumer loans at commercial banks, total consumer loans and leases securitized, and real-estate loans, grew at a slower pace than projected by the model estimated in pre-GFC data. This coincides with the period when lenders tightened lending standards by 44-50 percent in the wake of the mini banking crisis of early 2023 at rates similar to the 2001 and 2008 recessions. The mini banking crisis culminated with the collapse of Silicon Valley Bank, Signature Bank and a few other financial depository institutions as unrealized losses on the government debt securities spiked when the Fed aggressively raised interest rates in 2022. Sparking their deposits to drain as consumers shifted their money from demand deposits to higher-yielding alternatives such as money market funds offered by non-bank institutions, M1 and M2 also declined. This crisis was different from the crisis banks faced in 2008, when they had too much leveraged and their balance sheets were heavily exposed to the mortgage backed securities as the housing market collapsed. This time, banks repositioned and shored up their balance sheets - they tightened their underwriting standards, making it difficult for consumers and businesses to access credit and slowed the growth of loans. The plots reflect this divergence between OOS forecasts and actual growth rate of loans.

The OOS forecasts of the YoY growth rate of leverage of non-financial non-corporate businesses underestimate the actual rise in leverage from December 2008 to beginning 2010. However, the IS forecasts, which include post-crisis relationships, closely align with the actual growth of leverage. As the actual leverage rises much faster than that forecasted by the pre-crisis model, the divergence signals the presence of a structural break caused by the financial crisis. Since the recession began in Q1-2008, the total assets of non-financial non-corporate businesses plunged by the most - 10.9 percent in Q3-2009 as asset prices such as real estate and collateral values sharply fell, whereas the financial liabilities comprising of debt securities and loans only fell by 2.6 percent. Mechanically, this wanes book equity (denominator of book leverage), uplifting the actual leverage. Another structural break is present in the growth rate of tier 1 leverage capital. This time the OOS counterfactuals overestimate tier 1 capital, whereas in reality, it fell in Q1-2009. This is because the OOS model is trained only in pre-GFC data when banks were buffeted with fewer capital shocks, none as deep as the GFC that led to a systemic banking crisis. During the GFC, credit risk surged as many defaulted on loans, retained earnings fell, risky assets such as mortgage backed securities, collateralized debt obligations were writtendown. So, the model underestimates the tail risks to capital buffers. Furthermore, in post-GFC period, Basel III regulations became stricter and the US banks were hit with Prompt Corrective Action triggers, requiring banks to hold more high-quality capital.

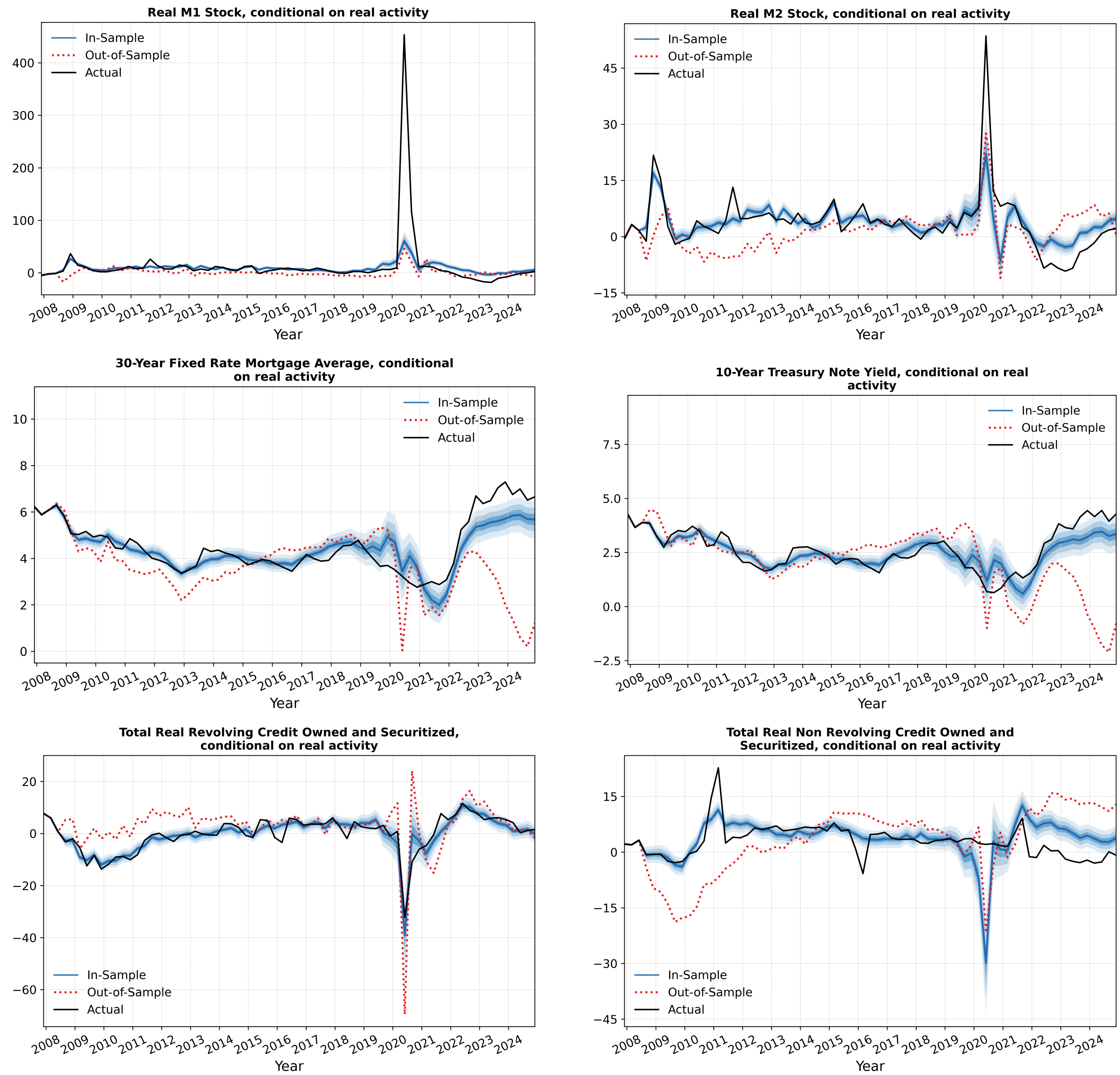

Figure 3. In-sample (IS) and out-of-sample (OOS) forecasts or counterfactual paths are conditional on the known paths of macroeconomic variables - real activity, labor, trade, and housing, from December 2008 to December 2024. All variables, except for mortgage rates and Treasury yields, are measured in year-over-year growth rates.

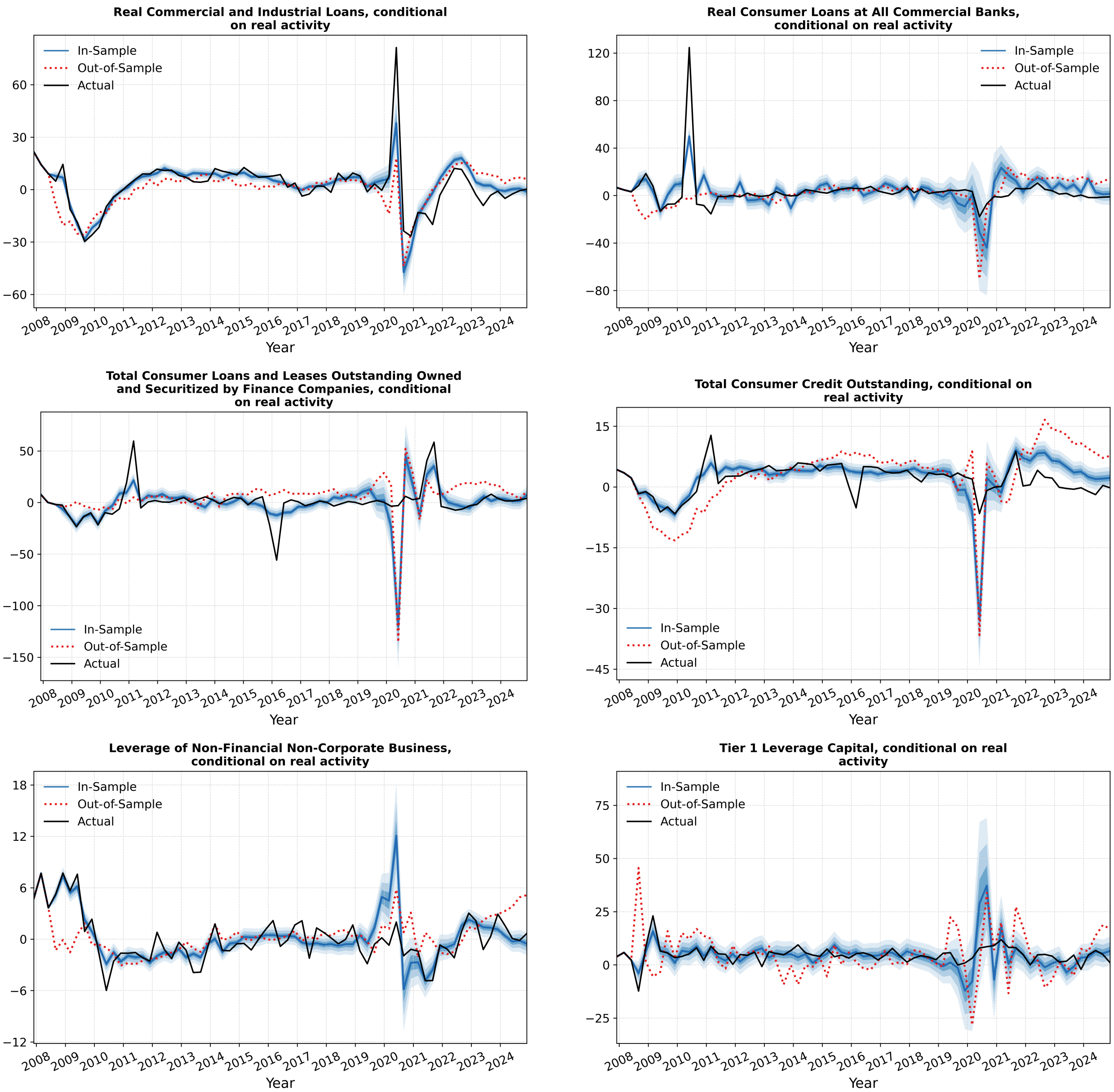

Figure 4. In-sample (IS) and out-of-sample (OOS) forecasts or counterfactual paths are conditional on the known paths of macroeconomic variables - real activity, labor, trade and housing, from December 2008 to December 2024. All variables are measured in year-over-year growth rates.

From Boom to Bust and Beyond: How Did The Stylized Facts Change?

I derived the initial stylized facts using the large BVAR model estimated in the pre-GFC sample, assuming the historical relationships among macroeconomic and financial intermediation variables. However, the counterfactual (out-of-sample) forecasts and actual data after the crisis period reveal structural breaks. To account for the regime shifts in monetary policy, dynamics of inflation, liquidity preferences, precautionary savings motives, etc, I revise the stylized facts.

First, The OOS forecasts reveal that the model underestimated Treasury yield post-2022 as the model forecasted yields to decline faster than their realized paths. After the GFC, QE and forward guidance made the long-term rates less responsive to policy rates. Furthermore, after the pandemic, short-term yields became more sensitive to inflation expectations relative to business cycles. Bauer, Pflueger, and Sundaram (2024) also found that Treasury yields and money market futures reacted more to inflation news after the Fed lifted the rates from the zero lower bound in March 2022.

Second, in the pre-crisis data, prices rise when unemployment rises. PCE and CPI are weakly correlated with spike in unemployment rate, slowing the delayed decline. After the GFC, the model overestimated core PCE inflation till 2012 as actual inflation remained subdued - aggregate demand was weak, and underestimated inflation after the pandemic. The model overestimated inflation in post-crisis periods because it expected inflation to be more responsive to policy shocks than it was, as evident from the historical correlations. However, the traditional Phillips Curve relationship became tenuous after the crisis. Also, since supply shocks drove the post-pandemic inflation more than the demand shocks, as Giannone and Primiceri (2024) elaborate, the supply-chain disruptions drove higher costs of goods and services for prolonged periods. Unlike in 2009-2012, this sticky inflation also unanchored inflation expectations post-2020.

Third, M1 was countercyclical, rising when the labor market slacked pre-crisis and M2 was weakly correlated with the business cycle. After the GFC, the excess reserves affected M2 growth as it reduced bank lending and loans. Fourth, pre-crisis, loans behaved pro-cyclically, lessening when unemployment rises. Relatedly, consumer loans slowly adjusted to monetary policy shocks. After the crisis, credit was strictly pro-cyclical, and lending standards tightened, dwindling the flow of credit even when interest rates were low. This is also reflected in higher-than-expected mortgage rates after 2022, capturing a persistent inflation risk premium.

Lastly, I recreate the scenario analysis of a rise in unemployment rate using the full-sample till Q4-2024 in figure 5 and re-assess the cyclical features. Juxtaposing the responses with more recent data including the observations seen during the COVID-19 pandemic, the elasticities are deeper even though the direction of the responses remain the same for most variables, except for prices. For instance, real activity variables like real GDP, personal consumption expenditure, residential and non-residential fixed investment all decline by greater magnitude and gradually revert back to the long-run levels when the model is estimated till Q4-2024. However, when I previously estimated the model till Q3-2008 only, they declined in the next quarter but immediately reverted back to the long-run levels. Similarly, M1 grows by 1.8 percent immediately after the shock, peaking at 2.2 percent over the course of three years when I estimate the model in the full-sample. However, M1 grows 0.8 percent after the shock using the model estimated till pre-GFC data and reaches 2 percent after two more years, showcasing the more persistent and prolonged impact of shocks. Interestingly, prices don't exhibit temporary countercyclical patterns as they did using the pre-GFC model where prices were counter intuitively rising - now, measures of prices decline on impact.

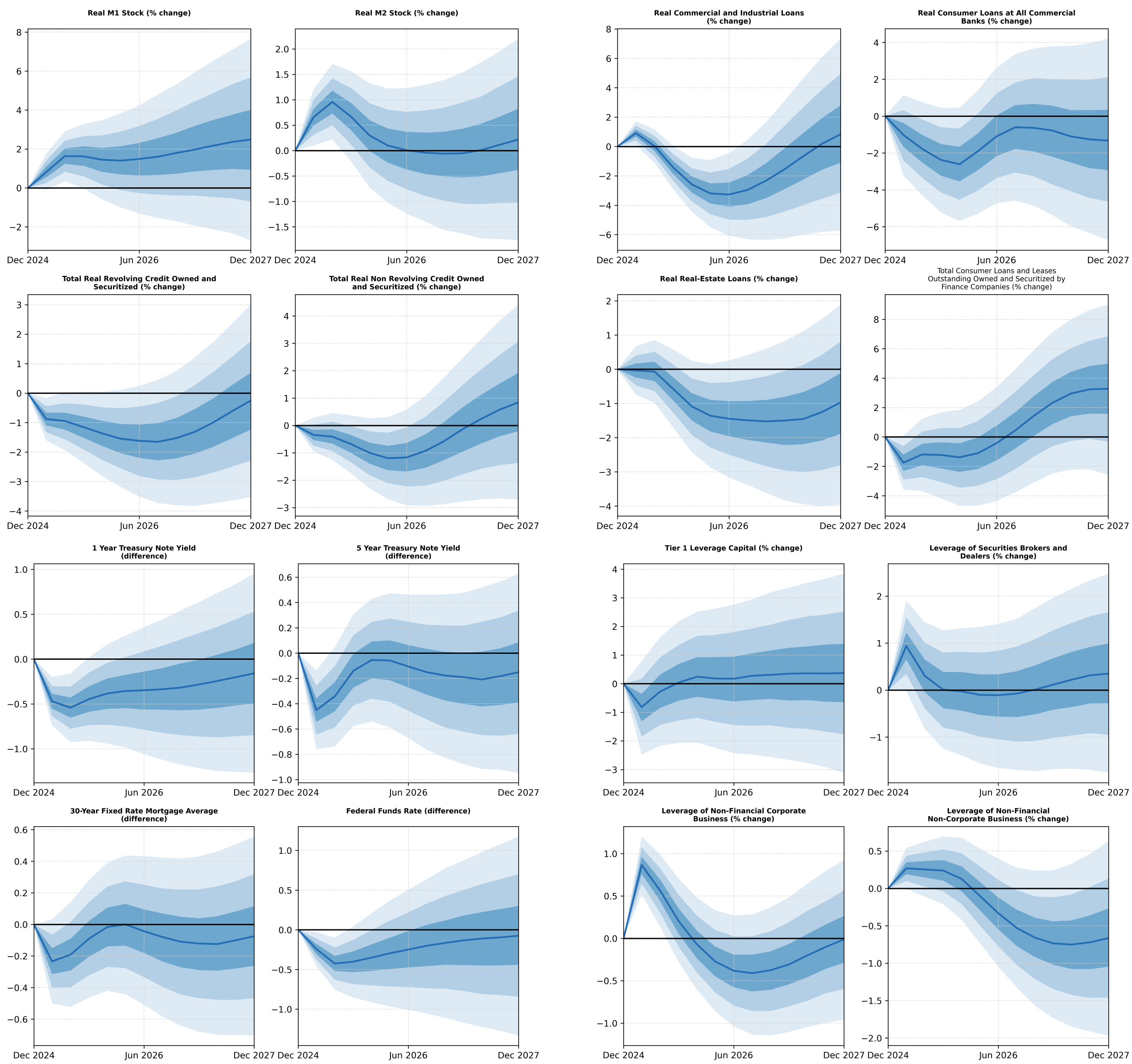

Figure 5a. Responses when unemployment rate rises by 1 percentage point in a model estimated till December 2024. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

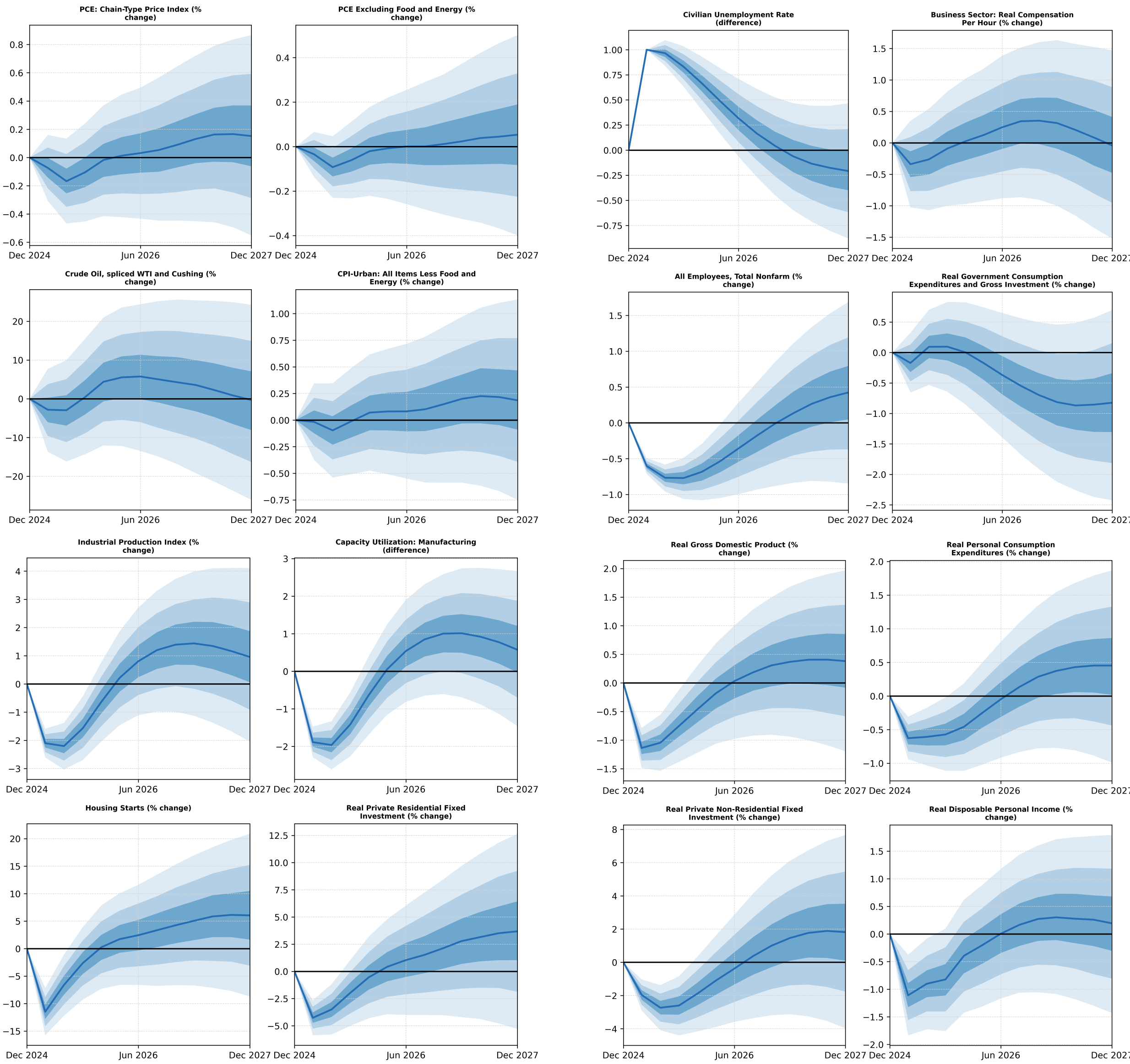

Figure 5b. Responses when unemployment rate by 1 percentage point after estimating the model in the full-sample till December 2024. The elasticities are more persistent and amplified when the model is fit in the full data with pandemic observations than when only fit in pre-GFC data.

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Appendix

A1. Description of Quarterly Macro and Financial Variables

Series Name	Units	Transformation	isFinancial	Prior
Real Gross Domestic Product	Billions of Chained 2017 Dollars	100×log	0	RW
Real Personal Consumption Expenditures	Billions of Chained 2017 Dollars	100×log	0	RW
Real Disposable Personal Income	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Non-Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Government Consumption Expenditures and Gross Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Industrial Production Index	Index 2017=100	100×log	0	RW
Capacity Utilization: Manufacturing	Percent of Capacity	Raw	0	RW
Housing Starts	Thousands of Units	100×log	0	RW
All Employees, Total Nonfarm	Thousands of Persons	100×log	0	RW
Civilian Unemployment Rate	Percent	Raw	0	RW
Business Sector: Real Compensation Per Hour	Index 2017=100	100×log	0	RW
GDP Deflator	Index 2017=100	100×log	0	RW
PCE: Chain-Type Price Index	Index 2017=100	100×log	0	RW
PCE Excluding Food and Energy	Index 2017=100	100×log	0	RW
CPI: All Items	Index 1982–1984=100	100×log	0	RW
CPI-Urban: All Items Less Food and Energy	Index	100×log	0	RW
Crude Oil, spliced WTI and Cushing	Dollars per Barrel	100×log	1	RW
10-Year Treasury Note Yield	Percent	Raw	1	RW
1-Year Treasury Bond Yield	Percent	Raw	1	RW
5-Year Treasury Bond Yield	Percent	Raw	1	RW
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw	1	RW
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw	1	RW
Real Exports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
Real Imports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
S&P 500 Index	Index	100×log	1	RW
CBOE Volatility Index: VIX	Index	100×log	1	WN
University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	100×log	0	RW
Real M1 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real M2 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real Commercial and Industrial Loans	Billions of 2017 US Dollars	100×log	1	RW
Real Consumer Loans at All Commercial Banks	Billions of 2017 US Dollars	100×log	1	RW
Real Real Estate Loans	Billions of 2017 US Dollars	100×log	1	RW
Total Consumer Credit Outstanding	Billions of 2017 Dollars	100×log	1	RW
Total Real Non Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Real Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Consumer Loans and Leases Outstanding Owned and Securitized by Finance Companies	Millions of Dollars	100×log	1	RW
Federal Funds Rate	Percent	Raw	0	RW
30-Year Fixed Rate Mortgage Average	Percent	Raw	1	RW
Tier 1 Leverage Capital	Millions of US Dollars	100×log	1	RW
Leverage of Non-Financial Non-Corporate Business	Ratio	100×log	1	RW
Leverage of Non-Financial Corporate Business	Ratio	100×log	1	RW
Leverage of Securities Brokers and Dealers	Ratio	100×log	1	RW

Entropic Tilting for Economy-Wide Banking Stress Tests

1. Introduction

The 2008 Global Financial Crisis (GFC) yielded substantial losses for banks, raising concerns about the loss-bearing capacity of the banking sector. Macro stress tests have been instrumental in identifying impending vulnerabilities rife in the banking sector. Central banks such as the Fed, and ECB employ macro stress tests to assess if banks are solvent and resilient (have solid capital buffers) to withstand adverse and unexpected shocks to their balance sheets. They subject the income statements and balance sheets of a group of financial institutions to a large recession(s) by deploying structural relationships or reduced form models. Then, they trace out how the shocks propagate through the system.

Why is it important to conduct stress tests? Aside from conducting monetary policy, central bankers are responsible for safeguarding financial stability. This requires assessing the sources of systemic risks to the financial system, potential magnitude of the risks, and impact on the economy should those risks materialize. Then, the central banks create macro-prudential oversight and policies to inhibit these systemic risk that are harbinger of widespread instability. They employ macro stress testing models to gauge the impact of the financial sector when the identified systemic risks materialize. These models serve as workhorse of analytical tools for macro-prudential risk assessments. Within the US, the federal Reserve runs two tests annually - Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act (DFA) stress tests. The CCAR is a micro stress test, wherein the Fed scrutinizes whether each financial intermediary has adequate capital, and how it plans to pay dividends, buy back shares or deal with losses under stress. If the Fed deems that the institution has insufficient capital, then it requests the institution to revise its capital redistribution plans such as pause on stock repurchases or dividend buybacks. On the other hand, the DFA stress tests are forward-looking macro stress testing exercises to ensure that institutions have adequate capital to absorb losses and lend money even when adverse perilous shocks buffet the economy. Since financial intermediation controls how credit flows to households and firms, any disruptions in the intermediation such as credit freezes can amplify economic contractions and expose financial vulnerabilities.

Historically, stress testing mechanisms have a few limitations. Regulators usually run stress tests on each bank separately answering questions like - how much losses on loans will bank A, B separately have if

GDP falls by 4 percent? Then, they add up the losses from individual banks to obtain the total aggregate losses. So, they treat each bank in isolation, when reality the economy and banks interact more broadly. For instance, if bank A fire-sales its assets and lowers the market prices, other banks' assets may be also valued less if they possess the same assets. If consumers withdraw money from one bank, fearing bankruptcy, a bank-run can ensue in other banks, spreading a contagion. Adding only the isolated results discounts general-equilibrium feedbacks, spillovers and systemic interactions. Moreover, most stress testing models don't capture the non-linear nature of systemic risks such as the counterparty and liquidity risks. Many models are partial equilibrium exercises (Summer (2007)) that disregard feedback loops. At the center of financial instability are the disruptive spirals between market and funding risk, that the stress test models fail to account for (Brunnermeier (2009), Gorton and Metrick (2009)). Jacobsen et al. (2906) link macro and balance sheet variable with companies' default frequencies in a reduced-form VAR model to allow the model to dynamically respond to macro variables. Hirtle et al. (2015) built a Capital and Loss Assessment under Stress Scenarios (CLASS) model, a top-down capital stress testing framework, that projects the impact of macroeconomic scenarios on US banking firms using regressions. Specifically, it projects income and capital of commercial banks and bank holding companies based on bank-level data on income, expense and loan performance coupled with assumptions on how dividends are provisioned, asset grows and other facts.

I stress test the entire banking system, and directly attack the problem at the aggregated-level. Rather than procuring bank-level proprietary data, I obtain flow of funds data from FRED to account for those neglected effects. I exploit the large BVAR model's versatile capabilities to mimic the baseline forecasts from the Fed's annual stress testing scenarios. By conditioning the BVAR on the stress test assumptions using an extension of Crump et al. (2021)'s entropic tilting approach, I evaluate how the macro and financial conditions interact under the baseline stress testing scenario. Specifically, I estimate the model from Q1-1984 till Q4-2024, adding features of COVID volatility that Lenza and Primiceri (2022) introduced, and illustrate how the forecasts evolve when certain variables follow pre-specified trajectories in the short and medium-term horizons. In the literature, economists incorporate judgement forecasts from central banks or a survey of professional forecasts because evidence points that such judgement forecasts shed useful information beyond that provided in econometric models (Ang, Bekaert and Wei (2007), and Faust and Wright (2013)). Introduced by Robertson, Tallman and Whiteman (2005), they show how to impose conditions on federal funds rate using entropic tilting in a small BVAR forecasting model. Cogley, Morozov and Sargent (2005) construct entropic-tilted BVAR forecasts conditioned on forecasts by Bank of England. Altavilla, Giacomini and Ragusa (2013) combine forecasts of short term interest rates from surveys with yield curve forecasts from econometric models. Kruger, Clark and Ravazzolo (2017) combine nowcasts from surveys and specialized models to show that entropic tilted forecasts enhance forecasts from BVARs. They tilt the BVAR forecast distributions towards the means and variances of nowcasts, and find that tilting enhances the accuracy of point and density forecasts. In fact, tilting towards the means and variances of nowcasts yield sharper distribution of forecasts than tilting towards nowcast means only. These studies show that entropic tilting is a very flexible, powerful and effective tool to blend forecasts from BVAR model with those of external sources. So, I leverage these features to condition the forecasts from the stress testing scenarios.

I contribute to the literature by building a large BVAR with COVID-volatility model that constructs multi-horizon entropic-tilted density forecasts, anchoring the short and medium term forecasts of several variables from the baseline stress test scenario. I also plot joint forecast density plot of GDP growth rate and 3 month Treasury yield to dissect tail risks of these metrics to the downside risks to GDP growth - in other words, what are the chances that GDP will grow at a substantially lower rate as connoted by the baseline scenario? This is crucial because traditionally economists generate point forecasts for macro variables such as GDP growth, ignoring the risks around the central forecasts. However, policymakers at the Fed often ask: what are the downside risks to GDP growth, upside risks to inflation and unemployment? Central banks and regulators increasingly care about the these risks on the tails of the distribution even if the average outlook is reasonable. Jointly modeling the dynamics of the variables with financial intermediary metrics can enable us to answer questions like - given the recessionary outcomes in baseline scenario, what are the downside risks to loans two years from now? To the best of my knowledge, this is the first research paper that (i) employs a large BVAR with COVID volatility (ii) uses aggregate balance sheet data to examine how the scenarios affect the density forecasts of balance sheets of financial intermediaries, departing from the standard bank-level analysis. The aggregate method to conditionally forecast macrofinancial outcomes under the Fed's baseline scenario has a few advantages. First, sidestepping the need for granular supervisory data, it's transparent and easy to replicate using public data. Second, it quantifies the joint forecast risks across economic and financial sectors using probabilistic methods with prior distributions. Third, it bridges stress testing with the density forecasting literature (Adrian, Boyarchenko, Giannone (2019); Adams, Adrian, Boyarchenko, Giannone (2020)). They produce conditional future distribution of GDP growth as a function of current financial and economic variables. Estimating the distribution semi-parametrically using quantile regressions, they find that current economic conditions forecast the median of the forecast distribution of GDP growth, but the financial conditions predict the tails of the distribution, especially the left tail of the distribution. For instance, a left-skewed distribution of GDP growth signifies higher recession risk. While I don't incorporate non-linearities or asymmetries in the standard BVAR model as Adrian et al. (2019) and Adam et al. (2020) did, the entropic tilted joint forecast distribution of forecasts of GDP growth and 3-month Treasuries in Q1-2028 suggest that the GDP growth rate projected in the baseline scenario is less likely to materialize based on information till Q4-2024.

The structure of the paper is as follows. Section 2 implements an extension of entropic tilting to construct forecasts conditioned on stress testing scenarios. Then, it delineates how the baseline stress test scenarios negatively affect loans and money supply. Via joint predictive density of GDP and Treasury yields, it shows, how likely is the baseline scenario three years into the future.

2. Banking Under Pressure: Forecasting Risks in Fed Stress Tests

Since the inception of the Dodd-Frank Act, the Federal Reserve Board annually assesses if the banks are amply capitalized to weather recessions, absorb losses, and meet obligations to counterparties and creditors while also lending to businesses and households. To assess banks' strength, the Fed releases two stress tests annually in February, known as the Dodd-Frank Act Stress Test (DFAST) and the Comprehensive Capital Analysis and Review (CCAR). They describe two hypothetical macroeconomic recession scenarios - a baseline scenario, and a severely adverse scenario, which entails periods of stress in the commercial real estate market, corporate debt market, downfall in the real activity, soaring unemployment rate, lower confidence among investors and consumers, etc. In each of these scenarios, the stress test enables us to calibrate banks' assets and liabilities - losses, revenues, capital, and revenue that banks would have under these hypothetical recessions. The two 2025 Stress Test Scenarios and Methodology reports, released by the Federal Reserve Board of Governors, provide historical data on the domestic and international variables integrated into their model, the projected paths of these variables in the baseline, and severely adverse scenarios from Q1-2025 to Q1-2028. The domestic metrics in the dataset include measures of prices and economic activity, aggregates measures of financial conditions and asset prices, and interest rates for the US. Since effects in the US economy have spillovers abroad, it includes data on GDP, price, and exchange rates on major global economies, namely the Euro Area, the UK, and developing Asian countries.

I employ the model to mimic the trajectory of variables in the baseline scenario in 2025 and 2026, and build the coverage intervals around them. To construct the forecasts, first I estimate the model in the full sample till Q4-2024 using the large BVAR with the COVID-volatility method described previously. Then, I condition the forecasts on the short-run and medium-run forecasts of certain variables defined in the stress testing scenarios. The actual baseline and severely adverse scenarios in the official stress testing exercise report the quarterly projections from Q1-2025 to Q1-2028 of all 16 domestic variables and 8 international variables. However, to simplify the modeling process, I condition on the annual projections of eight domestic variables that I derive from the quarterly projections as follows. First, I find the minimum and maximum projections for each year and variable and report them in Table 1. Second, I condition the forecasts on the average values of these ranges for each variable per year. I call these values the yearly short, medium, and long-term projections.

Variable	Projection for 2025 (%)	Projection for 2026 (%)	Long run projection (%)
CPI: All Items	2.6 – 2.8	2.4 – 2.8	2.1 – 2.3
Real GDP	1.9 – 2.1	2.0	1.9
Unemployment rate	4.3	4.3	4.2
3-Month Treasury Yield	3.8 – 4.3	3.5 – 3.7	3.4
10-Year Treasury Yield	4.3 – 4.4	4.1 – 4.2	4.1
Bank Prime Loan Rate	7.0 – 7.6	6.6 – 6.9	6.5
30-Year Fixed Rate Mortgage Average	6.0 – 6.4	5.7 – 5.9	5.6
BBB Corporate Index Effective Yield	5.6 – 5.8	5.8 – 5.9	5.9

Table 1. Supervisory baseline scenarios from Q1-2025 to Q1-2028. The ranges represent the lowest to highest growth rates of the quarterly values for a given year. These projections for 2025, 2026, and 2027 represent the short, medium, and long-run forecasts, respectively.

To anchor the unconditional forecasts to the short, medium, and long-run targets defined in the scenarios, I rely on the technique of Entropic Tiling that Crump et al. (2021) introduced. Instead of conditioning on the exact future values, I incorporate the belief that the median short and medium-run projections will be anchored to the targeted pre-specified values, but the exact values are uncertain. This is known as "soft conditioning" and it allows us to build coverage intervals around the median forecasts. While Crump et al. (2021) utilize entropic tilting to anchor to long-term targets set in the Summary of Economic Projections, I extend their method to allow us to anchor to multiple forecasting horizons: short and medium-term. The idea is to re-weight the MCMC forecast draws from the model to match the multi-horizon constraints from the Fed's stress testing scenarios and to modify the original forecast distribution $f(y_t)$ to the tilted distribution $\hat{f}(y_t)$ such that the tilted distribution remains as close as possible to the original while satisfying constraints. Given the forecast matrix $Y \in R^{K \times T}$, where N is the number of MCMC draws, $K = 9$ is the number of variables constrained, and $T = 2$ represents the short-term (2025) and medium-term (2026) horizon.

The constraint matrix $g_0 \in R^{K \times T}$ specifies the targeted forecast path for each variable at each horizon. Thus, the constraint imposed is:

$$E_{\hat{f}}[g(y_t)] = g_{0,t}, \quad t \in \{\text{short, medium}\}$$

where $\hat{f}$ is the tilted distribution, and $g_{0,t}$ are the target values from stress testing scenarios. The above moment conditions are the expected values of the selected variables at specified horizons. By constraining on these expected values, we lock in the scenario's path for those variables in the tilted forecast distribution.

The entropic tilting problem minimizes the Kullback-Leibler (KL) divergence between the original and tilted distributions subject to the multi-horizon constraints:

$$\min_{w_j^*} KL(\hat{f}, f) = \sum_{j=1}^{J} w_j^* \log(J w_j^*)$$

subject to:

$$\sum_{j=1}^{J} w_j^* = 1, \quad \frac{1}{J}\sum_{j=1}^{J} w_j^* g(y_{j,t}) = g_{0,t}, \quad w_j^* > 0$$

where w_j^* is the reweighted probability for draw j, and $g(y_{j,t})$ is the moment condition in the j^{th} forecast draw for time t.

I solve the optimization problem by introducing Lagrange multipliers γ_t for each horizon:

$$L(w^*, \gamma_{\text{short}}, \gamma_{\text{medium}}, \lambda) = \sum_{j=1}^{J} w_j^* \log(J w_j^*) - \sum_{t \in \{\text{short, medium}\}} \gamma_t' \left[\sum_{j=1}^{J} w_j^* g(y_{j,t}) - g_{0,t}\right] - \lambda \left[\sum_{j=1}^{J} w_j^* - 1\right]$$

Taking with first order conditions w.r.t. the weights, we solve for the optimal weights as follows:

$$w_j^* = \frac{\exp\left(\sum_{t \in \{\text{short, medium}\}} \gamma_t' g(y_{j,t})\right)}{\sum_{j=1}^{J} \exp\left(\sum_{t \in \{\text{short, medium}\}} \gamma_t' g(y_{j,t})\right)}$$

To optimize the Lagrange multiplier, I solve:

$$\gamma = \arg\min \sum_{j=1}^{J} \exp\left(\sum_{t \in \{\text{short, medium}\}} \gamma_t' g(y_{j,t})\right) - \sum_{t \in \{\text{short, medium}\}} \gamma_t' g_{0,t}$$

This ensures that for each short and medium-term horizon:

$$E_f[g(y_t)] = \frac{1}{J}\sum_{j=1}^{J} w_j^* g(y_{j,t}) \approx g_{0,t}$$

Tables 2a, and 2b presents the forecasts at varying percentiles predicted by the model and contrasts these model-estimated forecasts with the targets defined in the baseline scenario for 2025 (short), and 2026 (medium) term horizons. The model-estimated short and medium-term forecasts for most variables are very close to the target values. The medians for the short-run horizon (2025) are generally close to the targets, whereas the medians deviate more than the target in the medium-run horizon (2026). This is expected because uncertainty increases over the horizons, and the model isn't strictly forcing the forecasts to match the targets but is instead shifting them in the right direction while preserving the prior information.

Besides the median forecasts, the table denotes the probabilistic range of outcomes. For instance, at the 80th percentile, the CPI inflation rate in 2026 is 2.76 percent, meaning that 80 percent of the simulated paths predict a value less than 2.76 percent when the target is 2.7 percent. Representing the spread of the forecast distribution via (p10, p90), and (p20, p80), a wider distribution suggests more uncertain estimates. For instance, the coverage intervals for the bank prime loan rate in the short-term $(7.191, 7.684)$, indicating very low uncertainty in credit markets.

Nonetheless, a few caveats are present. Notably, the CPI inflation is lower in the medium term, connoting that the entropic tilted forecasts don't fully reflect the Fed's stress-testing baseline scenario as it expects inflation to fall further away from the Fed's target. Along the same veins, the long term interest rates, namely the 10-year Treasury, bank prime loan rates, and BBB Corporate Yield are lower but the target values are still within the coverage intervals. Economically, if longer maturity rates are lower than those defined in Fed's stress test scenario targets, the model infers lower-than-expected inflation, a more dovish policy where the Fed trims rates or weaker demand for credit. Given that I don't force the future values to match the exact target paths (hard constraints), and rather allow the forecasted median to fall within a range of target values, the soft-conditioning entropic tilting approach for multi-horizon successfully adjusts the forecast distribution to shift towards most of the imposed constraints.

Variable	**Short-Term Target (%)**	**Short-Term Median (%)**	**Short-Term (p10, p90)**	**Short-Term (p20, p80)**
CPI: All Items	2.7	2.23	(1.334, 2.692)	(1.786, 2.557)
Real Gross Domestic Product	2.0	2.53	(1.722, 3.3)	(2.152, 3.045)
Civilian Unemployment Rate	4.3	4.11	(3.712, 4.349)	(3.918, 4.268)
3-Month Treasury Rate	3.95	4.008	(3.464, 4.371)	(3.743, 4.247)
10-Year Treasury Rate	4.35	4.125	(3.566, 4.496)	(3.859, 4.309)
Bank Prime Loan Rate	7.3	7.451	(6.939, 7.797)	(7.191, 7.684)
30-Year Fixed Rate Mortgage Average	6.2	6.423	(5.89, 6.78)	(6.156, 6.65)
BBB Corporate Index Effective Yield	5.7	5.06	(4.346, 5.535)	(4.717, 5.377)

Table 2a. Actual and short-term median forecasts, forecasts at coverage intervals (p10, p90), (p20, p80) defined for eight constrained variables under the baseline stress scenarios for 2025.

Variable	Medium-Term Target (%)	Medium-Term Median (%)	Medium-Term (p10, p90)	Medium-Term (p20, p80)
CPI: All Items	2.6	1.615	(0, 3.327)	(0.247, 2.759)
Real Gross Domestic Product	2.0	2.666	(0, 4.03)	(1.337, 3.675)
Civilian Unemployment Rate	4.3	3.915	(2.554, 4.785)	(3.245, 4.49)
3-Month Treasury Rate	3.6	2.202	(0.045, 3.74)	(1.268, 3.182)
10-Year Treasury Rate	4.15	3.181	(1.687, 4.178)	(2.483, 3.82)
Bank Prime Loan Rate	6.75	5.614	(3.59, 7.261)	(4.745, 6.708)
30-Year Fixed Rate Mortgage Average	5.8	5.41	(3.972, 6.444)	(4.738, 6.038)
BBB Corporate Index Effective Yield	5.85	4.147	(2.103, 5.336)	(3.165, 4.957)

Table 2b. Actual and medium-term median forecasts, forecasts at coverage intervals (p10, p90), (p20, p80) defined for eight constrained variables under the baseline stress scenarios for 2026.

Figure 5 illustrates how lending rates and inflation rates in the US and Europe evolve in the baseline scenario, and contrast them with the unconditional forecasts when the model operates without external constraints. They reflect deflationary pressures and an environment of easing monetary policy as borrowing costs become cheaper, as implied in Tables 2. Furthermore, inflation rates in the UK and EU drop, indicating that any changes in the economic output in the US have rippling effects across the Atlantic. Note that since I impose constraints only in the short and medium term, the long-term projections from the entropic-tilted forecast distributions don't necessarily align with the paths defined by the Fed in the baseline scenario. In fact, the long-term paths for output and labor variables such as real and nominal GDP, and unemployment rate converge to the unconditional forecasts after they decline in 2025 and 2026.

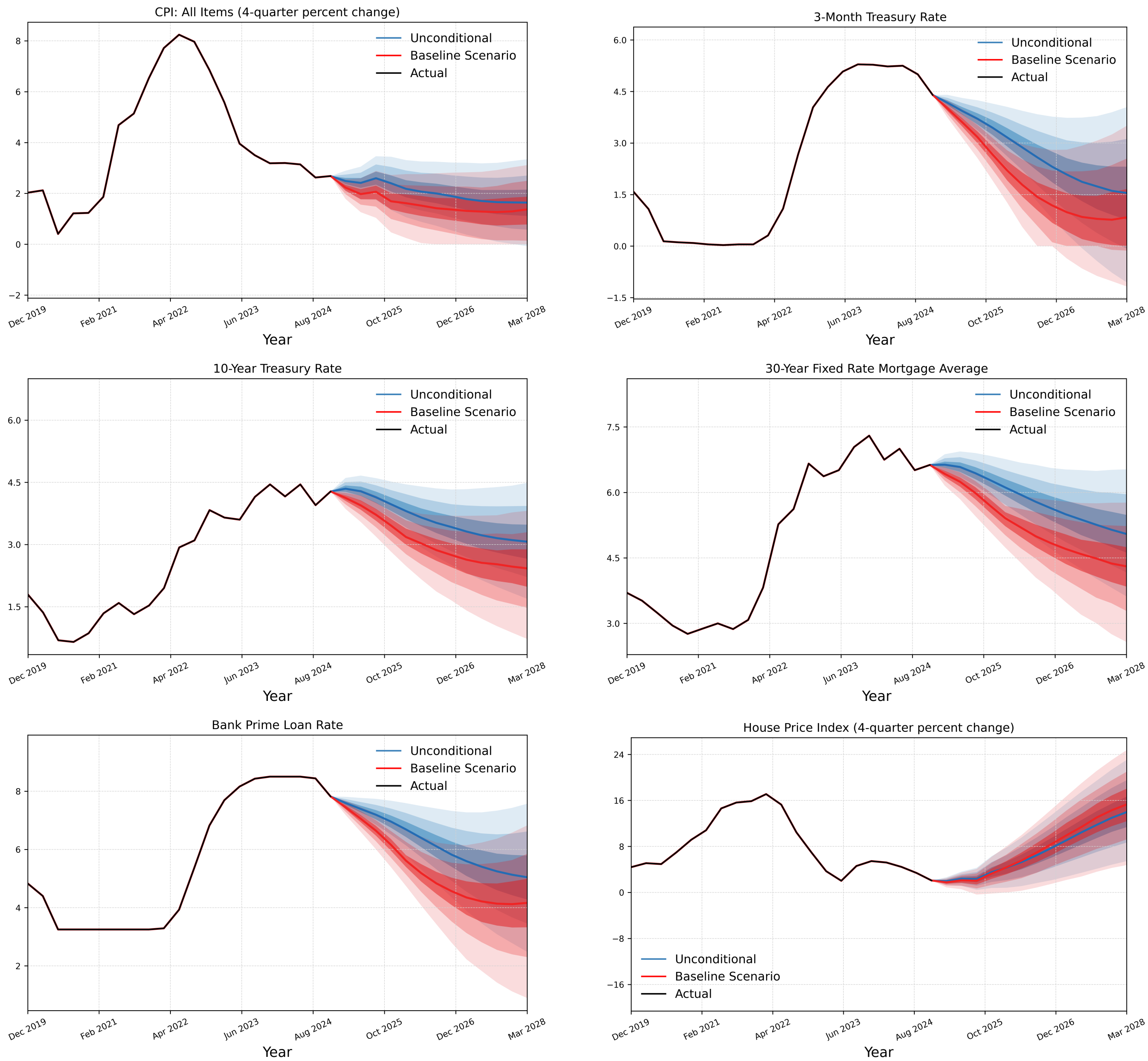

Figure 5a. Entropic-tilted forecasts are conditioned on the short and medium-run forecasts for 2025 and 2026 only. The dark blue lines represent the unconditional forecasts, which are the probabilistic median forecasts, and the shaded regions around them are coverage intervals at 60, 70, and 80 percentiles. The red lines are the forecasts conditional on the future evolutions of 9 variables at multiple horizons.

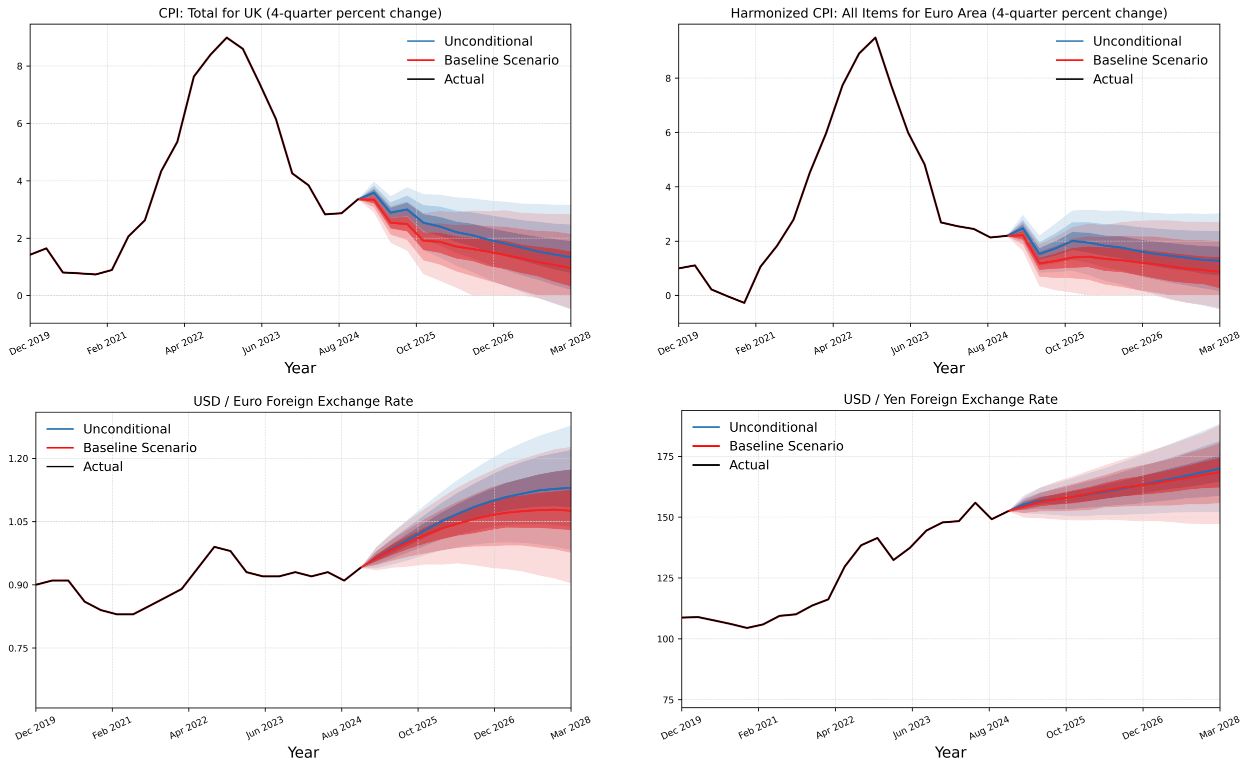

Figure 5b. Entropic-tilted forecasts of exchange rate and inflation rates of other countries are conditioned on the short and medium-run forecasts of eight US variables for 2025 and 2026 only.

Recessionary Risks and its Effects on Credit Liquidity

I expand the scope of the stress-testing model by incorporating metrics of financial intermediation such as monetary aggregates, various types of loans and credit to capture how credit flows, liquidity preferences, and monetary aggregates evolve under baseline path set by the Fed's baseline scenario. This time, I simultaneously constrain eight variables to their long-run forecasts for Q1-2028. This helps to assess whether the baseline scenario featuring monetary and macroeconomic assumptions affect the demand and supply for liquidity and credit and the balance sheets of the banking sector. To further dissect the tail risks of GDP and Treasury distribution, figure 6 illustrates the joint posterior distribution for real GDP and 3-month Treasury yields for Q1-2028. On the side panes, the black lines represent the model's original marginal forecast distribution for real GDP and 3-month Treasury. These are devoid of any constraints and are purely generated by historical correlations. The red curves represent the marginal distributions created after imposing long-term constrains that real GDP, and 3-month Treasury yield will fall to 1.9 and 3.4 percent, respectively. The blue dot in the outskirts of the joint forecast distribution in the center pane denotes this combination of forecasts. After imposing these constraints, the tilted distribution (in red) shifts towards the target region, while ensuring that the median aligns with the long-term projected paths in the scenario. The black contours in the center pane show where the BVAR model places most of its probability mass without external constraints. For instance, real GDP clusters around 3.2 percent, while the 3-month Treasury is centered at a lower value around 2-2.5 percent. On the other hand, the red contours are shifted after we reweigh the draws to satisfy the constraints. Intriguing to see the blue dot lying near the tails of the distribution, I attribute this to the reweighing process involved in soft conditioning. Albeit entropic tilting reweighs the forecast draws so that the median forecast of the tiled distribution matches constraints of all 9 variables, it doesn't force the highest-probability region (peak of the distribution) to lie exactly on the scenario point. Thus, the blue dot may fall within a lower-probability region if the original (unconstrained) draws only weakly support the projected forecasts of Treasury yields and real GDP growth.

Since the target scenario point sits on the outskirts of the distribution, the model projects a non-negligible but less typical chance of hitting the outcome. This implies that the scenario might be stringent as its more stressful but less likely to materialize. Furthermore, it could signal that the scenario assumptions are incongruous with the historical patterns. Unconditionally, the model is optimistic as the historical data suggests that GDP would grow near 3 percent, but conditionally, lower GDP growth in the red distribution pushes more weight into a recessionary tail. The marginal forecast distribution of the 3-month Treasury has a broader tail on the lower end, implying that yields may lower in the future with high degree of uncertainty. This corresponds with a scenario when the Fed adopts an accomodative monetary policy regime of trimming rates as the tail risks of recessionary levels of output and unemployment rise. On the supply-side, lower short-term rates can squeeze banks' net interest margins, particularly, if longer-term interest rates decline. On the demand side, a tepid economy will dissuade households and firms from borrowing, diminishing credit and loans issued. Consequently, investors might shift deposits to more liquid and safer assets, raising M1 and M2.

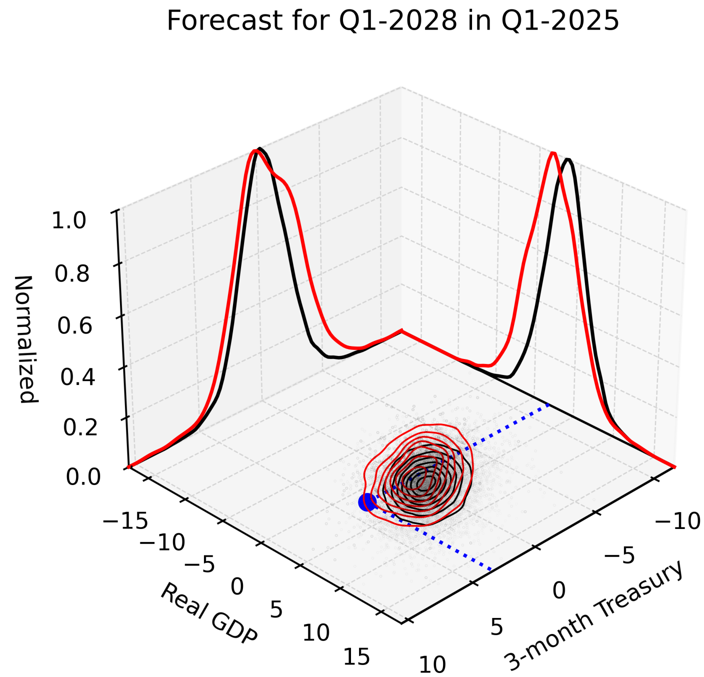

Figure 6. Joint forecast density functions of the forecast of the 3-month Treasury yield YoY growth rate of real GDP and inflation for Q1-2028. The black lines are the unconditional (baseline) forecast distribution, where the contours in the centers represent the joint distribution, and those on the side panes are the marginal distributions. The red curves are the "tilted" distributions obtained after adjusting the original forecast distribution to anchor to the long-run targets - 3.4 and 1.9 percent for 3-month Treasury yield, and real GDP growth rate, respectively.

Implications of the Baseline Scenario on Balance Sheet Variables

Figure 7 illustrates the original (blue shaded) entropic-tilted forecast distributions (red shaded) of the financial intermediation variables where the dark blue and red lines are the median forecasts under both original distribution, and entropic tilted distribution (condition on the projected paths of eight variables for 2026 and 2027). Both M1 and M2 grow, with the latter rising faster by 6 percent (year over year growth rate), which is 3 percent higher than the unconditional forecasts, when the model is unconstrained. These trajectories are directionally consistent with the pre-crisis stylized facts where M1 and M2 also rose in the scenario analysis where unemployment rate rose by 1 pp, behaving countercyclically. Conversely, all types of loans, namely the real commercial loans, real real-estate loans, and total consumer loans fall, potentially owing to weaker borrowing demand or tighter lending standards. These paths are also directionally consistent with the stylized facts as loans behave procyclically, and imply that households and firms might be accumulating liquid assets while relying less on bank lending. [1]

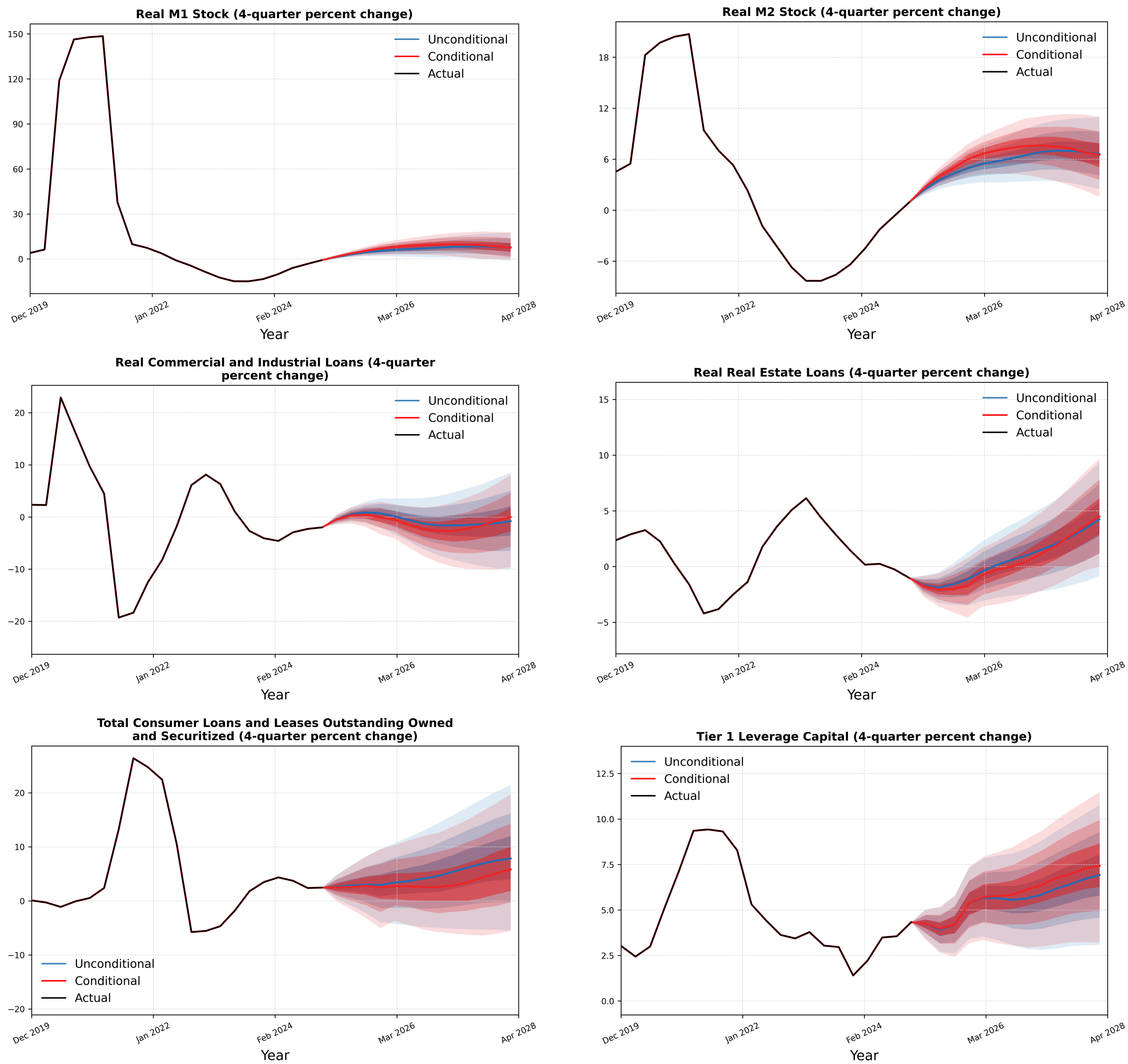

Figure 7. Entropic-tilted forecasts are conditioned on the short and medium-run forecasts for 2025 and 2026 only. The dark blue lines represent the unconditional forecasts, which are the probabilistic median forecasts, and the shaded regions around them are coverage intervals at 60, 70, and 80 percentiles. The red lines are the forecasts conditional on the future evolutions of 9 variables at multiple horizons.

[1] The Fed publicly releases the bank-level results of its annual "severely adverse" scenario only, not the results of the baseline scenario. It consists of bank-level projections of losses on various types of loans, revenue, net income before taxes, interest and non-interest income and expenses, and liquidity ratios. After projecting each variable for each bank, it aggregates by summing up the forecasts of all banks. I had hoped to compare those aggregated Fed projections to my large BVAR forecasts, but I couldn't find the exact historical data on any of the above projected variables in FRED.

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How do Surprise and Forward-Guided Monetary Policies Influence the Flow of Funds?

1. Introduction

How do contractionary monetary policy shocks affect the financial intermediary variables? Answering this question is germane in today's environment, where the financial and macroeconomic variables are highly interdependent with some degree of uncertainty around monetary policy actions. Financial intermediaries serve as conduits to effectively transmit monetary policy to the broader economy by not only altering the supply of credit but also impacting asset prices, liquidity, and appetite for risk across sectors. Much of the Bayesian VAR literature has emphasized real macro aggregates such as output, inflation, and employment, overlooking balance sheet variables of financial intermediaries. When the Fed tightens monetary policy, adding the financial intermediary variables is crucial to extricate the elasticities of balance sheets such as loan volumes, leverage, and monetary aggregates.

This relates to the work of Christiano, Eichenbaum, and Evans (1996), who evaluate the impact of orthogonalized shocks to federal funds rate and non-borrowed reserves on the flow of funds, such as firms' financial assets and liabilities, net funds raised by the business sector, household sector, financial, foreign, and government sectors using structural frequentist VAR frameworks. Similarly, Bernanke and Gertler (1995), discuss out how contractionary monetary policy affects credit intermediated via two credit channels, namely the balance sheet channel and bank lending channel. In the balance sheet channel, a rate hike raises interest payments that lower cash flows, and also reduces asset prices, shrinking collateral value. Resulting in weaker balance sheets, this surges the external finance premium, making credit more expensive or restricted, and eventually dwindling investment spending. On the other hand, the bank lending channel operates via the willingness of intermediaries to supply loans. In this channel, higher rates reduce liquidity as bank reserves and deposits shrink, restricting bank lending. Relatedly, Gertler and Karadi (2015) examine how exogenous monetary policy actions influence credit costs and economic activity, and to what extent the responses are consistent with economic theory. In particular, they evaluate monetary policy surprises as shocks to forward guidance using a hybrid approach - combining "money shock" VAR using Cholesky decomposition with high frequency identification (HFI) measure of policy surprises as external instruments to identify the effects of a 100 basis point increase in monetary policy shock. However, they utilize a few smaller-scaled frequentist VAR models to overcome the problem of multicollinearity instead of a large BVAR approach.

However, two limitations exist in the approaches of the aforementioned papers. First, instead of building one big VAR with all the variables, they build small-scale VARs. For instance, Christiano, Eichenbaum, and Evans (1996) build six 7-variable VARs, each having a different set of variables corresponding to various sectors in the Fed's flow of funds. So, they adopt a marginal approach of adding one variable at a time, which omits the joint dynamics or interaction of a large number of variables, especially in the current environment where macro and financial variables are tightly interconnected. Second, their analysis is based on historical data that is devoid of episodes when the federal funds rate was constrained by the zero lower bound (2008-2015, March 2020-2022). Therefore, their analysis doesn't address constraints in policies or non-linearities that erupted due to the 2008 GFC. As stated in chapter 1, during these episodes, the federal funds rate couldn't decline below in nominal terms, and the Fed resorted to unconventional tools to stimulate the economy as the federal funds rate becomes less effective when the rate approaches zero. The BVAR's linear equations cannot easily capture the effective "floor" at zero. To avoid accounting for non-linear trends and lack of variation when the zero lower bound (ZLB) binds, I substitute the federal funds rate with the Wu-Xia shadow federal funds rate variable hosted by the Federal Reserve Bank of Atlanta and designed by Wu and Cynthia (2016). Many researchers, notably Kim and Singleton (2012) and Baur and Rudebusch (2013), utilize shadow rate models to characterize the term structure of interest rates in ZLB environments. Bullard (2012) and Krippner (2013) quantify the stance of monetary policy using shadow rates. The Wu-Xia shadow federal funds rate is a model-implied interest rate that takes negative values during the ZLB phases. Outside of the ZLB phases, the shadow rate is approximately the same as the federal funds rate. Incorporating the shadow rate for my analysis is useful because it allows us to define a monetary policy shock that reflects both conventional and unconventional policy actions.

In this chapter, I empirically study how monetary policy transmits through the economy and financial system and affects the flow of funds using a large BVAR with COVID-volatility. Spanning 50 variables on sectoral balance sheets, credit supply, I build two different scenario analyses - responses of variables to an unanticipated rise in the shadow federal funds rate by 100 basis points one quarter ahead; and responses to an anticipated hike of the shadow federal funds rate by a 100 basis points 2-3 years ahead. There are a few advantages of constructing a scenario analysis over impulse response functions to a singular shock to the shadow federal funds rate at the initial horizon. First, the responses preserve historical correlations across variables, ensuring that the variables co-move realistically, as estimated from the data. Second, I fix macroeconomic variables on impact, and only allow financial variables to move first. So, this exercise mirrors a recursive identification scheme more transparently and flexibly without hard ordering any variables, as done in Christiano, Eichenbaum, and Evans (1998). I directly impose the condition on the forecast errors of the shadow federal funds one-quarter ahead, accounting for the multiple structural shocks that most likely drive the shadow federal funds rate 1 pp higher than its baseline. Third, policy institutions such as the ECB, Fed, and IMF often use scenario analysis in stress testing and examining the transmission of monetary policies, making it very relevant to answer policy-based questions. Antolin-Diaz et al. (2021) link conditional forecasting and scenario analysis to entropic tilting, build economically meaningful scenarios using structural VARs, and assess how plausible the scenarios are. Fourth, we can impose shocks on multiple periods and variables at any time in the horizon, and not necessarily at horizon 0 as typically done in impulse response functions. For instance, in chapter 1, I showcase the responses to a medium-run version of Blanchard and Quah (1989)'s long-run shock wherein the level of GDP permanently increases. Specifically, I illustrate the effects of a combination of shocks that most likely lift the level of GDP two years ahead in Chapter 1.

In section 2 of this chapter, I examine how unanticipated or surprise changes in monetary policy affect financial intermediary variables. But this misses the expectations channel of monetary policy, which is the idea that monetary policy affects the economy and financial system not just via the current changes in interest rates, but also by expectations of future policy, economic activity, and inflation. In section 3, I combine the logic of long-run restrictions and recursive identification - I develop a scenario of an anticipated monetary policy shock of a 100 basis point hike in the shadow federal funds rate expected to occur 8-12 quarters in the future coupled with the assumption that "slow moving" macro variables don't adjust contemporaneously to anticipated changes in policy rates, while "fast moving" financial markets can. Grounded on how central banks communicate, shape expectations in the present about future policy paths, and how financial markets respond to credible changes in monetary policy and guidance from the Fed, this mimics the Odyssean forward guidance wherein the Fed commits to tighten the policy in the future for a prolonged period. In macro models such as DSGE and rational expectations models, agents (households, firms, investors, etc) act on expectations and make real decisions based on the intertemporal marginal rate of substitution. Believing that rates will be higher in the future propel firms to adjust investment plans now, households alter consumption and savings behavior, and financial markets reprice bonds, equities, and credit spreads instantaneously. Gurkaynak, Sack, and Swanson (2005), and Campbell, Evans, Fisher, and Justiniano (2012) show that FOMC guidance statements significantly affect Treasury yields and federal funds futures prices that are unrelated to unexpected changes in the federal funds target. Thereby, market participants credibly believe that such statements contain useful information about the future monetary policy actions.

Juxtaposing the posterior median responses from both scenario analyses, I find that responses change more abruptly when faced with a surprise shock as opposed to gradually changing behavior when agents anticipate long-term shifts in monetary policy. To corroborate, first, M1 and M2 contracts instantly when deposits and reserves decline due to a hike in interest rates one-quarter ahead, curtailing liquidity immediately. However, agents reallocate assets from more liquid (M1 and M2) to less liquid but higher-yielding assets more gradually in the second scenario when agents anticipate future hikes in the policy rate. Second, while all loans dip initially in the first scenario, tightening credit, they incrementally increase in the second scenario as households, firms, and other businesses preemptively borrow. Third, the net worth of households and nonprofit organizations, including financial assets, declines instantly in scenario one, but they incrementally rise over 2-3 years. Although the leverage of securities brokers and dealers and nonfinancial corporations drops in both scenarios, the decline is faster and more pronounced in the first scenario. In a nutshell, the forward guidance or news shock enables borrowers to prepare and adjust their portfolios in advance, smoothing and diminishing the absolute value of the elasticities over the horizon.

2. Scenario Analysis - Effects of a Surprise 100 bps Rise in the Shadow Federal Funds Rate

I estimate the model from Q1-1984 till Q4-2024 on the macro and financial intermediary variables obtained from FRED-QD as elucidated in chapter 2. In addition, I add the net worth of household and non-profit organizations, the non-financial corporate business sector, the non-financial non-corporate business sectors, and the real total federal debt. Net worth is the difference between total assets and total liabilities of the intermediaries. Together, the list of fifty variables is in Appendix A1. I construct scenarios using the same procedure defined in Chapter 2 to a 100 bps hike in the shadow federal funds rate relative to unconditional forecasts. However, unlike in chapter 2, the responses of variables in scenario analysis don't represents the multiplicity of disturbances that drive the forecast errors of the shadow federal funds rate one-quarter ahead. Additionally, I fix the Q1-2025 forecasts of macroeconomic variables only to their unconditional forecasts. So, the difference between the unconditional forecasts of macro variables one quarter ahead with the conditional forecasts is zero. This mirrors a recursive identification scheme where "slow-moving" macro variables don't contemporaneously respond to "fast-moving" financial variables. In other words, the financial variables respond immediately, while the economic variables respond with a lag. By conditioning on a rise in the shadow federal funds rate while affixing macro variables on impact, the scenario analysis mimics the impulse response function of a contractionary monetary policy shock identified recursively, raising the borrowing costs (Banbura, Giannone, and Lenza (2015)). We can structurally interpret this exercise as this exogenous monetary policy coincides with a rise in the yield curve (1, 5, and 10-year Treasury yields rise on impact) without affecting the slow-moving macro variables. This restricted scenario assesses how monetary policy transmits (Christiano, Eichenbaum, and Evans (1999), Rotemberg and Woodford (1997), and Sims (1980b)), and the responses in Figure 2 are consistent with what we would expect from a monetary policy shock.

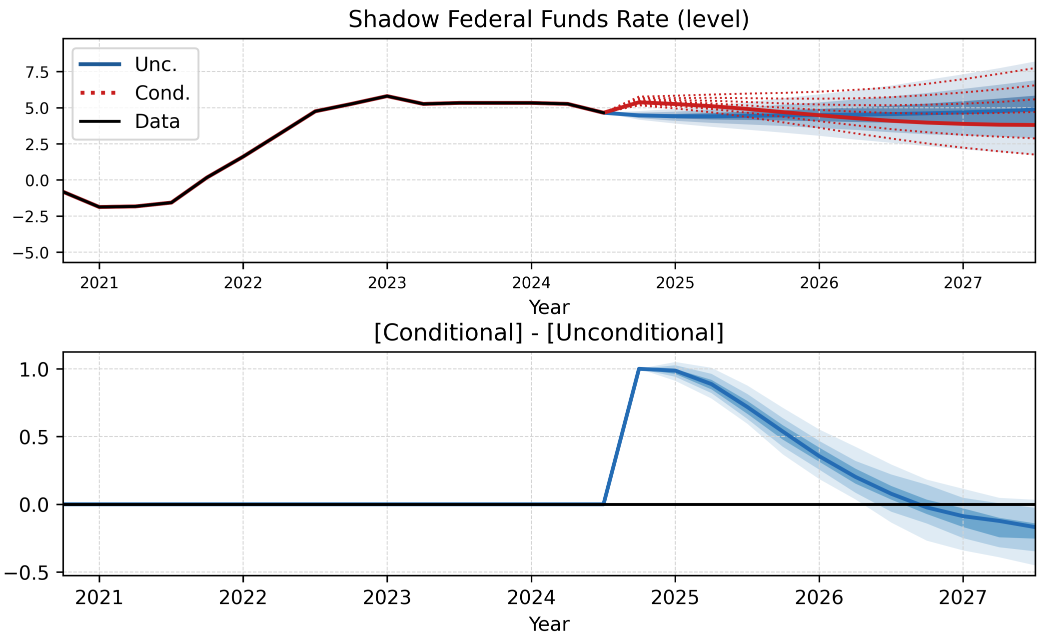

Figure 1. The top row depicts the unconditional (shades of blue bands) and conditional (red dotted lines) foreacsts at various quantiles of the predictive distribution. The bands are the 60, 70, and 80-percent coverage intervals around the median forecasts. The bottom row depicts the difference between conditional and unconditional forecasts.

Figure 2 presents the scenario analysis where the dark blue lines are the median elasticities or responses to the shock, and shaded blue regions are the 60, 70, and 80-percentile coverage intervals around the median responses. Notably, the Treasury yields and Moody's seasoned Aaa and Baa corporate bond yields rise immediately by 0.3-0.5 pp. The 5-year yield outpaces the 10-year Treasury on impact, inverting the yield curve. This is because when the Fed hikes interest rates, short-term Treasury bills and notes rise, shrinking the spreads between long and short-term Treasuries. Also, if markets expect these hikes to slow the economy and inflation down in the future, yields on long-term Treasuries fall, flattening the yield curve. Both corporate bond yields Aaa and Baa rise comparably by 0.2 pp, implying that the tightening broadly raises borrowing costs.

On the macroeconomic front, all measures of prices - PCE and CPI, core PCE and core CPI, and WTI oil prices tick downwards one-quarter ahead, before trending upwards, consistent with economic theory, albeit I place no restrictions on the signs. Unsurprisingly, real exports and imports rise with a lag of one quarter as they are macro variables constrained to be constant on impact. Additionally, both aggregates of money supply M1 and M2 decline upon impact, tightening liquidity conditions as consumers and investors shift away from liquid assets to assets with longer maturities and higher returns. However, the economic agents adjust over time, and the money supply reverts to the long-term levels, expanding again. These responses of money supply are consistent with those of Christiano, Eichenbaum, and Evans (1996), who find strong evidence of the liquidity effect where contractionary monetary policy is linked to a rise in the federal funds rate and a fall in measures of money.

In contrast, real consumer loans at all commercial banks are slow to adjust as they respond with a lag of a few quarters, but eventually, it declines by 1.8 percent by December 2027. This confirms that consumer loans are sticky and do not react immediately to monetary shocks. Besides, while households may not immediately curtail spending, as time passes, higher rates discourage them from refinancing and borrowing. Similarly, revolving credit dips after the rate hike but rises for a few quarters, exceeding the pre-shock level before normalizing. Total consumer loans and leases securitized by finance companies and total consumer credit outstanding, including consumer loans by commercial banks, decline without reverting to their long-run levels. Historically, higher interest rates discourage agents from incurring more debt when the interest payments on the credit card debt become more expensive. Yet, as liquidity constraints tighten, they may increasingly compensate by borrowing more in the short run. Abdelrahman, Oliveira, and Shapiro (2024) point out that middle and low-income households' liquid assets have fallen since the pandemic, prompting consumers to rely on credit cards to manage their expenses. Aside from the consumers, Berrospide and Meisenzahl (2015) found that firms with lower cash reserves significantly increased their credit line usage, drawing on existing credit lines to increase liquidity levels.

Likewise, real commercial and industrial loans, and real estate loans, uptick when the model is hit by the shock. Mirroring the findings of Giannone, Lenza, and Reichlin (2019), they notice that short-term consumer and commercial loans temporarily rise as monetary policy tightens in the Euro Area. This signals the historical trends that firms draw down pre-committed credit lines before borrowing costs escalate further. Lastly, the 30-year mortgage rate rises by 0.35 pp, but declines at a faster pace. Moving in tandem with the 10-year Treasury rate, which also hikes at its peak by 0.35 pp, the long-term mortgage rate tracks the 10-year Treasury rate. This is because the long-term mortgage rate responds more to long-term economic expectations (which are, in turn, captured by the hikes in the 10-year Treasuries) than to short-term hikes in the shadow policy rate.

Tier 1 leverage capital, which measures the core high-quality capital of banks, drops on impact by 0.9 percent and stays at lower levels for the full horizon, implying that banks may have insufficient capital to absorb losses and to weather shocks. Tighter monetary policy increases the risks of defaults in loans, mark-to-market losses, and diminishes the value of collateral. Banks become more risk-averse, and undercapitalized banks may restrict lending, reflected in lower flows of credit and loans to households and businesses. The leverage of non-financial corporate and non-corporate business both decline, although the latter is sticky at first, declining with a lag of two quarters. Higher borrowing costs make it more expensive to accumulate more debt to fund assets, causing intermediaries to delever. However, the leverage of securities brokers and dealers temporarily spikes on impact, but declines subsequently. Adrian and Shin (2010) confirm that the procyclical nature of leverage means that leverage rises in expansions but contracts during tightening, which is evident in the scenario analysis.

The net worth of household and non-profit organizations drops, which is also economically consistent after a contractionary monetary policy shock. Historically, higher interest rates coincide with declining equity markets and bond prices, causing the financial assets and net worth to lose value initially before bouncing back. This is especially true for liquid financial assets such as stocks, bonds, and mutual funds that are continuously traded and whose prices adjust in real-time to changes in interest rates, inflation expectations, and risk premia. Alternatively, more illiquid assets that aren't continuously traded, such as real estate, depict signs of nominal rigidity or stickiness, responding to monetary policy with a lag and gradually rising by 0.5 percent at its peak in two years before slowing thereafter. Christiano, Eichenbaum, and Evans (1996) found that households don't adjust their financial assets and liabilities immediately after a monetary shock, aligning with the "limited participation" assumption postulated in monetary business cycle models. Albeit the real-estate assets of households and non-profits don't change for a few quarters in the scenario analysis, aligning with the "limiting participation" assumption, the immediate decline in real financial assets of households and non-profit organizations suggests otherwise.

In the business sector, the net worth of the nonfinancial corporate sector mechanically rises, reaching its peak in two years by 2 percent. This may seem counterintuitive at first glance, but it can happen when higher borrowing costs dissuade firms from issuing more debt, lowering the liabilities in their balance sheets. A similar but more sticky and inelastic rise (less than 1 percent) of the net worth of the nonfinancial noncorporate sector is evident. Real disposable business income falls on impact when a tighter monetary policy raises interest payments and diminishes corporate profits, to lower after-tax business income. For the US government, higher interest rates elevate the cost of servicing debt as interest payments on newly sold Treasuries rise, raising debt by a minuscule 0.3 percent on impact. Economically, Treasury yields of all maturities escalate on impact as seen in the scenario analysis, making them cheaper to buy as yields are inversely proportional to prices.

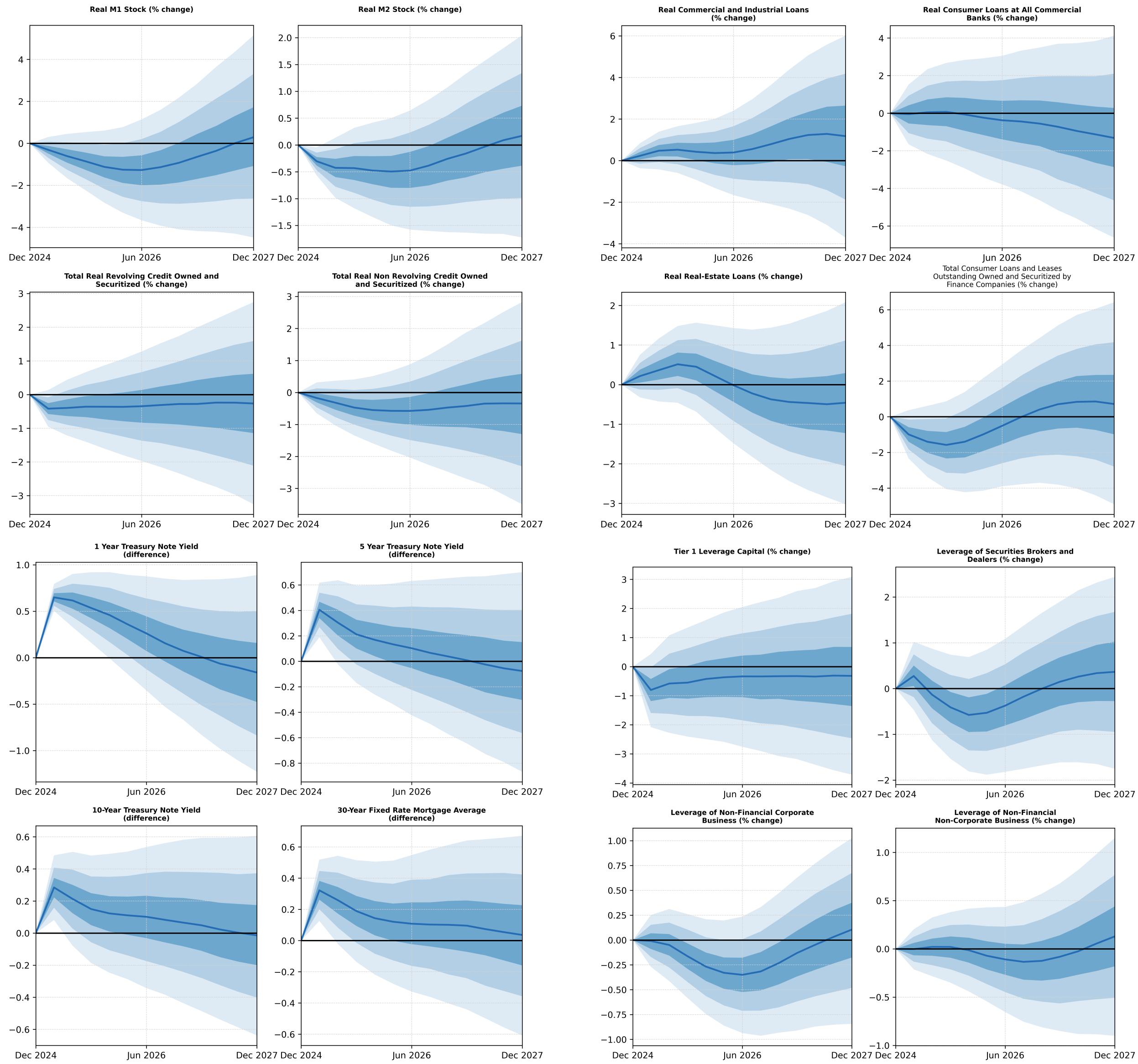

Figure 2a. Responses of variables to contractionary monetary policy shock where the shadow federal funds rate by 100 basis points. This is analogous to IRFs of a surprise monetary shock identified recursively. The dark blue lines are the median responses, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts.

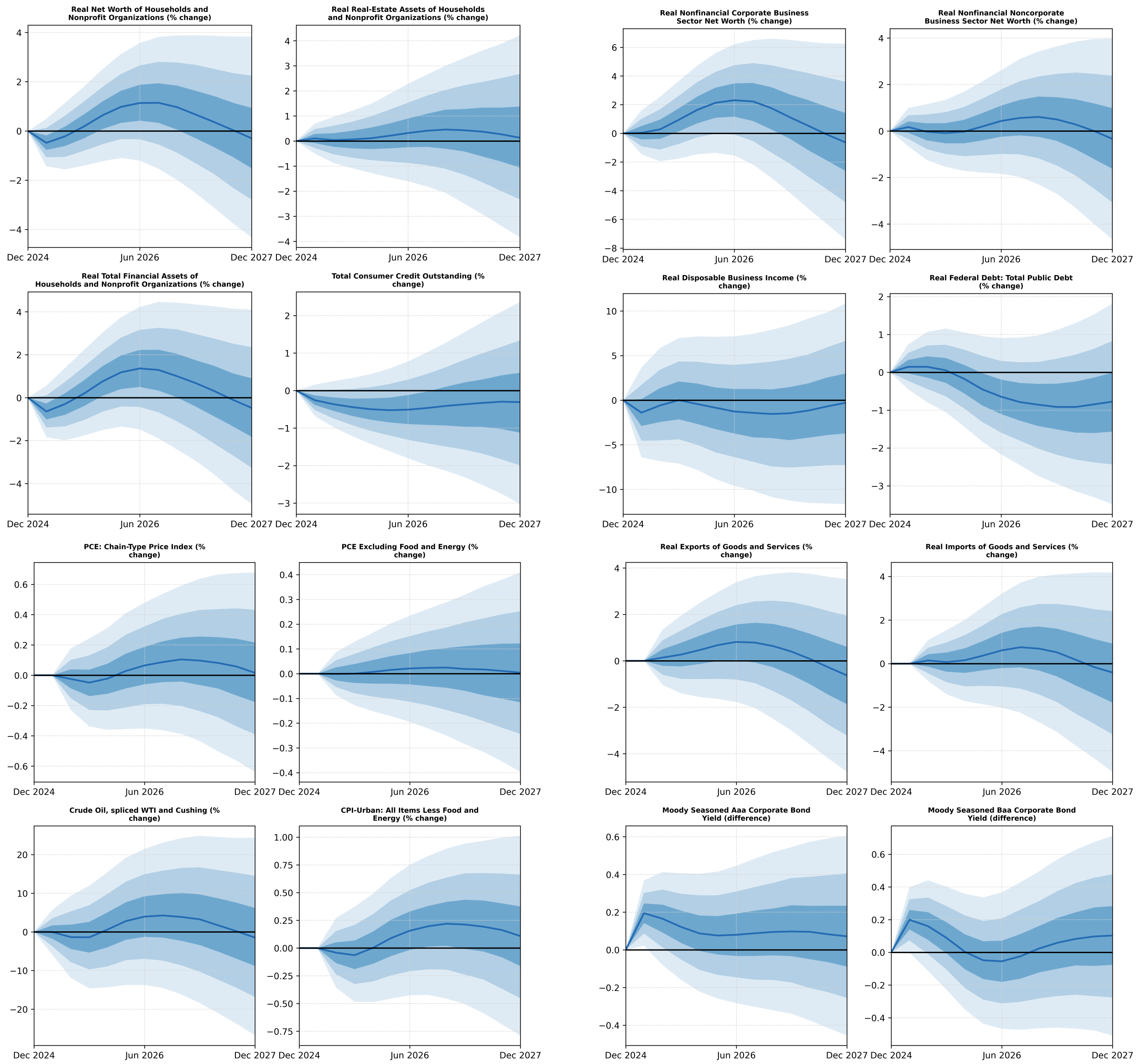

Figure 2b. Responses of variables to contractionary monetary policy shock where the shadow federal funds rate by 100 basis points. This is analogous to IRFs of a surprise monetary shock identified recursively. The dark blue lines are the median responses, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts.

3. Odyssean Forward Guidance: Anticipated Medium-Run 100 bps Hike in Shadow Federal Funds Rate

Historically, the FOMC's statements have publicly committed to a pre-specified future action. For instance, during the 2008 GFC when the Fed had trimmed the federal funds rate to zero in December 2008, it employed quantitative easing and Odyssean-style forward guidance to strengthen the economy as recovery was sluggish. Also known as the calendar-based forward guidance, in August 2011, the FOMC declared that tepid economic conditions *"likely warrant exceptionally low levels for the federal funds rate at least through mid-2013"*. Then, as the FOMC realized that the existing macro conditions weren't favorable to raise the federal funds rate after mid-2013, it shifted from the calendar-based to state-based forward guidance defined under the Evan's Rule. At the FOMC meeting in December 2012, it stated that the target federal funds rate of 0–0.25 pp *"will be appropriate at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored."* Since then, the Fed has shifted gears in its approach to setting the interest rates that depends more on data and effective communication, especially after 2015. Albeit the Fed no longer explicitly resorts to Odyssean guidance by promising a future rate path, markets form expectations about policy based on dot plots, FOMC's Summary of Economic Projections, Blue Chip Forecasts, press conferences, and term structure of interest rates. I simulate a scenario where the shadow federal funds rate spikes by 100 bps in 2–3 years ahead as this scenario transmits the expectations. Moreover, balance sheet metrics of financial intermediaries transmit monetary policy by altering credit supply, consumption and investment, engineering financial accelerator effects (Bernanke, Gertler, Gilchrist (1999)). As agents anticipate an impending tighter monetary policy, they change the composition of portfolio, liquidity preferences, and the amount of credit to supply before the rates actually hike.

Many standard VARs simulate contemporaneous and unanticipated monetary shocks, but ignore the expectations channels of policy. By conditioning on a rise in shadow federal funds rate by 1 pp 2-3 years ahead, and fixing the macro variables to their unconditional forecasts one-quarter ahead, the scenario analysis is equivalent to an IRF of news or forward guidance shocks identified recursively. While expectations adjust, real variables such as GDP, unemployment, and inflation rate don't instantly respond, reflecting realistic frictions seen in the macroeconomy - sticky prices and wages, delayed investment and consumption decisions. The idea is that financial intermediaries transmit monetary policy, and they respond immediately to expectations, even if the real economy lags. This lets us understand how information about future hikes tightens liquidity, how intermediaries re-balance their portfolios, how leverage and credit supply evolve before actually tightening the policy, whether asset prices adjust preemptively, and do firms accumulate excessively to build leverage.

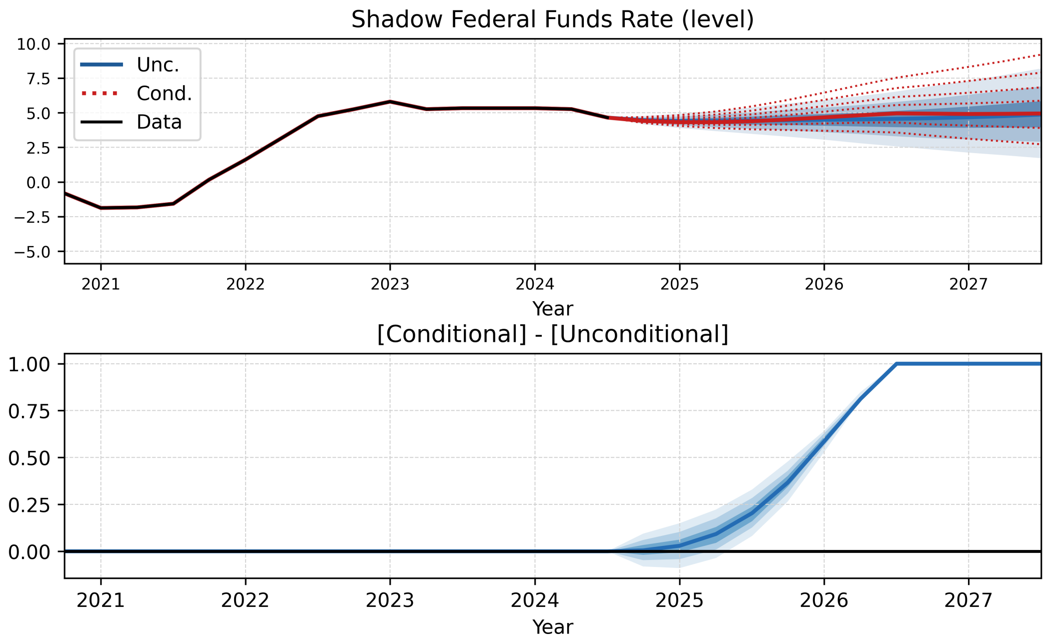

Figure 3. The top row depicts the unconditional (shades of blue bands) and conditional (red dotted lines) foreacsts at various quantiles of the predictive distribution. The posterior uncertainty bands are the 60, 70, and 80-percent coverage intervals around the median forecasts. The bottom row depicts the difference between conditional and unconditional forecasts. The conditioning assumptions are (i) anticipated forwards guidance shock: shadow federal funds rate 2-3 years ahead, (ii) macro variables don't respond contemporaneously one quarter ahead.

Figure 4 illustrates the simulated responses of the forward guidance scenario. Treasury yields of maturity 1, 5, and 10 years rise by 0.7, 0.3, and 0.2 pp at their peak after 2 years. This connotes that the short-term Treasuries rise more than the long-term counterparts, suggesting that the slope of the yield curve mildly steepens and then flattens. On impact, they don't move, which is expected due to the delayed policy shock. Mostly, the responses are conspicuous from 2025-Q3, and the 1-year yield starts to rise before others. The 30-year fixed mortgage rates move in lockstep with the 10-year Treasuries, which we expect as mortgages are driven by movement in long-term Treasuries. Monetary aggregates contract after a lag of a few quarters. While M1 continues to fall by more than 2 percent by the end of the horizon, M2 falls by 0.4 percent and stabilizes at that level. Anticipating higher interest rates, agents shift from more liquid to less liquid but higher-yielding, longer-duration, and interest-bearing assets such as money market mutual funds and long-term time deposits.

All loans, except total consumer loans, securitized, increase after a year in anticipation of higher rates. Firms may draw on existing credit lines or preemptively borrow before higher rates set in. Interestingly, the net worth of households and non-profit organizations, their rest-estate assets, and total financial assets gradually rise till the end of the horizon, instead of falling as we saw in the one-quarter ahead surprise monetary policy shock. The forward guidance gives more time to households and markets to gradually adjust expectations in anticipation of tightened monetary policy. Asset prices smoothly grow, and volatility progressively subsides. This contrasts with the immediate hike in yields, correction in asset prices, and balance sheet losses, where the net worth of households and non-profit organizations dwindled in the surprise monetary tightening case. Likewise, the net worth of nonfinance corporate and non-corporate business sectors follows the same trajectory, rising by 3.5 and 1 percent by December 2027. Overall, the outcomes from anticipated shocks are less disruptive than the unanticipated ones, as firms have time to adapt.

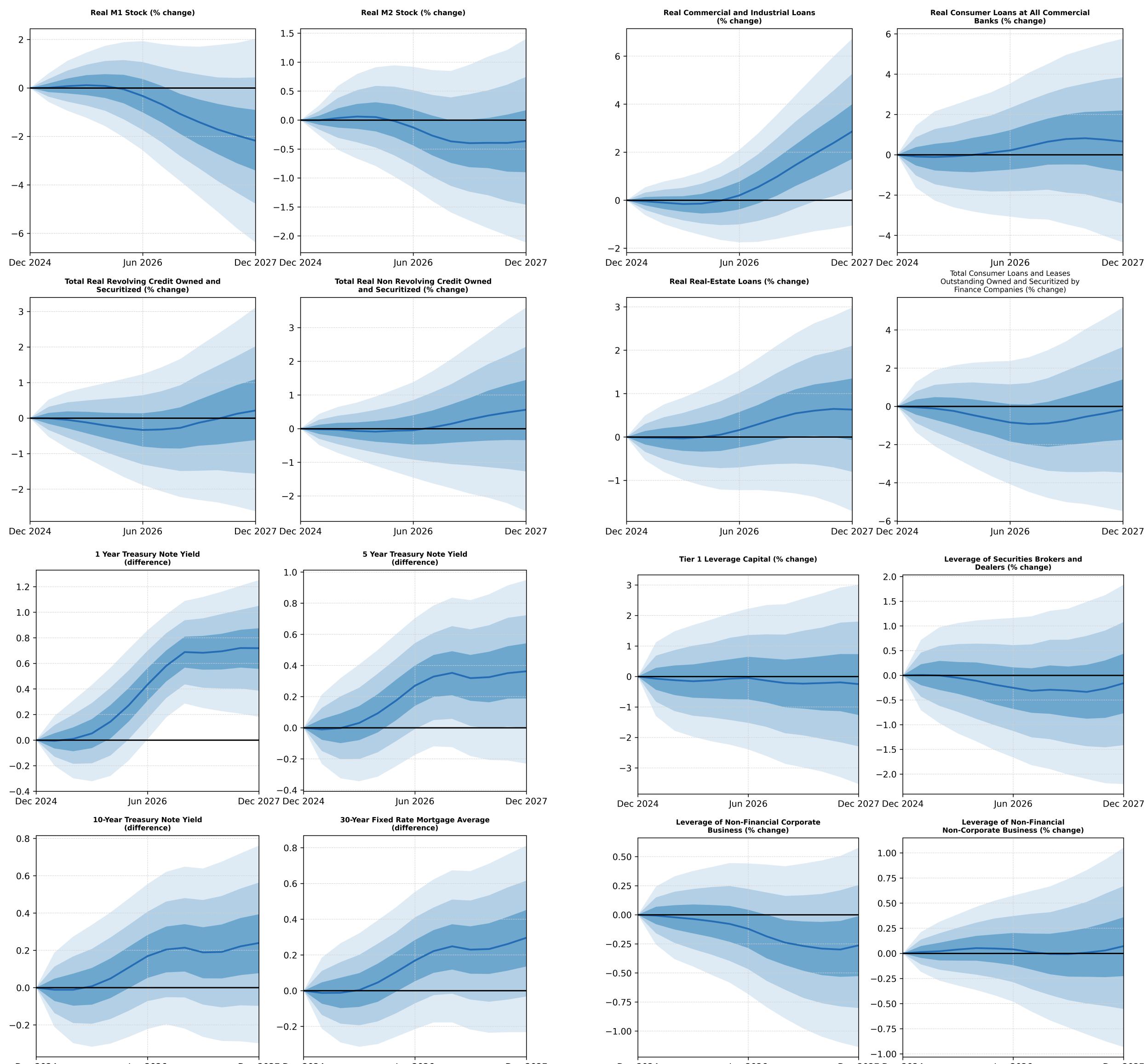

Figure 4a. Responses of an anticipated long-run contractionary monetary shock where the shadow federal funds rate rises by 100 basis points in 2-3 years. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

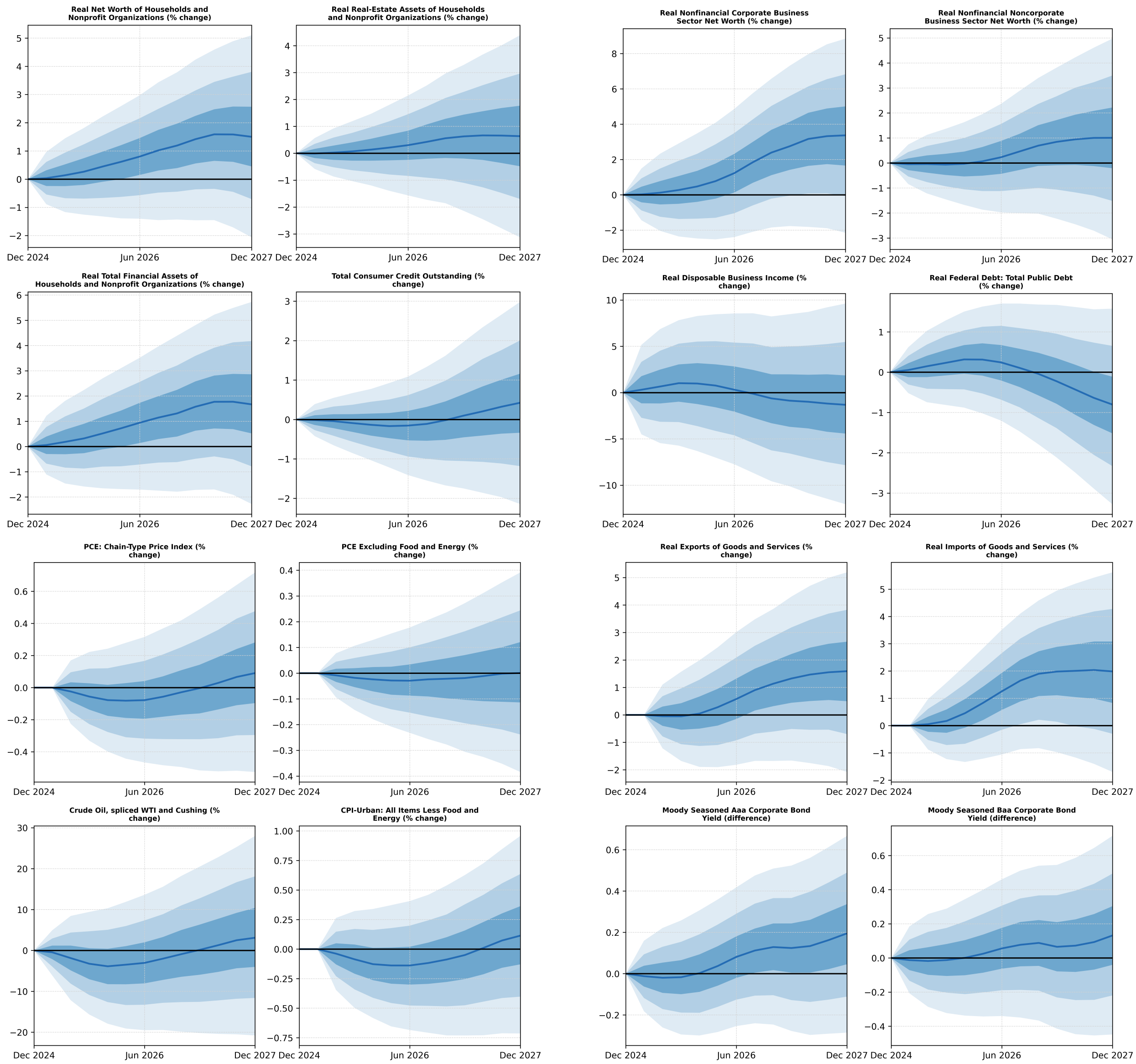

Figure 4b. Responses of an anticipated long-run contractionary monetary shock where the shadow federal funds rate rises by 100 basis points in 2-3 years. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

4. Bivariate Joint Densities of Forecast Distributions Under Contractionary Monetary Policy Shocks

In sections 2 and 3, the scenario analyses show how variables individually evolve over time under the conditional scenario. Treating each variable's response independently, these responses stem from their marginal distributions. Now, the joint predictive density plots in figure 5 reveal not only the direction of individual responses, but also the cross-sectional conditional and unconditional relationship between two variables at a fixed time. It summarizes a full range and likelihood of potential scenarios, how two variables co-move and correlate with one another, and the degree of joint uncertainty. It statistically identifies where tail risks are concentrated. For example, what is the combination of shadow federal funds rate and growth rate of M1 that is least likely to occur? To remove the extreme outliers that would otherwise distort the contours in the middle pane, I discard the top and bottom 0.5 percent of the distribution and show the central 99 percent of the distribution in the plots. Visually more informative than showing the full distribution, we see the shifts in the curves, contours, and posteriors draws denoted by the dots more clearly. Without clipping, the contours in some cases may be stretched by a few distant points, if any, giving a misleading impression that the core densities are compressed. In each plot, the black curves in the side panes represent the unconditional marginal forecast distribution of the variables in Q4-2025 based on the model estimated till Q4-2024. Alternatively, the red curves denote the marginal distribution of conditional forecasts under the scenario where the shadow federal funds rate rises by 1 pp one-quarter ahead. The dot clouds are the posterior draws from the BVAR predictive densities for the variables jointly. The contours are the estimates from the kernel density fitted over the dot clouds that represent regions of higher joint probabilities. If the dots are clustered more tightly, the probability density is higher.

In the joint forecast predictive density plots of shadow federal funds rate and real M1, M1 contracts, as it is a "fast-moving" variable, as also illustrated in the scenario analysis. This shifts its marginal distribution to the left of the black unconditional distribution. On the other hand, the marginal distribution of the shadow federal funds rate shifts to the right after a tighter monetary policy shock. In the middle pane, the center of mass of the red dot clouds moves diagonally southeast relative to the grey cloud of points. On average, the red points have higher shadow rates and lower M1 growth rates. The cloud of red points explicitly depicts a negative slope, suggesting an inverse relationship between the shadow federal funds rate and growth in M1 supply. In other words, under contractionary monetary policy, a high shadow federal funds rate is systematically associated with low growth of M1. Aligning with the liquidity effect from the scenario analysis, it provides cross-sectional instead of temporal evidence. This directional movement portrays how the shock affects both the location and correlation of the forecasted variables.

Relatedly, the bivariate forecast densities depict correlated risks, which are more informative than marginal risks. For example, it shows not just that M1 declines but also that the decline happens concurrently when the shadow federal funds rate hikes. The red dots tightly cluster in the bottom right corner, illustrating the position of "tail risks" - liquidity arrests strongly when rates rise. In contrast, the red contours and dots of shadow federal funds rate and mortgage rate in the center shift north-east. This positively sloped relationship shows that mortgage rates are directly proportional to shadow federal funds rate. The shape and the spread of the conditional density shed light on the expected direction in the scenario and how confident the projections are, or the risks surrounding them. In most plots, the marginal conditional distributions are narrower than their unconditional counterparts, reflecting reduced uncertainty.

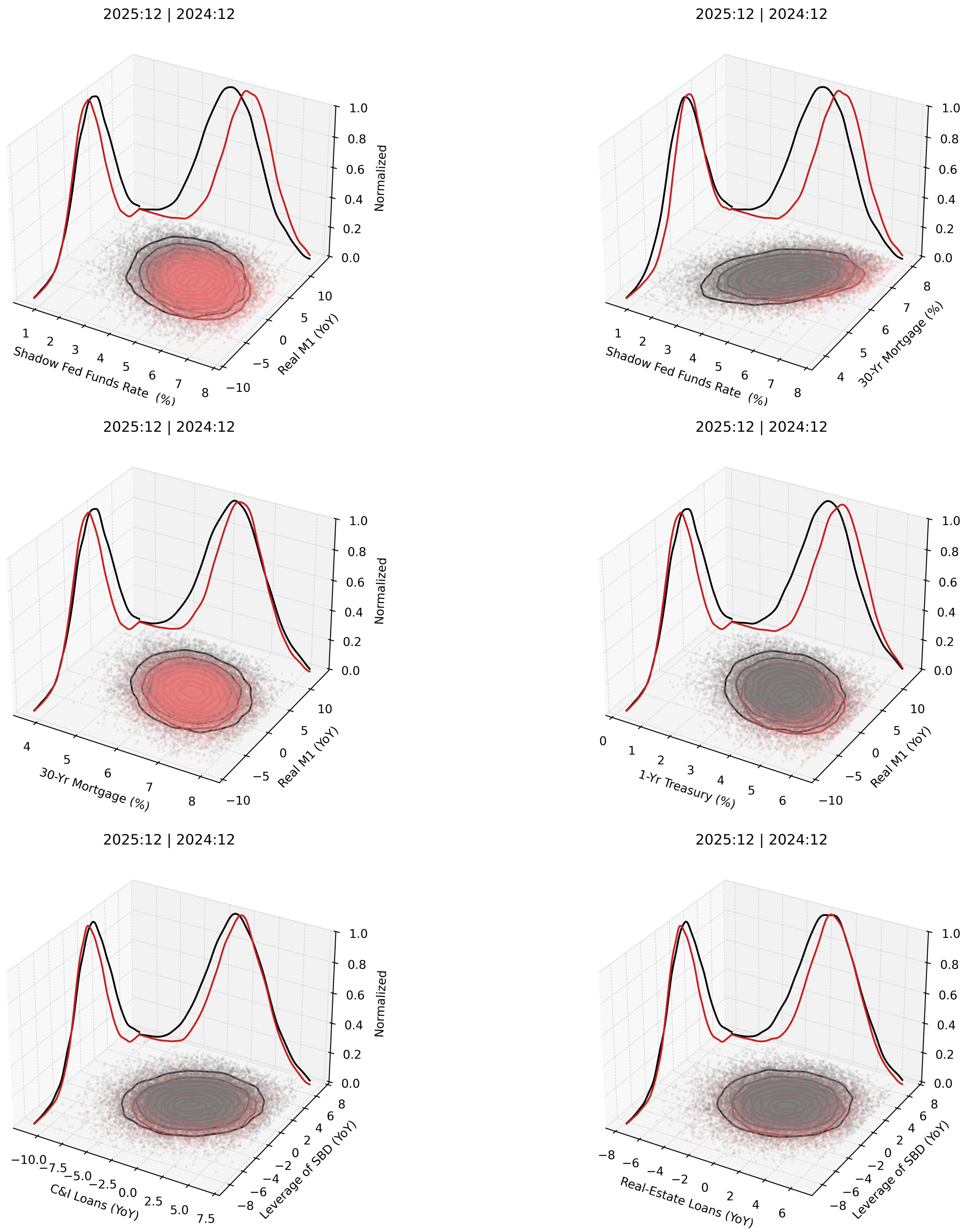

Figure 5a. Joint predictive densities for Q4-2025 using data till Q4-2024 under the unconditional and the conditional scenario that the monetary policy contracts one-quarter ahead. To remove extreme outliers, it shows the central 99 percent of the distribution, after clipping the top and bottom 0.5 percent of the distribution.

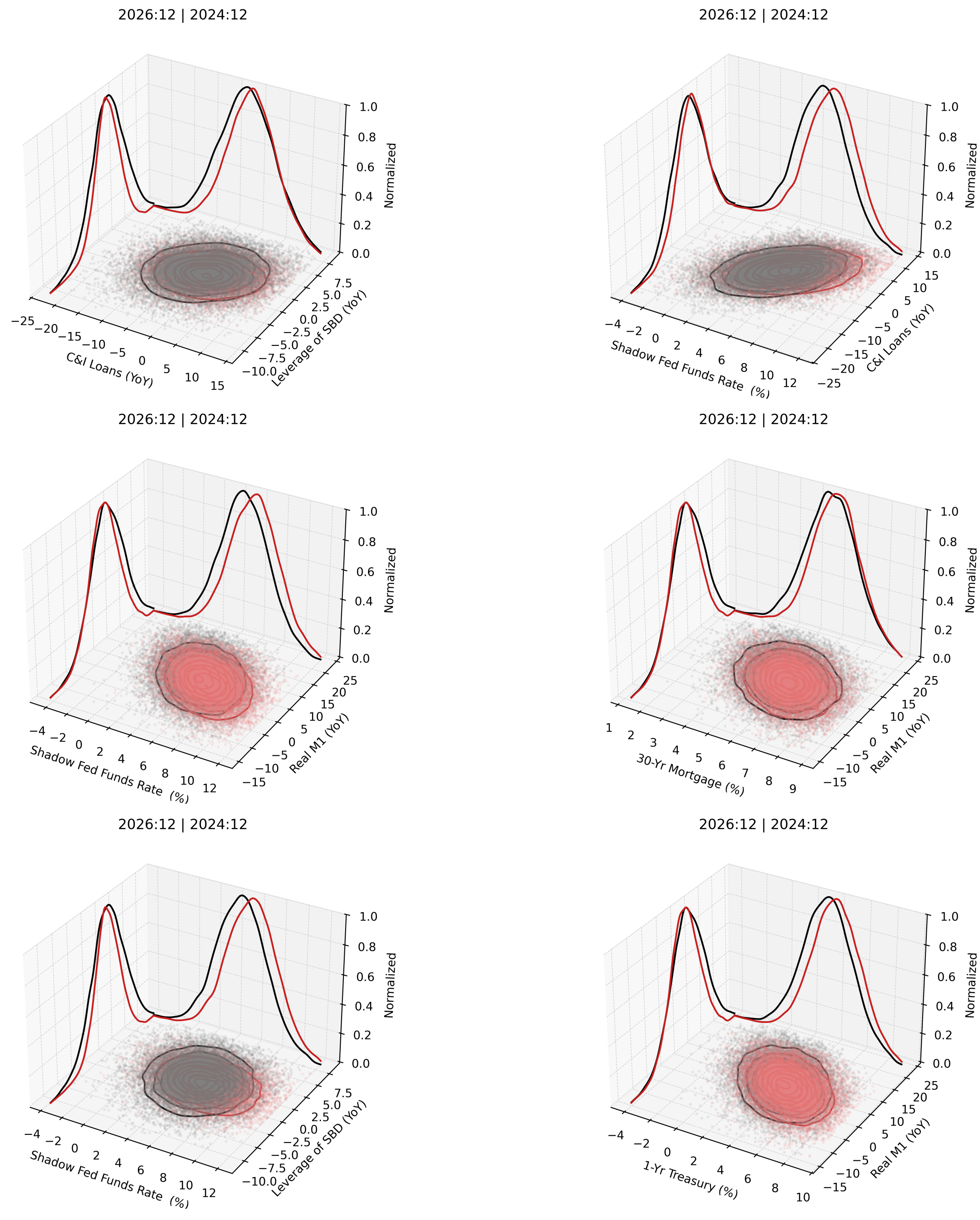

Figure 5b. Joint predictive densities for Q4-2026 using data till Q4-2024 under the unconditional and the conditional scenario that the monetary policy contracts 2-3 years ahead. To remove extreme outliers, it shows the central 99 percent of the distribution, after clipping the top and bottom 0.5 percent of the distribution.

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Appendix

A1. Description of 50 Quarterly Macro and Financial Variables

Series Name	**Units**	**Transformation**	**isFinancial**	**Prior**
Real Gross Domestic Product	Billions of Chained 2017 Dollars	100×log	0	RW
Real Personal Consumption Expenditures	Billions of Chained 2017 Dollars	100×log	0	RW
Real Disposable Personal Income	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Non-Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Government Consumption Expenditures and Gross Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Industrial Production Index	Index 2017=100	100×log	0	RW
Capacity Utilization: Manufacturing	Percent of Capacity	Raw	0	RW
Housing Starts	Thousands of Units	100×log	0	RW
All Employees, Total Nonfarm	Thousands of Persons	100×log	0	RW
Civilian Unemployment Rate	Percent	Raw	0	RW
Business Sector: Real Compensation Per Hour	Index 2017=100	100×log	0	RW
GDP Deflator	Index 2017=100	100×log	0	RW
PCE: Chain-Type Price Index	Index 2017=100	100×log	0	RW
PCE Excluding Food and Energy	Index 2017=100	100×log	0	RW
CPI: All Items	Index 1982–1984=100	100×log	0	RW
CPI-Urban: All Items Less Food and Energy	Index	100×log	0	RW
Crude Oil, spliced WTI and Cushing	Dollars per Barrel	100×log	1	RW
10-Year Treasury Note Yield	Percent	Raw	1	RW
1-Year Treasury Bond Yield	Percent	Raw	1	RW
5-Year Treasury Bond Yield	Percent	Raw	1	RW
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw	1	RW
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw	1	RW
Real Exports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
Real Imports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
S&P 500 Index	Index	100×log	1	RW
CBOE Volatility Index: VIX	Index	100×log	1	WN
University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	100×log	0	RW
Real M1 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real M2 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real Commercial and Industrial Loans	Billions of 2017 US Dollars	100×log	1	RW
Real Consumer Loans at All Commercial Banks	Billions of 2017 US Dollars	100×log	1	RW
Real Real Estate Loans	Billions of 2017 US Dollars	100×log	1	RW
Total Consumer Credit Outstanding	Billions of 2017 Dollars	100×log	1	RW
Total Real Non Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Real Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Consumer Loans and Leases Outstanding Owned and Securitized by Finance Companies	Millions of Dollars	100×log	1	RW
Shadow Federal Funds Rate	Percent	Raw	0	RW
30-Year Fixed Rate Mortgage Average	Percent	Raw	1	RW
Tier 1 Leverage Capital	Millions of US Dollars	100×log	1	RW
Leverage of Non-Financial Non-Corporate Business	Ratio	100×log	1	RW
Leverage of Non-Financial Corporate Business	Ratio	100×log	1	RW
Leverage of Securities Brokers and Dealers	Ratio	100×log	1	RW
Real Net Worth of Households and Nonprofit Organizations	Billions of 2012 Dollars	100×log	1	RW
Real Real-Estate Assets of Households and Nonprofit Organizations	Billions of 2012 Dollars	100×log	1	RW
Real Total Financial Assets of Households and Nonprofit Organizations	Billions of 2012 Dollars	100×log	1	RW
Real Federal Debt: Total Public Debt	Millions of 2012 Dollars	100×log	1	RW
Real Nonfinancial Corporate Business Sector Net Worth	Billions of 2012 Dollars	100×log	1	RW
Real Nonfinancial NonCorporate Business Sector Net Worth	Billions of 2012 Dollars	100×log	1	RW
Real Disposable Business Income	Billions of 2012 Dollars	100×log	1	RW

A2. Conditional and Unconditional Forecasts of Balance Sheet Metrics under the Scenario where the Shadow Federal Funds Rate Rises by 100 bps 1-Quarter Ahead.

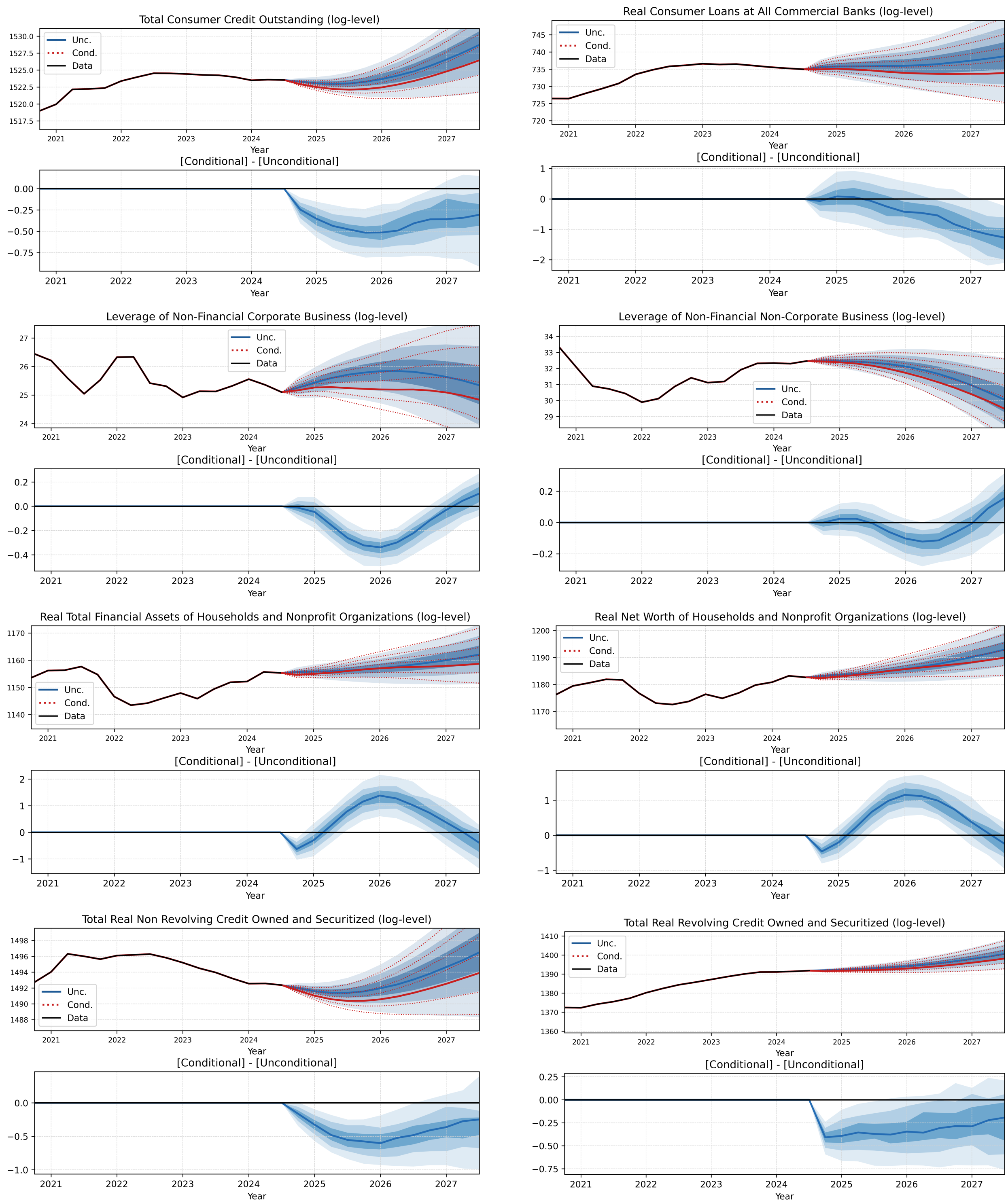


Figure A1. In each subplot, the top row depicts the unconditional (shades of blue bands) and conditional (red dotted lines) foreacsts at various quantiles of the predictive distribution. The bands are the 60, 70, and 80-percent coverage intervals around the median forecasts. The bottom row depicts the difference between conditional and unconditional forecasts.

The Financial-Trade Nexus: International Shocks, and Tariff Transmission

Abstract

What is the cyclicality of international economic indicators, and are there any structural breaks? This provides a quick overview of the correlations and co-movements of the international economic variables and sheds light on whether the 2008 GFC altered those patterns. I conclude that there are no structural breaks - treasury securities held by foreign investors and import price index are countercyclical; export price index, real exports and imports are procyclical. Then, with the recent developments in the trade war, I model a few scenarios: What are the implications of the Reverse Greenspan shocks: reduced foreign purchases of US Treasuries? Most importantly, how do the tariffs affect the US aggregate economy? I gauge the effects using a novel approach of changes in the import price index. A cost-push shock, this is a stagflationary scenario analogous to a recursively identified IRF with slow-moving macro and fast-moving financial variables, generating structurally interpretable responses. Then, I extend the analysis using finer-grained sector-specific disaggregated data to evaluate the impact of tariffs on various sectors of the US economy, such as the services, durables, non-durables, retail sector, etc, using a very large dataset of 127 variables.

1. Introduction

In chapter 2, I study the relationship between the business cycle and financial intermediation for the US economy, establishing stylized facts and refining them after observing structural breaks. In this chapter, I extend the analysis by adding the data on international variables and probing into how they interact with financial intermediation and business cycles, establishing new stylized facts on the cyclical nature of international economic indicators, and answer other policy-relevant questions. Including data on international trade and capital flows will shed light into how exports and imports respond to shifts in business cycles, credit conditions, tariffs, and financial crises. How does the US financial intermediation affect trade balance and inflows of foreign capital? Trade and financial variables are correlated with the US business cycles, and tight credit conditions and reduced liquidity affect imports more than exports as domestic firms are financially constrained. Moreover, changes in the US credit cycle have spillover effects on emerging markets. Related literature by Rey (2015, 2018) introduced the concept of the global financial cycle, highlighting three key findings. First, financial markets in countries where credit flows inward are more sensitive to global cycles. Second, the cycle co-moves with a measure of global risk aversion - volatility index (VIX). Third, monetary policies in large economies like the US impact the leverage of global banks, capital flows, and how credit moves in the international financial system. Similarly, Miranda-Agrippino and Rey (2019) find that shocks to the monetary policy in the US alter the behavior of the international financial variables, and higher federal funds rate globally shrinks credit, liquidity, agents deleverage, and financial conditions tighten even in countries with floating exchange rates. Changes in the balance sheets of financial intermediaries affect exchange rates theoretically (Gabaix and Maggiori, (2015)) and empirically (Du, Hebert, and Wang (2021)).

By incorporating data on international trade and capital flows, I study how interconnected they are with the domestic financial and macroeconomic conditions. A commonly established empirical regularity in international real business cycle literature is that net exports are countercyclical. Using a 25-OECD-country data in an international RBC model, Engel and Wang (2011) document that real imports and exports are thrice as volatile as GDP is, and find that real imports and exports behave pro-cyclically, and are positively correlated with each other. This relates to the stylized facts that I establish using the large BVAR model - pro-cyclical real imports and exports of goods and services. However, empirical literature has not discerned the cyclical patterns of export and import price indices and foreign purchases of US treasuries, a measure of capital inflows. I find that that Treasury securities held by foreign central bankers, and other international investors are countercyclical, export price index are procyclical but import price index is countercyclical.

Also, this study is timely as the Trump administration has levied reciprocal tariffs on its trading partners, and tariffs on specific sectors such as imports of steel, aluminium, auto and auto parts, and threatened to impose tariffs on copper, foods, semiconductors, electronics, minerals, pharmaceuticals, timer and lumber. This triggers inflation, which can be transitory or persistent depending on how long the tariffs last. The tariffs directly affect prices of everyday household goods and indirectly affect the prices of intermediate goods such as steel and aluminium, thereby influencing both CPI and PPI. Moreover, tariffs have spiked short-term volatility in the credit markets and reduced liquidity - the pace of lending and refinancing in the commercial bond market has slowed; sale of leverage loans have paused; transactions on riskier debt postponed or pulled; risk premium for high yield debt spiked; and corporate bond spreads have ballooned to widest levels since the 2020 pandemic. This underscores the strong linkages between financial intermediary and international economic indicators. To that end, I construct the responses of 52 aggregate macro, financial and international economic indicators when tariffs are imposed on all goods imported from Mexico, Canada and China. In the conditional forecasting exercise, I show how we can replicate a recursive identification scheme to model cost-push shocks where tariffs transmit through the economy via increase in import price index, allowing us to structurally interpret the responses. To my knowledge, I have not found another paper in the literature that studies the impact of tariffs via import price index in the same approach that I apply with a rich dataset. Also, the effects of the price and GDP variables from the model are consistent with those found by the Peterson Institute of International Economics and OECD.

Moreover, since the Trump administration first announced tariffs in February 2025, the ISM index of factory orders slumped to the lowest levels in March 2025 - biggest fall since May 2023, and inventories rose. To beat the tariffs, companies front-loaded purchases of imported goods before duties take effect and now have excess inventories. As tariffs have differentiated effects on varying sectors of the US economy, I also assess the historical correlations of higher import prices on more granular disaggregated data on prices, industrial production, employment, inventories, orders and sales. In the literature, Boer and Rieth (2024) estimate the impact of trade policy uncertainty and import tariffs using theory-consistent and narrative sign restrictions in BVARs using seven variables and exclude the pandemic period. They find that tariff shocks persistently depress investment, trade and output. Albeit I don't structurally identify the variables, I estimate a large BVAR model comprises using 127 variables (of sector-specific granular data) with COVID volatility and track the magnitude of responses driven by historical correlations.

Besides dampening manufacturing, the dollar has fallen 4.7 percent in the first quarter - a conundrum calling into question the US dollar's status as "safe haven" - typically dollar rises when times are more uncertain. Emerging markets like China and Japan have slowed their purchases of US Treasuries lately, prompting a scenario analysis where I assess the responses of reduced Treasury purchases. Beltran et al. (2012) employ a cointegrated VAR model to show that if foreign official institutions reduce the inflows into US Treasuries by $100 billion in a month, then the 5-year Treasury yields will hike by 40-60 basis points in the short run. Through scenario analysis, I notice that the Treasury yields of maturities 1,5 and 10 years rise by about 50 basis points when there is a combination of structural shocks that most likely decline the foreign purchases of US Treasury yields by 10 percent.

The remainder of the chapter is as follows. Section 2 introduces the international economic indicators and the rationale for adding them in the analysis. Section 3 establishes stylized facts on cyclical nature of the international economic indicators. In section 4, I examine the responses of variables to reduced inflow of foreign credit in the financial markets, known as the Reverse Greenspan Effect. Section 5 and 6 examine the effects of tariffs on aggregate data, and sectoral data, respectively through the lens of import price index. In section 7, I construct an index, similar to the Trade Weighted Dollar Index, using the large BVAR with COVID-Volatility, and incorporate financial intermediation variables as empirical scenario analyses suggest a strong correlation between financial intermediary and international variables. This is a Forex Trade Index, that provides a snapshot of the health of various trade and financial indicators in a single measure. To the best of my knowledge, no one has constructed one before using a COVID-volatility large BVAR model. Section 8 concludes and provides ideas for further research.

2. Data on International Economic Indicators

In addition to the financial intermediation variables defined in chapter 2 and its Appendix A1, I add international-oriented data capturing import price index, and export price index, US debt held by all foreign investors, and long-term treasury yields of foreign countries. For instance, the import price index measures the prices of all commodities imported into the US, reflecting inflationary or deflationary trends in prices of foreign goods sold domestically. In particular, this is crucial in current times as it helps to analyze the impact of tariffs, disruptions in the global supply chains (as seen in the COVID-19 pandemic), and its implications in the business cycles, especially inflation rates. A depreciated US dollar and additional tariffs increase import prices, potentially influencing domestic prices and real income. This is noted by Caldara et al. (2019) where they investigate how trade policy uncertainty and tariffs affect investment decisions and GDP growth. Notably, the import price index fell in both crises - plummeted by 19.5 percent in July 2009 relative to a year ago during the GFC, and by 6.3 percent in May 2020 when measured in YoY growth rates, highlighting its procyclical nature. Similarly, the export price index tracks the prices of commodities exported from the US to its trading partners. If domestic financial conditions such as liquidity, credit availability, and borrowing costs affect production costs, they can pass through the prices of exports.

Additionally, I add variables that capture the global demand of the US financial assets, via the federal debt held by foreign investors to quantify the total amount of US federal government debt purchased by all official institutions (e.g., foreign central banks, foreign governments, sovereign wealth funds), and private investors (e.g., foreign banks, pension funds, mutual funds, individual investors, hedge funds, and corporations). As a broader measure, higher holdings of US Treasuries suggest that the global risk appetite for US bonds is strong as foreigners are increasingly confident in the economy. In the wake of the pandemic and the 2008 GFC, domestic and foreign investors undertook a “flight to safety”, increasingly purchasing Treasuries, as they are perceived as safe haven relative to other risky assets, and are more liquid. Foreign investors deem the US Treasuries safer as the risk from fluctuating exchange rates affects the dollar-denominated assets lower than alternative assets denominated in other currencies. Whilst flight-to-safety reasons have diminished as economies have normalized from downturns, international investors still seek Treasuries as the US dollar serves as the world’s reserve currency. So, the Treasuries are in permanent demand as they are considered collateral in financial transactions and a temporary, stable, and liquid store of value when transactions or trades are executed. Economically, the ballooning deficits in the US make it a net borrower, partly financing the fiscal outlay by selling Treasuries abroad and importing more than exporting to foreigners. If this borrowing has stimulated the economic output, then it is beneficial in raising the domestic real income (Congressional Research Service, 2024).

I also include a variable that tracks the total customs duty revenue that the federal government collects from imported goods. Categorized under tax receipts, it directly reflects revenue collected from tariffs. Adding this variable reveals whether the revenue from tariff behaves procyclically with tariff rate, via the import price index channel. In other words, are tariff revenue positively correlated with import price index, and the impact on the real economy? This has implications for policymakers, few of whom have stated that the revenue collected from higher tariffs or import duties will contribute towards paying the US debt. Finally, I add data on the UK and German 10-year government bond yields. As a major trading partner of the US, its bond yield serves as a benchmark for global financial conditions, and changes in its yield curve can shift global liquidity, affecting the financial intermediation in the US. Likewise, the German government bond yield represents long-term borrowing costs in the Eurozone's largest economy. The complete list of the variables are in Appendix A1.

3. Stylized Facts on International Economic Indicators from Pre-GFC Sample: 1986-03-01 to 2008-09-01

As detailed in chapter 2, I now establish pre-crisis stylized facts, examining the relationship between financial intermediation and global variables from a scenario where unemployment rate rises. In other words, the scenario analysis plots the responses to a the linear combination of shocks that are very likely to drive unemployment rate upwards by 1 pp. In other words, they are drive by a multiplicity of structural disturbances that drive the forecast error of unemployment rate one-quarter ahead. In the financial intermediation front, the variables behave as described in chapter 2. Notably, both M1 and M2 rise as agents shift from less liquid (interest bearing) assets to more liquid assets (cash and demand deposits). Revolving credit which comprises credit cards, home equity lines of credit, etc, is relatively elastic - declining instantaneously.

Foreign investors possess 2 percent more US federal debt, and foreign central banks purchase about 4 percent more Treasuries after unemployment rises, evincing a "flight-to-safety" mechanism, wherein international investors shift capital toward US Treasuries amid uncertain economic times (Krishnamurthy and Vissing-Jorgensen (2012)). Mirroring historical trends observed in the 2008 GFC, and the COVID-19 pandemic, the foreign demand for US government securities surged as investors sought safe-haven assets. Output metrics deteriorate as non-residential fixed investment, and real GDP fall by 2.4, and 1 percent, respectively. If the government resorts to expansionary fiscal policies to simulate the tepid economic growth, the Department of Treasury issues more debt, raising the supply of Treasuries purchased by investors globally. Helping finance deficits, these foreign purchases fuel credit boom, and eventually depress the yields on the Treasuries. Furthermore, a downturn in the US labor market may prompt foreign central banks to accumulate more reserves to stabilize exchange rates or shield their economies from spillovers in the US, reflecting heightened global demand for risk-free assets. As global reserve assets, the Treasury purchases behave countercyclically during economic stress.

Real exports and imports fall by 2.4 and 2.3 percent, respectively, indicating they are procyclical. However, exports rebound after a quarter of slowdown. Along the same lines, real disposable personal income wanes by 0.75 percent and employees in non-farm payrolls slump by 0.5 percent. Just as exports fall, over time after a lag of one quarter, the export prices also diminish by 0.8 percent. Historically, and as noted in the literature, prior contractual agreements between domestic and foreign buyers attribute to the sticky nature of the import and export prices, but lower foreign demand for US products may warrant the domestic exporters to lower prices to stimulate sales abroad, exhibiting pricing-to-market behavior. Alternatively, the scenario analysis shows that import prices rise and stay elevated for a year and a half. While this could potentially be due to supply-side factors (higher foreign energy costs, supply chain disruptions, tariffs, and other trade restrictions, etc) instead of demand-side factors, the BVAR model doesn't attribute to any one reason, as historical correlations between the variables drive the responses. Revealing signs of price rigidity, the export price index moves procyclically, but import prices move countercyclically.

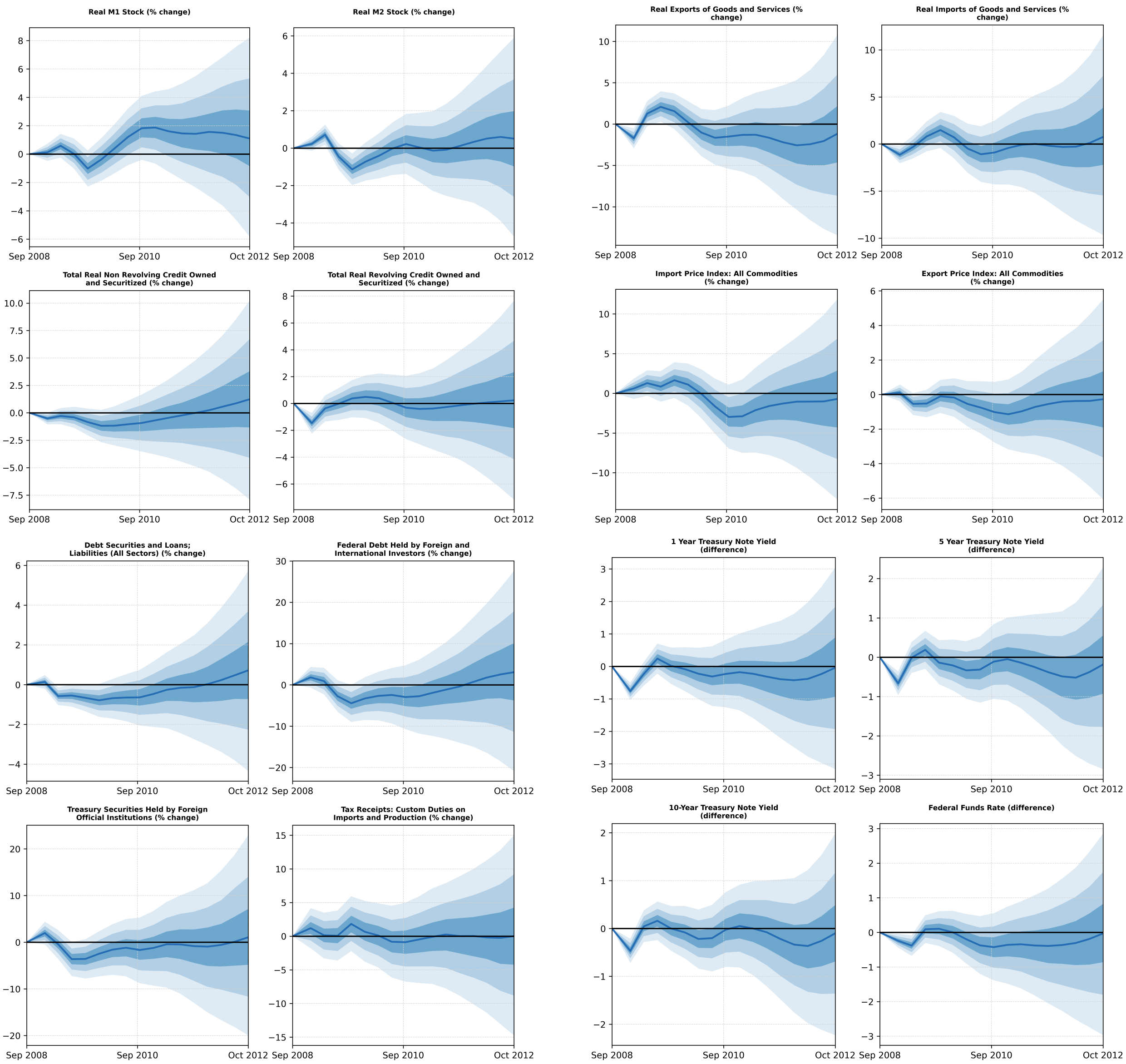


Figure 1a. Responses of 1 pp rise in the unemployment rate. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

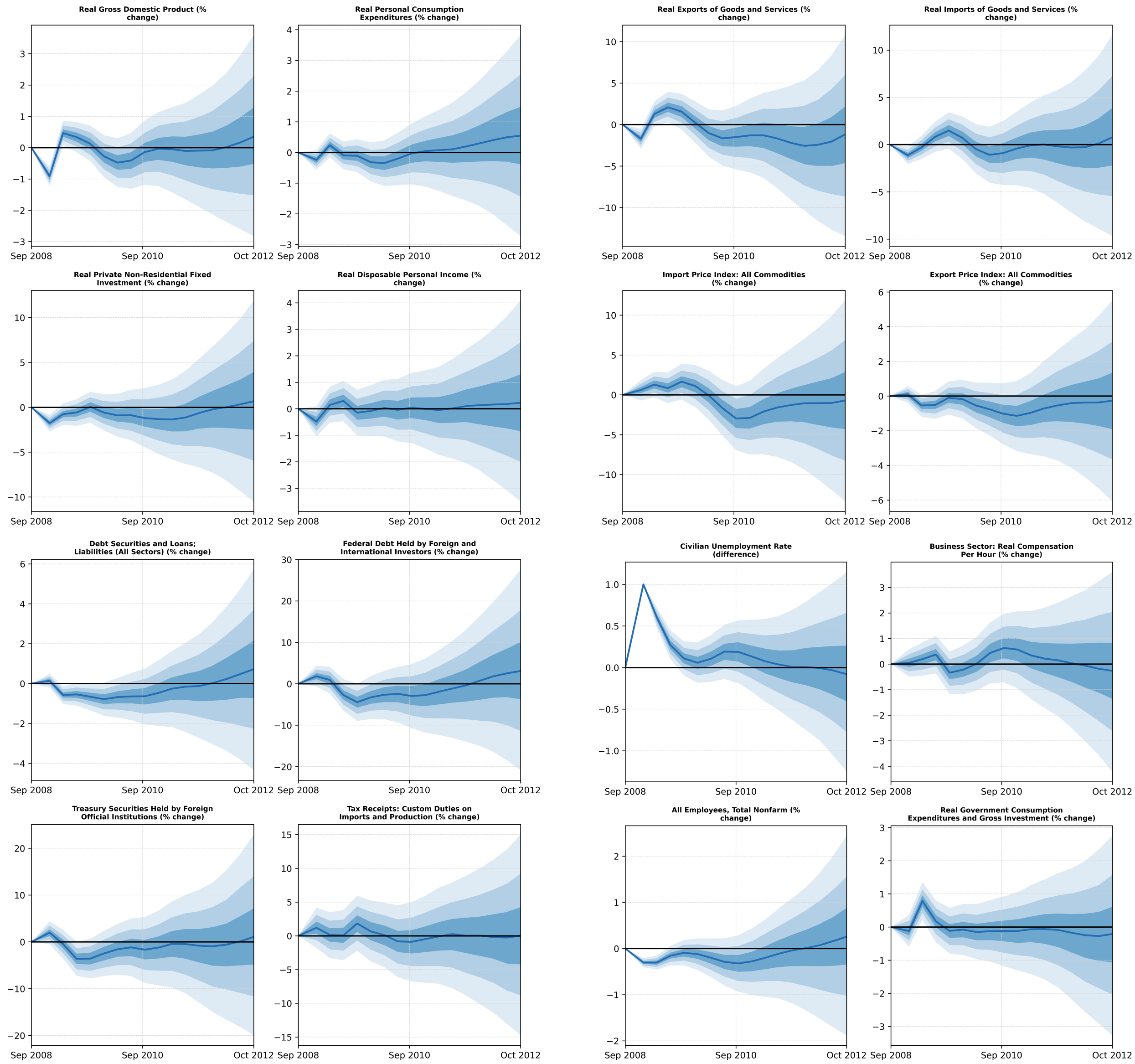


Figure 1b. Responses of 1 pp rise in the unemployment rate. The dark blue lines are the median responses, and the shaded regions are the 80, 70 and 60-percent coverage intervals around the median forecasts.

Through plots of global trade-related variables measured in year-over-year growth rates in Figure 2, I evaluate if structural breaks are present in the relationship among macro, financial intermediation, and international variables. While clear structural breaks were evident in the financial intermediation variables as evident from chapter 2, they are not so prominent for the international variables except the export price index. The OOS forecasts from the large BVAR model estimated till the pre-crisis data underestimate the realized changes in export prices during and after the 2008 GFC (2009-2011) and COVID-19 pandemic (Q2-2020 - Q2-2022), indicating a break from the pre-GFC historical regularities. Disrupting global trade severely during the pandemic, export prices surged more than that forecasted by the model. Supply-side constraints pushed up the prices of several exported goods such as agricultural, and industrial materials. Moreover, the model doesn't capture the post-pandemic inflationary pressures owing to expansionary stimulus packages. On the other hand, during the GFC, the Fed trimmed the rates to near zero and engaged in quantitative easing, depreciating the US dollar. This makes the US exports cheap, allowing firms to raise prices without losing competitive advantage.

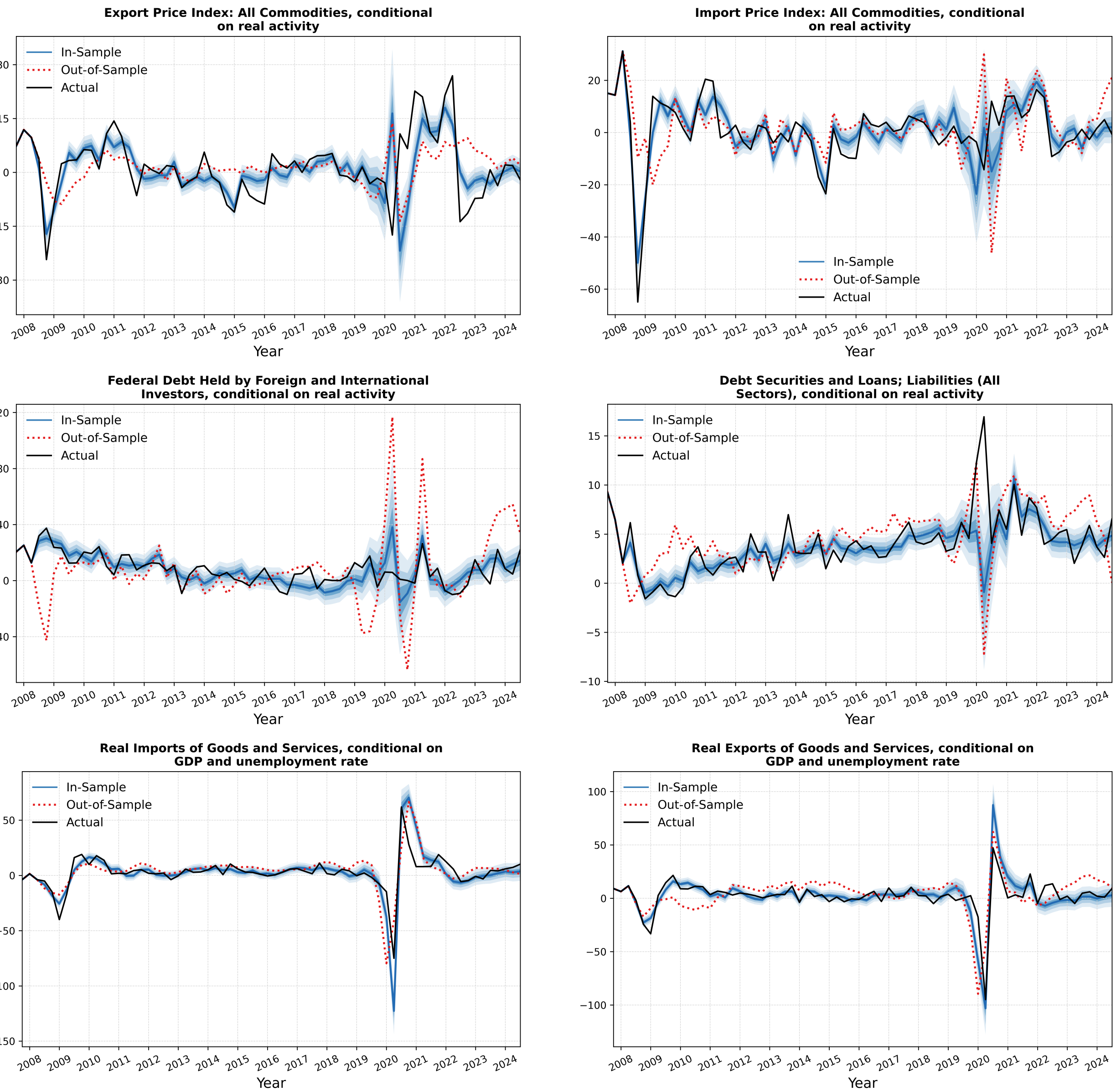


Figure 2. In-sample (IS) and out-of-sample (OOS) forecasts or counterfactual paths are conditional on the known paths of macroeconomic variables - real activity, labor, and housing, from December 2008 to September 2024.

4. Reverse Greenspan Conundrum in Effect: What Happens when the World Buys Less US Debt?

Standing tall at $1.83 trillion, the US federal fiscal deficit in 2024 was the third-highest in record, and the national debt clambered to a whooping $36.85 trillion (as of May 13, 2025). This amount surpasses the average annual GDP for the fiscal year of 2024 - $28.83 trillion, soaring the Debt to GDP ratio at 123 percent. Given that the debt is burgeoning unsustainably, the federal government will have a greater difficulty repaying its debt, particularly at a time when the interest rates are high. The debt to GDP ratio worsened from 2013, when both debt and GDP were approximately $16.7 trillion. As of Q4-2024, foreign creditors held approximately 24 percent of the outstanding US federal debt, largely owned by countries with current account surpluses - Japan, China, and countries in the Euro Area. Warnock and Cacdac (2009) uncover that foreign inflows significantly and economically reduce the US treasury yields, concluding that without the foreign inflows, the 10-year Treasury yields would have been 90 basis points higher. This implies that the Treasury yields are very sensitive to foreign inflows, and that foreign holdings of the US Treasuries critically influence domestic interest rates, financial conditions, and macroeconomic stability. For instance, between 2004 and 2006, when the Fed aggressively raised the federal funds rate from 1 to 5.25 percent, the long-term bonds failed to rise, contradicting conventional monetary theory that long-term rates are expected to rise higher as the Fed constricts monetary policy. Known as the Greenspan Conundrum, a major driver of this was that countries with large trade surpluses such as China and Japan were buying vast quantities of the US Treasuries to manage their reserves and stabilize their currencies, suppressing the long term yields. According to Bernanke (2005), a “global savings glut” had lowered the long-term interest rates in the US and other advanced economies at a time when the foreign exchange reserves have sharply risen. Historically, prior to the 2008 GFC, the foreign holdings of US treasuries rose from $1 trillion in June 2001 to $2.2 trillion in June 2007, skyrocketing 120 percent, and even during the GFC, it rose by 42 percent (between Q1-2008 and Q3-2009). However, over the past decade, countries have been reducing their holdings of US treasuries. Lately, the Treasury markets have witnessed a phenomenon opposite of the Greenspan conundrum, known as the Reverse Greenspan Conundrum, wherein the long-term yields have fallen even though the Fed hiked the federal funds rate by 100 basis points between September 2004 and December 2024. Rather than declining, the long end of the yield curve has risen. We partly attribute this to lessening foreign capital inflows as the global demand for US Treasuries have declined.

In light of the shifting trends, I model a scenario where the foreign and international investors decline their purchases of US Treasuries by 10 percent, and illustrate the results in figure 3. I estimate the model in the full-sample, till December 2024. Notably, the 1, 5, and 10-year Treasury yields all rise by about 50 basis points, consistent with the Reverse Greenspan Conundrum, where declining foreign purchases correlates with steepening yield curve instead of the flattening curve observed in the 2000s. Higher Treasury yields coincide with elevated costs of borrowing such as mortgage rates, albeit the responses vary across different types of loans. The scenario analysis connotes that real consumer loans modestly decline by less than 0.5 percent, suggesting that consumer loans are inelastic, and that households reduce discretionary borrowing.

Real commercial and industrial loans also gradually decline with a lag of a year, falling by 3 percent over the forecast horizon, highlighting the procyclicality of business lending. On the other hand, real estate loans don't change on impact for two years, implying they are uncorrelated or weakly correlated with foreign purchases of Treasuries. However, from September 2026, they rise by 0.5 percent, moving in the opposite direction of commercial and industrial loans. On the real economy side, all measures of output such as industrial production, capacity utilization, and real GDP fall, and the US exports 2 percent fewer goods and services.

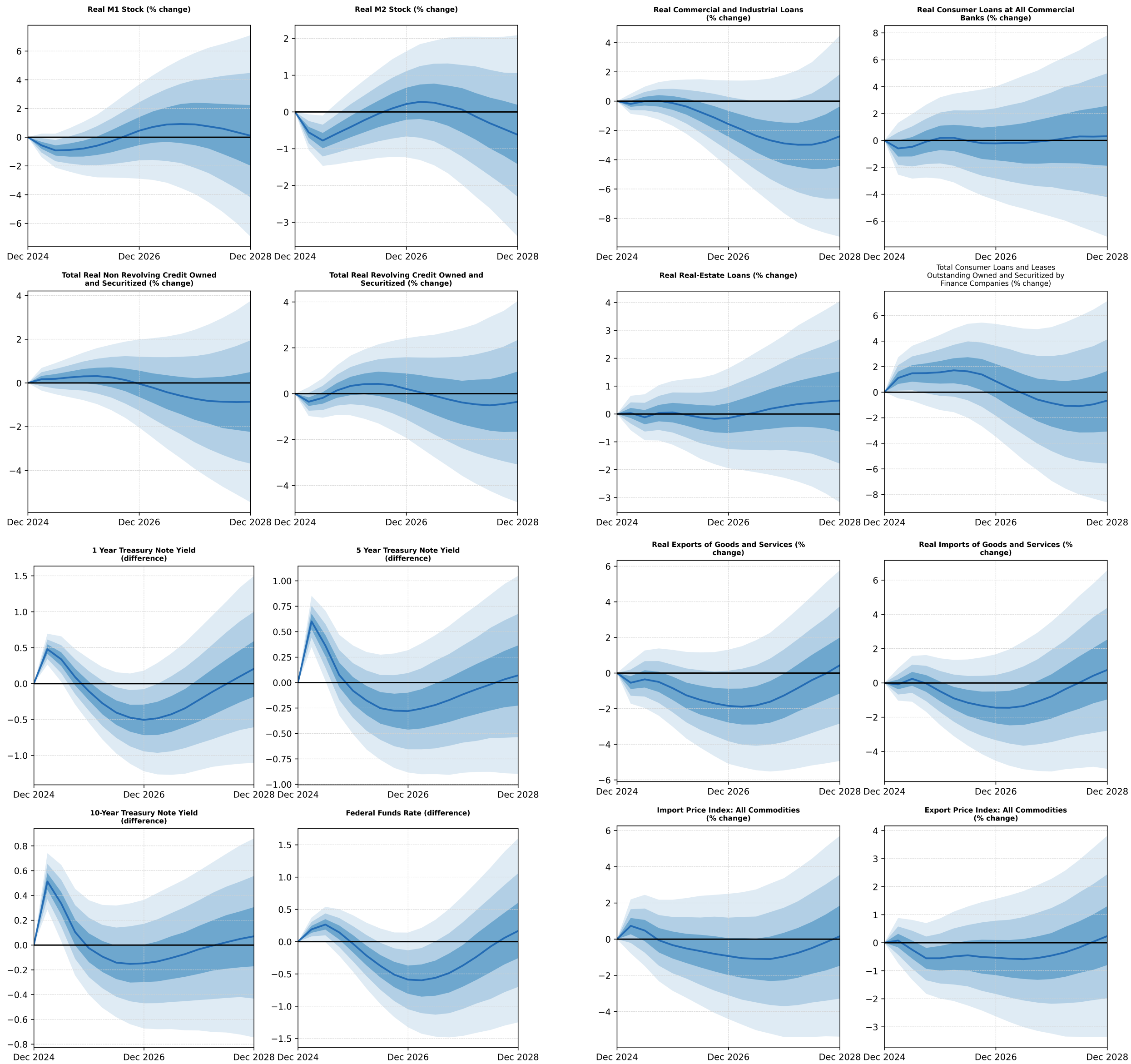


Figure 3a. Responses of variables when foreign investors reduce the Treasury purchases by 10 percent for one quarter. The dark blue lines are the median responses, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts.

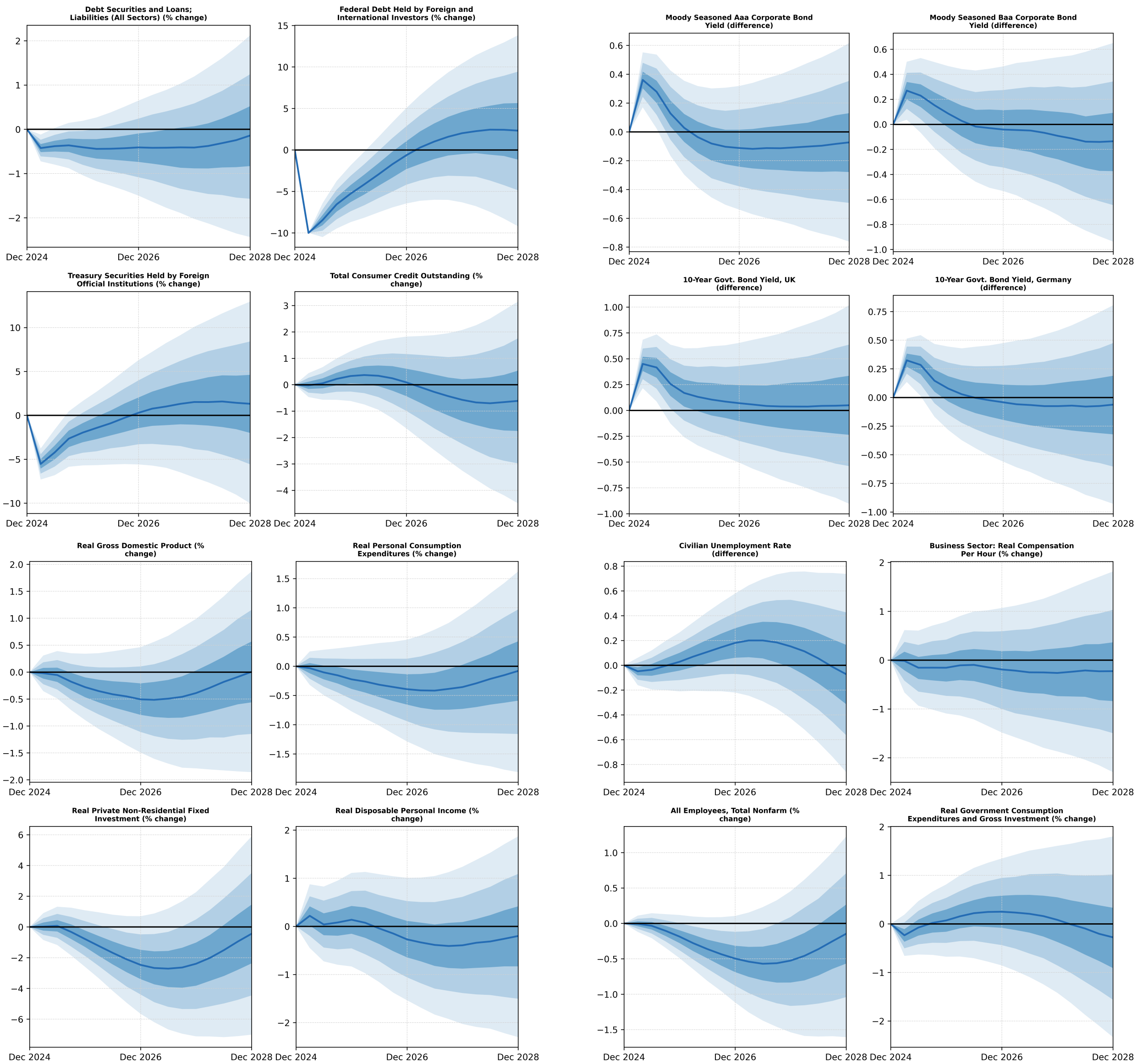


Figure 3b. Responses of variables when foreign investors reduce the Treasury purchases by 10 percent for one quarter.

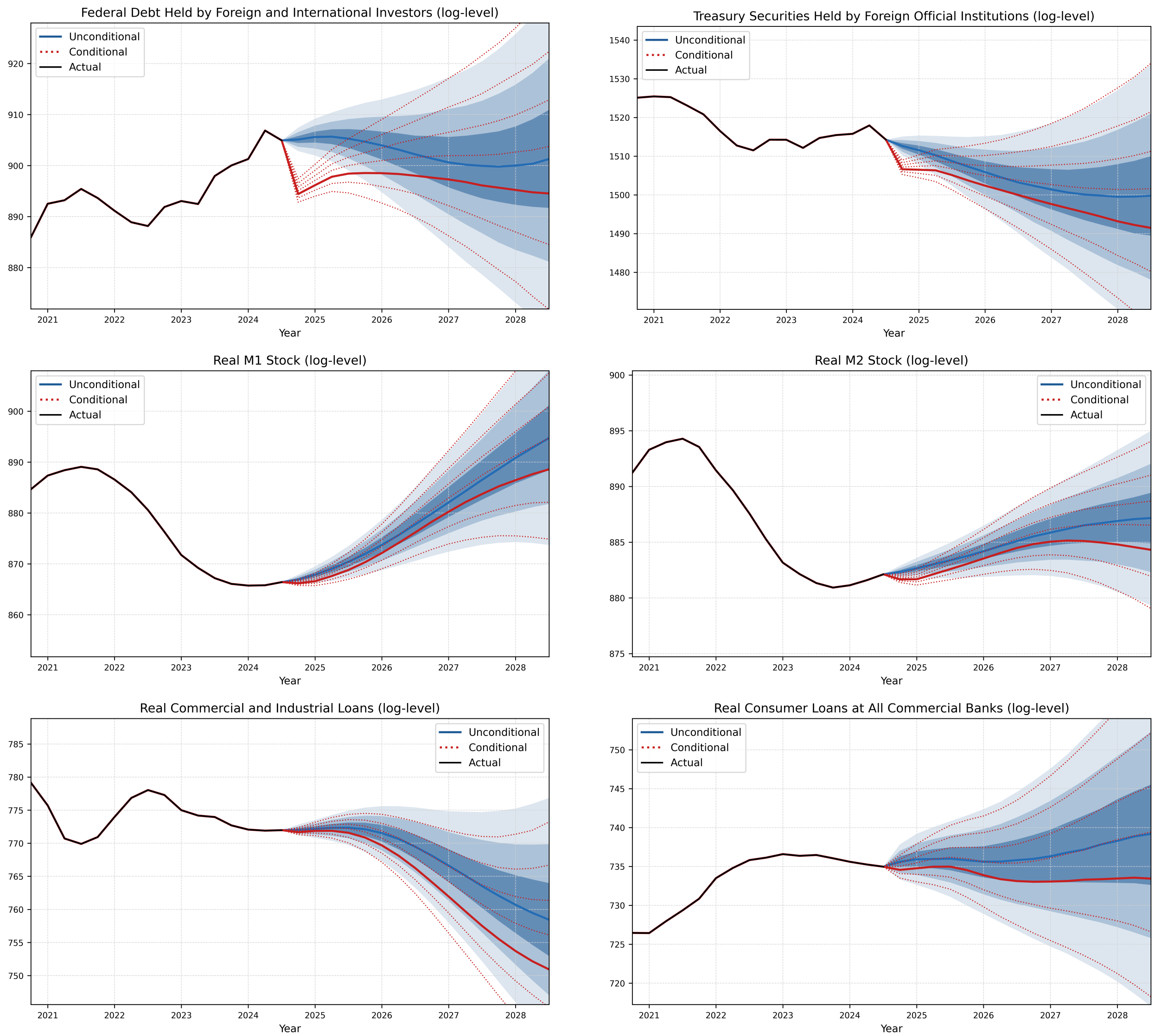


Figure 4a. Forecasts conditional on Reverse Greenspan Conundrum: the dark red lines depict the median forecasts under a scenario where foreign institutions and international investors reduce purchases of US Treasuries by 10 percent one quarter ahead. The dark blue lines are the median baseline forecasts devoid of any shocks, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts. The red dotted lines are the conditional forecasts at the 80, 70 and 60-percent coverage intervals.

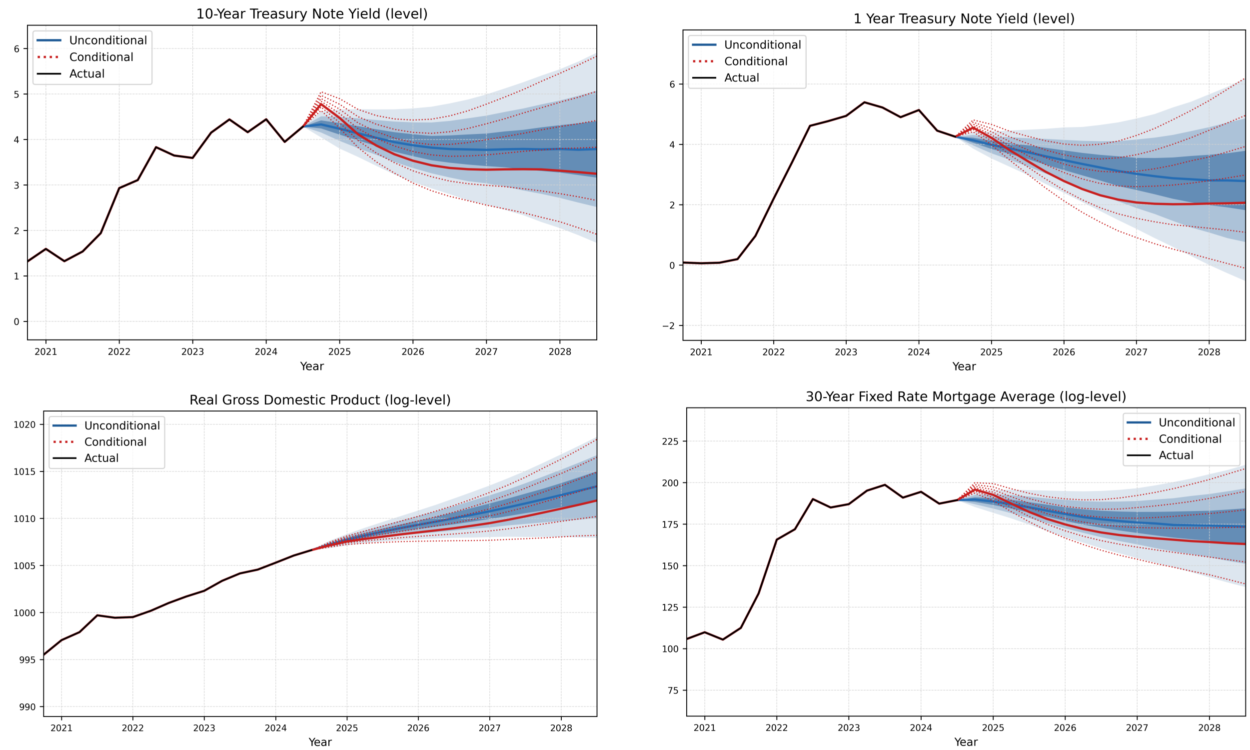


Figure 4b. Forecasts conditional on Reverse Greenspan Conundrum: the dark red lines depict the median forecasts under a scenario where foreign purchases of US Treasuries decline by 10 percent one quarter ahead.

5. Cost of Protectionism: A Stagflationary Scenario

The Trump administration imposed 10 percent tariffs in Chinese imported goods on February 4, 2025; 25 percent tariffs on imports from Mexico and Canada, and additional 10 percent on imports from China on March 4, 2025. In addition to targeting the imports of countries, the administration has added tariffs on certain sectors, such as an additional 25 percent tariff on imports of steel and aluminum, potentially raising the cost of foreign and US-built vehicles. Other industrial sectors such as automobiles, pharmaceuticals, and semiconductors may bear the brunt of 25 percent tariffs. Using the import price index as a proxy to reflect changes in import costs due to levies, I simulate the economic impact of recent tariffs via scenario analysis. The import price index (IPI) measures the average prices paid for imported goods. How do tariffs affect IPI? This partly depends on how much the foreign firms pass through the burden of the tariffs onto US buyers at the borders. Foreign suppliers of goods may absorb part of the costs due to competitive pressure, adjustments in the supply chain, and fluctuations in exchange rates. Foreign manufacturers may lower the pre-tariff prices they charge for the goods to keep selling to the US at competitive rates, otherwise, they may run out of business should the US firms purchase from buyers in tariff-free countries, or nations where the burden of tariff is less. The passthrough rate in the above equation doesn't capture how higher tariffs are passed further downstream in the supply chain - US producers, wholesalers, retailers, and final consumers.

Using disaggregated micro data on imports and prices, Amiti, Redding, and Weinstein (2019) find that the tariffs imposed by the Trump administration in 2018 were entirely passed to domestic consumers in the form of higher prices, without changing prices charged by foreign exporters to the US. As firms passed the full burden of tariffs to domestic consumers, revenue collected from tariffs wasn't sufficient to compensate for the losses borne by the consumers who bought imported goods; and reduced the US real income by $1.4 billion per month by the year's end. Alternatively, Cavallo, Gopinath, Neiman, and Tang (2021) demonstrate using good-level data that the tariff pass-through at the border is much higher than the exchange rate pass-through, and retail margins had fallen while the prices modestly rose, suggesting that the US firms bore the brunt of tariffs. To corroborate, a 20 percent hike in tariff is associated with a 18.9 percent increase in prices paid by importers at the border. In contrast, if the US dollar appreciates by 20 percent, the dollar price of imports minutely fall by 4.4 percent. Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020) also conclude that prices of imports hit by tariffs didn't fall and tariff hikes befell to consumers, yielding the real aggregate income to truncate by $7.1 billion, or 0.04 percent of GDP. Exchange rates pass-through play a vital role too. Using transactional-level data, Gopinath, Itskhoki, and Rigobon (2010) find that when foreign goods are priced in US dollars, only 25 percent of exchange rate movements pass through to the final import price as foreign exporters absorb most of the exchange rate fluctuations. On the other hand, if goods are invoiced in foreign currency, then 95 percent of exchange rate changes pass through to import prices.

To examine the pass-through of tariff hikes on the import price index, I estimate the BVAR with COVID-19 volatility in the full sample till Q4-2024. Then, for simplicity, I assume that the tariff pass-through rate is 90 percent. The following equation estimates the direct effect of tariffs on import prices in a country:

$$\Delta\,\text{import price index}_{jt} = \text{tariff rate}_{jt} \times \text{passthrough rate} \times \text{import share}_{jt} \times 100$$

where, I calculate the import share from country j at time t as

$$\text{import share}_{jt} = \frac{\text{imports from country } j_t}{\text{total goods imported to US}_t}, \quad j \in \{\text{Mexico, China, Canada}\}$$

I derive the above equation in Appendix A4. In Q4-2024, the US imported 865,273 million USD of goods, of which $126,966 million was imported from Mexico, $116,775 million from China, and $103,358 million from Canada. This means that Mexican imports accounted for 15.02 percent of the total imports, followed by China and Canada trailing at 13.81 and 12.22 percent, respectively.

In the scenario, from Q1-2025 till the end of the forecast horizon, I calibrate the effects of 25 percent tariffs on imports from Mexico, and Canada, and 20 percent on China. Through this simple calculation, I expect that IPI rises by 8.61 percent from Q1-2025 for fifteen quarters. Additionally, I fix the Q1-2025 forecasts of macroeconomic variables (except for pricing variables) only to their unconditional forecasts. So, the difference between the unconditional forecasts of macro variables one quarter ahead with the conditional forecasts is zero. This mirrors a recursive identification scheme where "slow-moving" macro variables don't contemporaneously respond to "fast-moving" financial variables. In other words, the financial variables respond immediately, while the economic variables respond with a lag. By conditioning on rise in import price index while affixing macro variables on impact, the scenario analysis mimics the recursive identification of a cost-push shock. A cost-push shock is an adverse supply shock that exogenously raises prices of goods and services. Examples of cost-push shocks covered in the literature are supply chain disruptions (Gordan and Clark (2023)) and how rise in oil price drive inflation expectations (Barsky and Kilian (2002)). The seminal paper of Blanchard and Gali (2007) measures cost-push shocks in the New Keynesian Phillips Curve framework augmented with real rigidities, wherein inflation rises without increasing the output gap. These can be attributed to markup shocks where firms charge higher prices for the same output, oil price shocks, wage shock, etc. Crucially, I allow the pricing variables - CPI, PCE, GDP deflator and import duties to adjust contemporaneously to capture the inflationary effects of a cost-push shock, while holding other macro variables fixed on impact. If the scenario analysis illustrates that macro aggregates remain intact while the financial and pricing variables respond immediately one quarter ahead, we can structurally interpret the elasticities as impulse responses of a tariff-induced cost-push shock, analogous to the identifying monetary policy shock in Crump et al. (2021).

Simulated Responses of the Real Economy Variables to Tariff-Driven Changes in Import Prices

Figure 5 illustrates the elasticities of the variables when I estimate the model till Q4-2024, and is hit by these tariff shocks starting Q1-2025. Constituting as a persistent or semi-permanent negative supply shock, it lasts long enough to alter agents' expectations in ways that mirror long-term shifts in trade policy. Higher import prices raise all measures of prices as headline and core PCE inflation rates rise by 0.7 and 0.2 percent, respectively, staying there for a few quarters before gradually declining. Domestic prices of goods and services also rise, consistent with the empirical evidence in this literature. Except for core PCE, prices don't reach their long-run steady-state levels after the forecast horizon. Albeit tariffs are directly inflationary as they raise the costs of imported goods and intermediate inputs sold to final consumers and producers domestically, the results from the scenario analysis suggest that these tariff hikes don't tantamount to a one-to-one increase in domestic inflation rates. OECD has projected that PCE inflation will rise by 0.7 - 2.8 percent annually in 2025.

Measures of real activity underperform as real GDP drops by 0.55 percent in Q3-2026 and stays at that level till Q4-2028. The Peterson Institute for International Economics (PIIE) projects that real GDP declines by 0.52 percent annually in 2026, aligning with the responses of the BVAR model. Tariffs act as a tax on consumption as higher prices erode purchasing power, diminishing the real disposable personal income by 1 percent over the horizon. With fewer people employed, unemployment rate elevates by 0.1 percent two years into the future and staying there in the long run. Real personal consumption expenditure decreases by 0.8 percent. Declining consumer spending feeds back into lower real GDP as consumption is the largest component of GDP, consistent with the findings of Amiti, Redding, and Weinstein (2019) who note that the 2018-2019 US-China trade war yielded higher consumer prices, losses in real income and consumption. Together, inflation coupled with stagnated output resembles a stagflationary environment, reminiscent of the 1970s stagflation.

Declining real personal consumption expenditure by 0.8 percent evinces patterns consistent with "wealth effect", where people spend less when asset prices plummet and vice versa. (Simsek and Caballero (2024)). The strength of consumer spending and the economy is strongly tied to the stock market, as wealth erased from plummeting stock indices softens consumption, and spending. This is true in the American top-heavy business cycle, where the wealthiest 10 percent of US households account for almost half of the nation's consumer spending, owning half of the stock (around $23 trillion worth). Housing starts and real private residential fixed investment slump by 3 and 4 percent, respectively. Costly import prices raise construction costs as many construction materials such as steel, aluminum, and lumbar are imported, discouraging new real estate and residential buildings. Also, as the Fed raises the federal funds rate by 25 basis points to combat inflation, remaining at that level for a year, an uptick in mortgage rates makes housing less affordable.

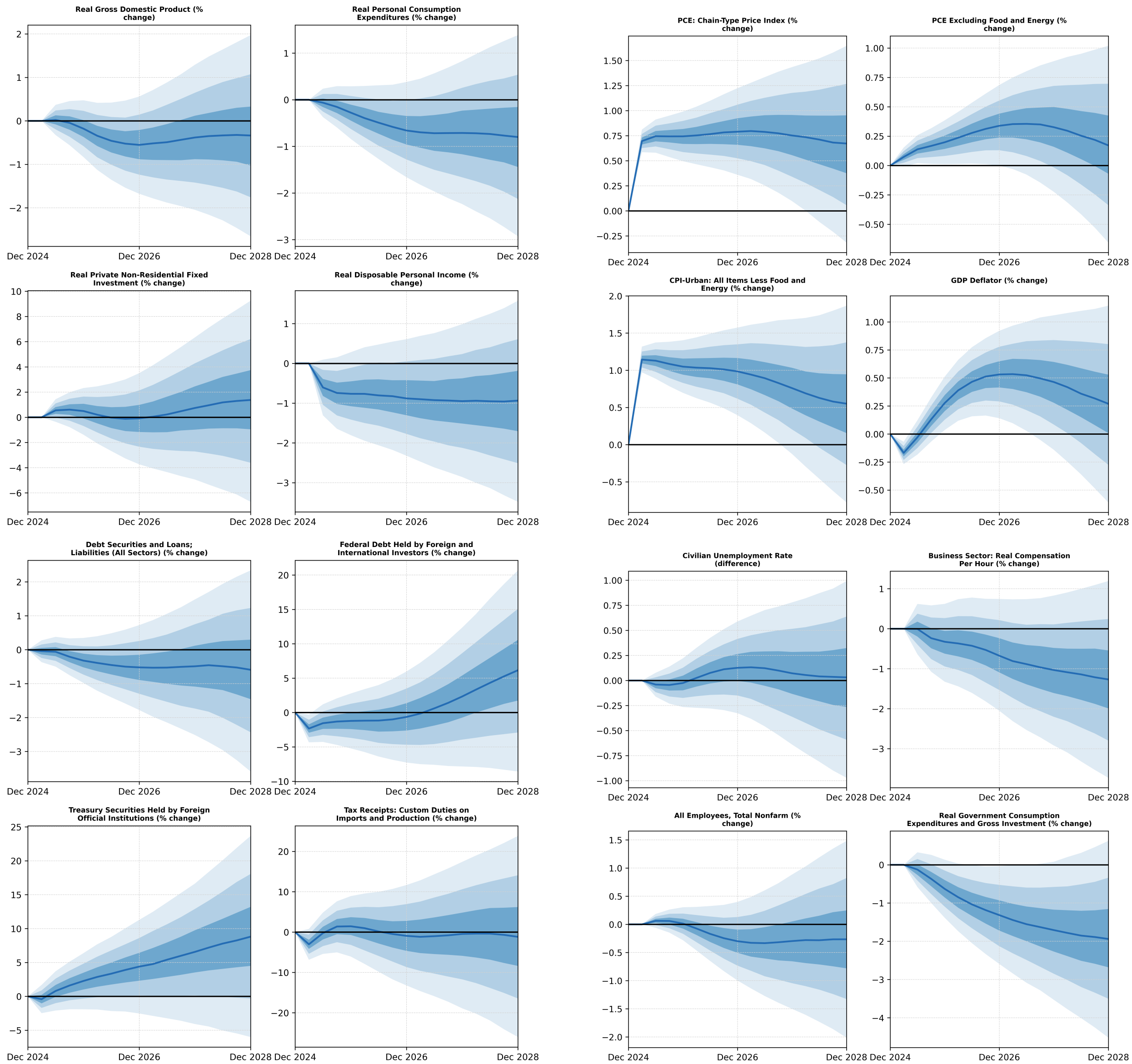


Figure 5a. Responses of tariff shocks: a scenario where the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports. The dark blue lines are the median responses, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts.

Simulated Responses of the Financial Intermediary Variables to Tariff-Driven Changes in Import Prices

Both monetary aggregates fall as M1 and M2 decline by 2.4, and 1.8 percent, respectively. We observed earlier that inflation and policy rates are higher in this scenario. Agents shift from liquid assets (M1) into longer-term, interest-bearing assets such as time deposits, displaying flight from liquidity effects. Total real revolving credit owned and securitized (such as credit cars) rise by 2 percent over the course of the horizon. The scenario analysis shows similar patterns for consumer loans and leases, which increase by 4 percent over four years. Non-revolving credit is very inelastic and does not respond to tariff shocks immediately. Typically contracted under fixed-rate agreements, non-revolving credit (e.g., student loans, auto loans) is less sensitive to short-term inflationary shocks. Revolving credit, on the other hand, dips then rises - falling when federal funds rate increases on impact, and rising when the federal funds rate declines in the medium-term.

The Treasury yields of varying maturities 1, 5, and 10 years rise for nearly two years and then trend downwards. 10-year yields of the UK and Germany exhibit similar patterns. The scenario analysis depicts that foreign central banks keep buying more Treasury securities over the years. The increased demand for these Treasuries pushes their prices up, depressing the yields and flattening the yield curve (as prices and yields are inversely related). Graphically, rising official purchases of US Treasuries coincides with the falling yields of 1,5 and 10 year maturities.

Real commercial and industrial loans rise by 2.6 percent for the remainder of the forecast horizon, although they initially fall for two quarters by 0.4 percent when policy rate increases. Despite tighter credit conditions, firms, especially domestic manufacturing companies that benefit from tariffs, borrow to finance working capital. Businesses may preemptively borrow before rates rise further to mitigate the impact of higher impact costs. As discussed before, higher mortgage rates make homes less affordable. Besides falling housing starts, real estate loans decline by 3 percent.

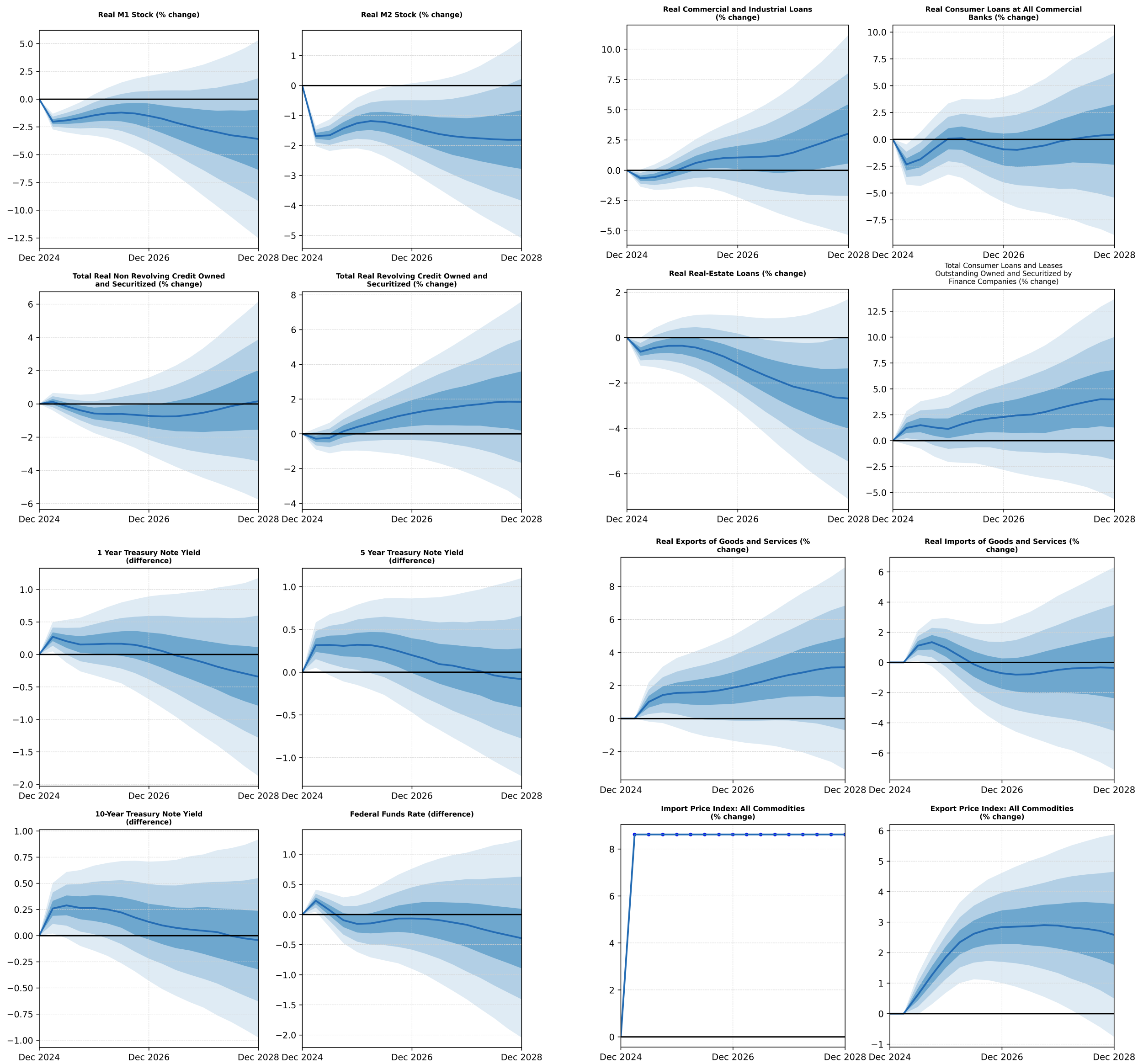


Figure 5b. Responses of tariff shocks: a scenario where the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports. The dark blue lines are the median responses, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts.

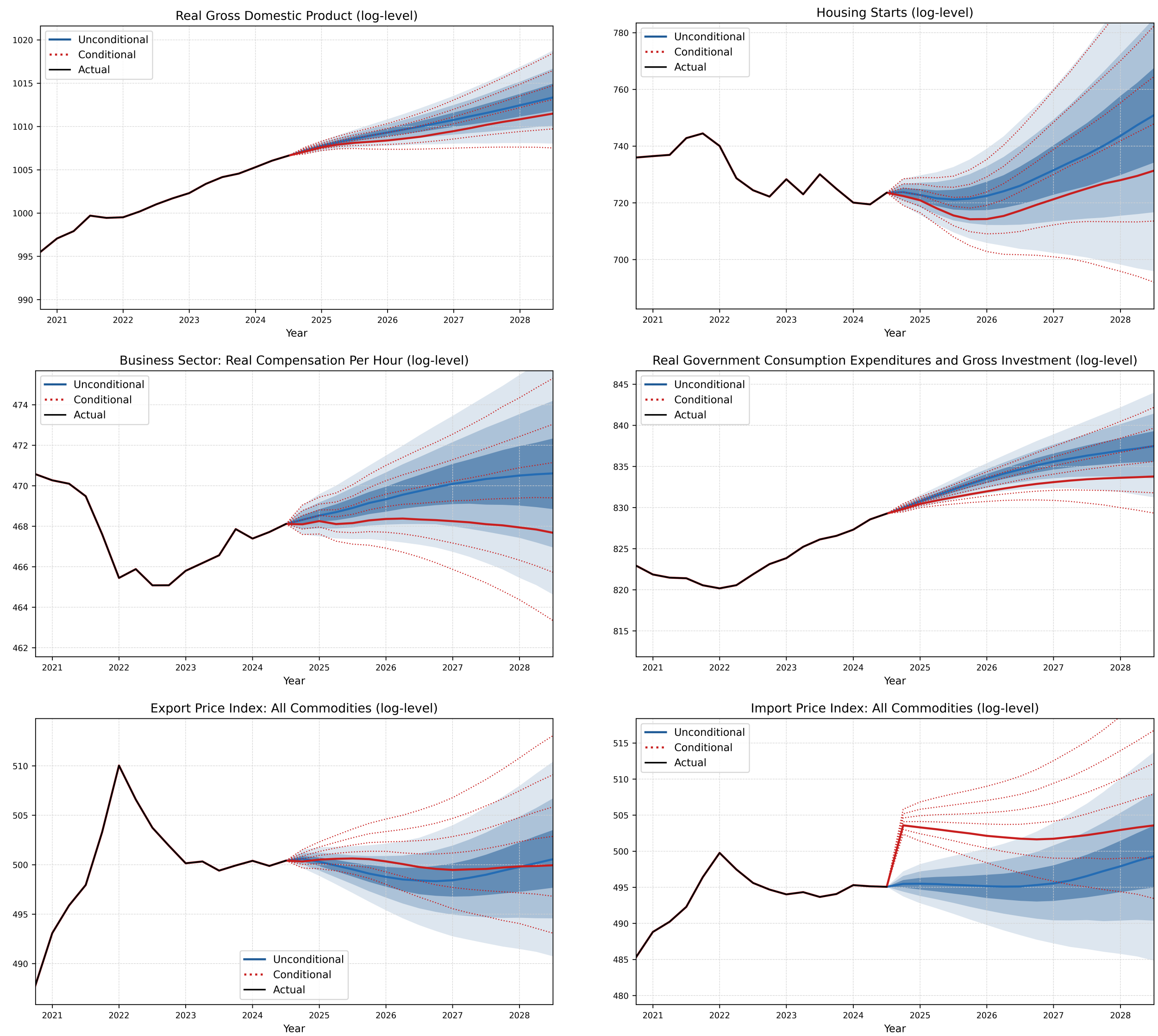


Figure 6a. Forecasts conditional on tariff shocks: the dark red lines depict the median forecasts under a scenario where the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports. The dark blue lines are the median baseline forecasts devoid of any shocks, and the shaded regions are the 80, 70, and 60-percent coverage intervals around the median forecasts. The red dotted lines are the conditional forecasts at the 80, 70 and 60-percent coverage intervals.

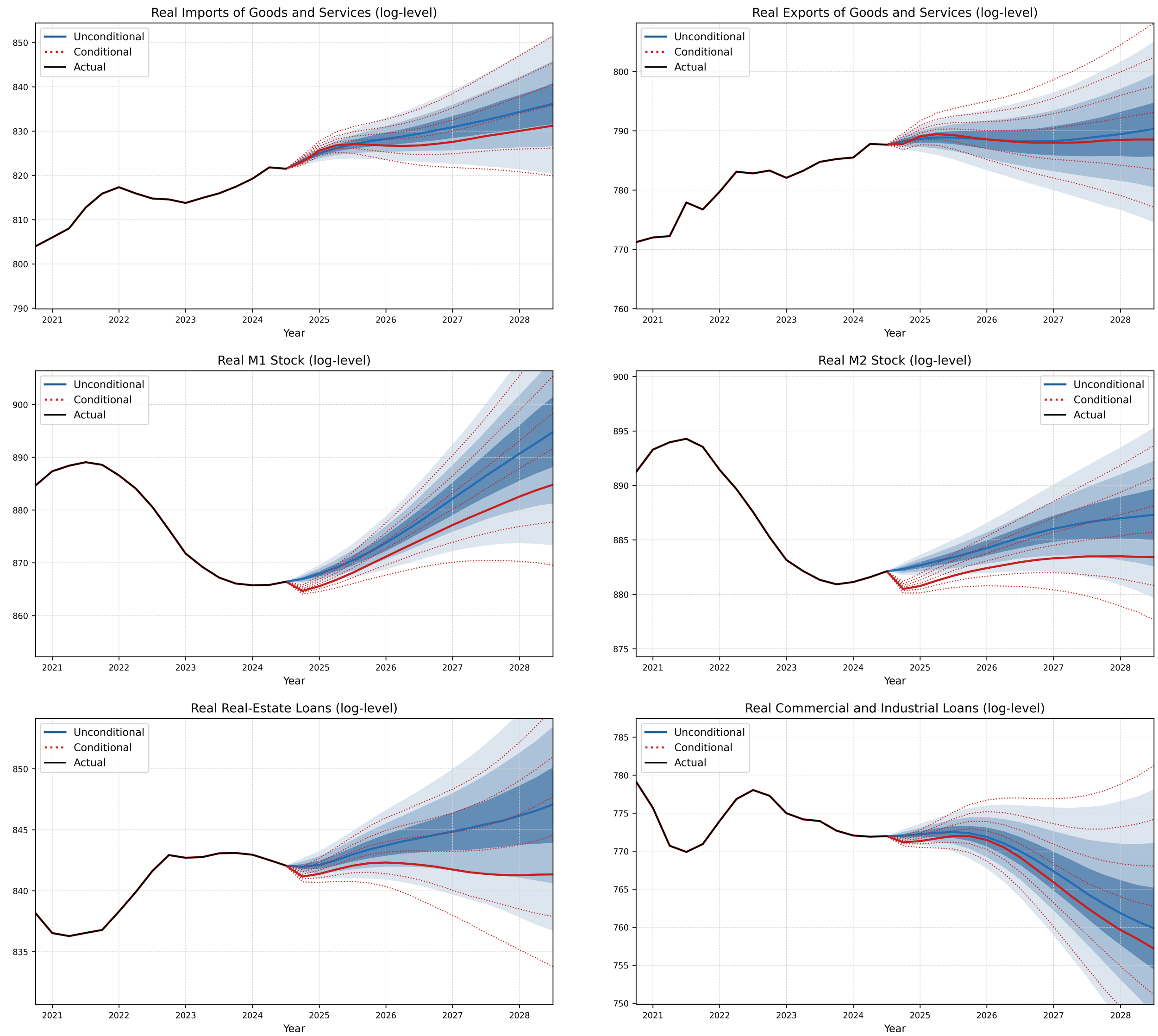


Figure 6b. Forecasts conditional on tariff shocks.

6. Sector-Specific Analysis of Tariffs: How Elastic are Prices, Production, Employment, Inventories and Sales?

Previously, I examined how tariffs affect the aggregate real-economy, international economic and financial intermediary variables. I expand the scope of the existing work by studying the effects on granular-level, sector-specific measures of industrial production, employment, inventories, sales and prices. FRED-QD has a vast repository of sector-specific data on industrial production (consumer goods, manufacturing, materials, durable and non-durable materials, durable automotive parts, residential utilities, etc), number of employees the aforementioned sectors along with those in the construction, education and health services, mining and logging, retail trade, wholesale trade, three tiers of government, etc. Likewise, it contains inventories, orders and sales data for capital goods, durable and non-durable goods ordered and sold, total business inventories, and inventories to sales ratio. Whilst tariffs primarily raise import costs, ultimately it affects how firms adjust production, manage inventories, place new orders for immediate and final goods. New orders of all durable goods, durable consumer goods and non-defense capital goods are leading indicators of future production. When tariffs accelerate import prices, businesses may adjust their stock of inventories by either accumulating more inventory to hedge against future increases in costs, or by reducing them to avoid stocking higher-priced goods and instead stocking domestically-produced substitutes. Not all sectors respond equally to tariffs. For instance, prices of durable goods are more sensitive than those of non-durable goods. While the model doesn't parse out why variables respond in a certain way, the heterogeneous responses of various sectors helps to understand how likely prices and other metrics of various sectors evolve based on historical correlations. By incorporating these variables, I trace the immediate pass-through of the aforementioned tariffs to import prices, domestic consumer and producer prices of various sectors including those that are potential targets for higher tariffs namely metals, commodities, etc.

Finer Granularity Data

Overall, the model has 127 variables, excluding most financial intermediary variables on credit supply. The table in Appendix A2 lists the complete set of the variables and transformations applied. I include sectoral data that tracks how much consumers spend on various kinds of goods and services in the US national accounts measured via personal consumption expenditure. For instance, PCE of motor vehicles and parts captures spending on automobiles, and is highly responsive to higher import prices of automotive vehicles, parts and engines. PCE of clothing and footwear encompass items commonly imported from low-cost producers. On the other hand, PCE of transportation services, health care and financial services show how items less-exposed to imports are sticky and are inelastic to changes in higher import prices. Additionally, I incorporate CPI data to track housing costs, costs of commodities, transportation, medical care, etc; and prices spent by producers - producer price indices on finished goods, intermediate materials, fuels, industrial commodities, etc. So, I track the evolution of producer prices of upstream variables (like PPI for crude materials, intermediate inputs) and downstream variables (like PPI of finished goods). Labor in key sectors such as goods, services, durable, and non-durable are crucial indicators of hiring plans. Higher import prices may prompt firms to hire more in certain industries if firms substitute purchasing imported goods with domestically produced goods, or might curtail staff in other industries if soaring costs hurt profit margins.

I obtain the data on trade, inventories and sales for the following variables. The real manufacturing and trade industrial sales measure the inflation-adjusted sales revenue from the manufacturing, wholesale and retail trade, gauging the total activity in industrial and trade sectors, and is very strongly correlated (0.98) with real GDP. Total business inventories represents the dollar (nominal) value of all inventories such as finished goods, and raw materials across all sectors, and have historically fallen in recessionary periods. Inventories to sales ratio capture the supply of goods that firms have on hand relative to current levels of sales. This has historically peaked during recessions (as sales had shrunk sharply when demand was lower, driving the ratio upwards), and fallen at the tail end of recessions.

Real retail and food services sale measure the inflation-adjusted sales from retail stores and food service establishments to capture the broadly how much consumers spend on goods such as grocery, electronics, clothing and food services such as restaurants. More broadly, this includes purchases in consumables, hardlines, softlines, and everyday essentials categories. As private consumer spending accounts for 68.8 percent of GDP, firms monitor this indicator closely to gauge the health of consumer demand. The year-over-year growth rate of retail sales and food services plummeted by 20.12 percent in April 2020 when the pandemic shook the world, and by 11.13 percent in March 2008 during the global financial crisis. Real manufacturing new orders of durable goods track the orders placed with the US manufacturers for goods expected to last at least three years, such as automobiles, appliances and machinery. As a leading indicator of future manufacturing, higher orders often increase production, and declining orders are a harbinger of softening demand. Real manufacturers' unfilled orders for durable goods industries tracks the number of orders of durable goods that manufacturers are yet to complete. If the existing backlog of unfilled orders is high, it may be because the demand exceeds production capacity or supply chains and production are disrupted. If orders are unfilled for too long, it may slow down deliveries and hamper customer satisfaction.

Reduced-Form Scenario Analysis

Figure 7 shows the median elasticities of various metrics at the sectoral level and the degree of uncertainty derived from the quantiles of the predictive distributions. Unlike in the previous section, I don't fix the conditional forecasts of macro variables to the unconditional forecasts one quarter ahead. Because the scenario analyses stem from an unorthogonalized BVAR model, these responses reflect the historical comovements in consumer and producer prices, inventories, orders and sales when import price index rose in the past. They don't capture the direct causal impact of tariffs. The scenario analysis captures the combination of shocks that most likely drive up the aggregate import price index by 8.61 percent in Q1-2025. In other words, the graphs reflect the multiplicity of structural disturbances that increase the forecast error of import price index one quarter ahead. In the data, whenever import price index rose substantially in the past, it typically coincided with multiple overlapping shifts in prices, number of employees, industrial production, inventories and manufacturing, etc.

Notably, prices in transportation and commodities (excluding service) sectors rise the most - 5.8 and 2.6 percent, followed by the broad-based goods excluding shelter costs (1.6 percent), all items except medical care

(1.2 percent). Auto, parts, and fuel are one of the most import-sensitive sectors, particularly when nearly half of the automobiles sold in the US have components made abroad. Thus, higher prices of imported goods directly raise the costs of transportation (vehicles, parts, gasoline, etc) for consumers. Alternatively, price of services (such as education, health, hospitality, law, consulting, etc) rise by only 0.4 percent at its peak after three years. The scenario assumes that tariffs are imposed on goods only, and services aren't heavily dependent on foreign goods imported. Also, the scenario analysis indicates that prices in the service sector incrementally rise with a delay, and tend to be sticky. Reflecting cost pressures in housing market, the implicit rental value of owner-occupied housing is also very sticky, unchanging for a few years, then rising by mere 0.2 percent in 2027. Owner's equivalent rent of residences (OER) is one of largest components of shelter costs in CPI, and adjusts slowly. Rent prices are typically fixed in advance, and don't move in tandem with fluctuations in import prices.

Likewise, Fed's preferred gauge of inflation - PCE, shows similar trends as PCE of goods rise greater than that of services, 2.1 and 0.3 percent, respectively. Among the goods, prices of durable goods are less elastic than their non-durable counterparts. Defined by the Bureau of Economic Analysis as items that are expected to last at least three years, example of durable goods are motor vehicles and parts, furnitures and appliances, recreational goods like televisions and sport equipment, jewelry, etc. On the other hand, non-durable goods have short lifespans and consumed quickly, such as food and beverages, clothing and footwear, fuel for vehicles, heating oil, and everyday essentials. Overall, non-durable goods are more sensitive to import prices, rising 3 percent one quarter ahead, as opposed to durable goods, which gradually rise by 0.8 percent in three years.

The uniform tariff shock transmits through the economy based on historical co-movements. So, the differentiated responses in various measures of producer prices reflect how strongly each sector's prices have historically been linked with changes in import price index. Out of all the sectors, the producer price indices for copper and copper products, and fuels and related products - natural gas rise the most, 15 and 14 percent, respectively from the baseline level. As a globally traded commodity used in industries such as wiring, electronics, and construction, copper markets are very liquid and price-sensitive. The producer pries for raw materials such as metal and metal products and intermediate products rise by 5 percent. These contrast with the producer prices of finished goods domestically produced, which rise meagerly by 1.6 percent. While I cannot attribute the reasons for the slower response of finished good prices through the reduced-form model, a potential explanation could be that firms may absorb or delay increasing the costs.

Manufacturing and industrial sales (retail and wholesale) uptick by 1 percent before slowing down. Historical relationships suggest that as import costs stay elevated for longer periods, manufacturing and sales soften and eventually dip. Furthermore, businesses across the entire economy preemptively build up inventories by 2 percent over the course of a year while they are still cheaper to hedge against rising expected costs. A subset of all business inventories - real manufacturing and trade inventories modestly rise by 0.5 percent, suggesting that manufacturers stockpile slightly more. Building a smaller buffer, these excess-build up of inventories slow down after a year. The broader measure of total inventory is statistically more sensitive than the narrower measure of trade inventories. Similarly, the inflation adjusted new orders of durable goods - goods expected to last longer than three years such as vehicles, appliances and machines - boost by 5 percent. The new orders of consumers goods, non-defense capital goods, and unfilled orders of durables goods also tick upwards by 5.2, 8, and 3.8 percent, respectively.

The scenario analyses of earnings and productivity metrics show that rise in import price index is accompanied with hike in average hourly earnings of goods producing industries, real output per hour in overall business sector and non-farm business sector by 0.2-0.3 percent. Yet, the real average hourly earnings in private sector, construction and manufacturing sectors decline modestly by less than 0.1 percent, reflecting episodes when manufacturing and output gained slightly in the past at the expense of stagnated average hourly earnings. These results are not surprising when lower wages are accompanied with higher producer prices of upstream pricing variables such as supplies, components, metals and metal products. Industrial production of durable materials, non-durable consumer goods, durable consumer goods, and business equipment rise the most - between 2.5 to 3 percent, whereas industrial production of final products mildly rise 1 percent. This could happen when firms ramp production domestically or substitute imported goods facing higher tariffs with locally produced goods. Overall, sectors relying more on imported inputs (upstream) exhibit are more elastic than those sectors further downstream - final products.

The scenario analyses of employees working in various sectors show that number of employees in mining and logging rise the most over the course of 1.5 years, reaching its peak at 5 percent in June 2026 before gradually reversing course. Durable goods producing sector sees a 1.8 percent growth in the labor relative to its non-durable goods counterpart, which mostly grows by 0.4 percent. Similarly, employees in manufacturing and goods producing industries grow by nearly 1 percent, while growth of labor in information services, service-providing is very muted. In contrast, employment shrinks in the financial activities sector and retail trade over the horizon.

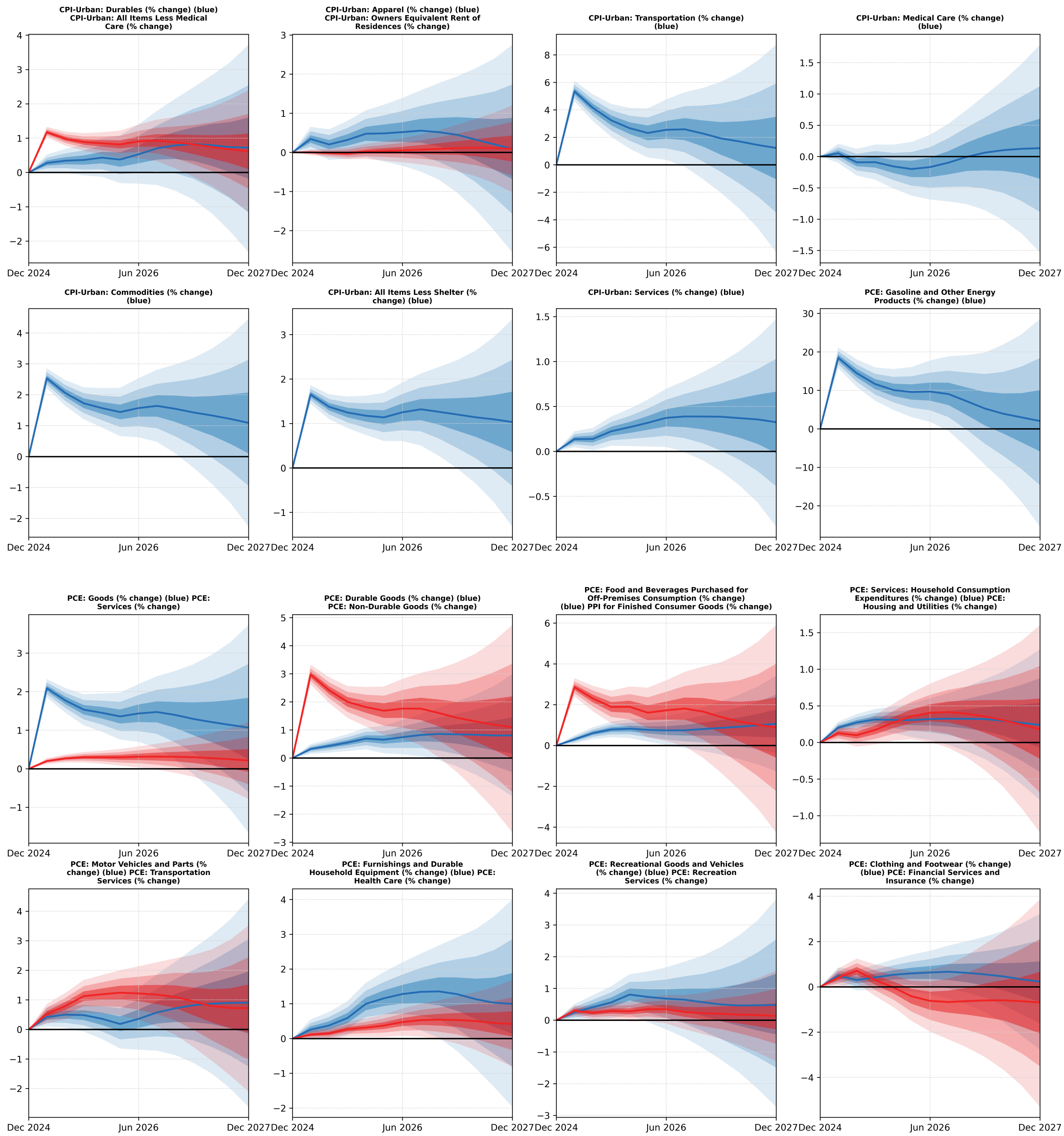


Figure 7a. Responses of various measures of CPI and PCE when the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports.

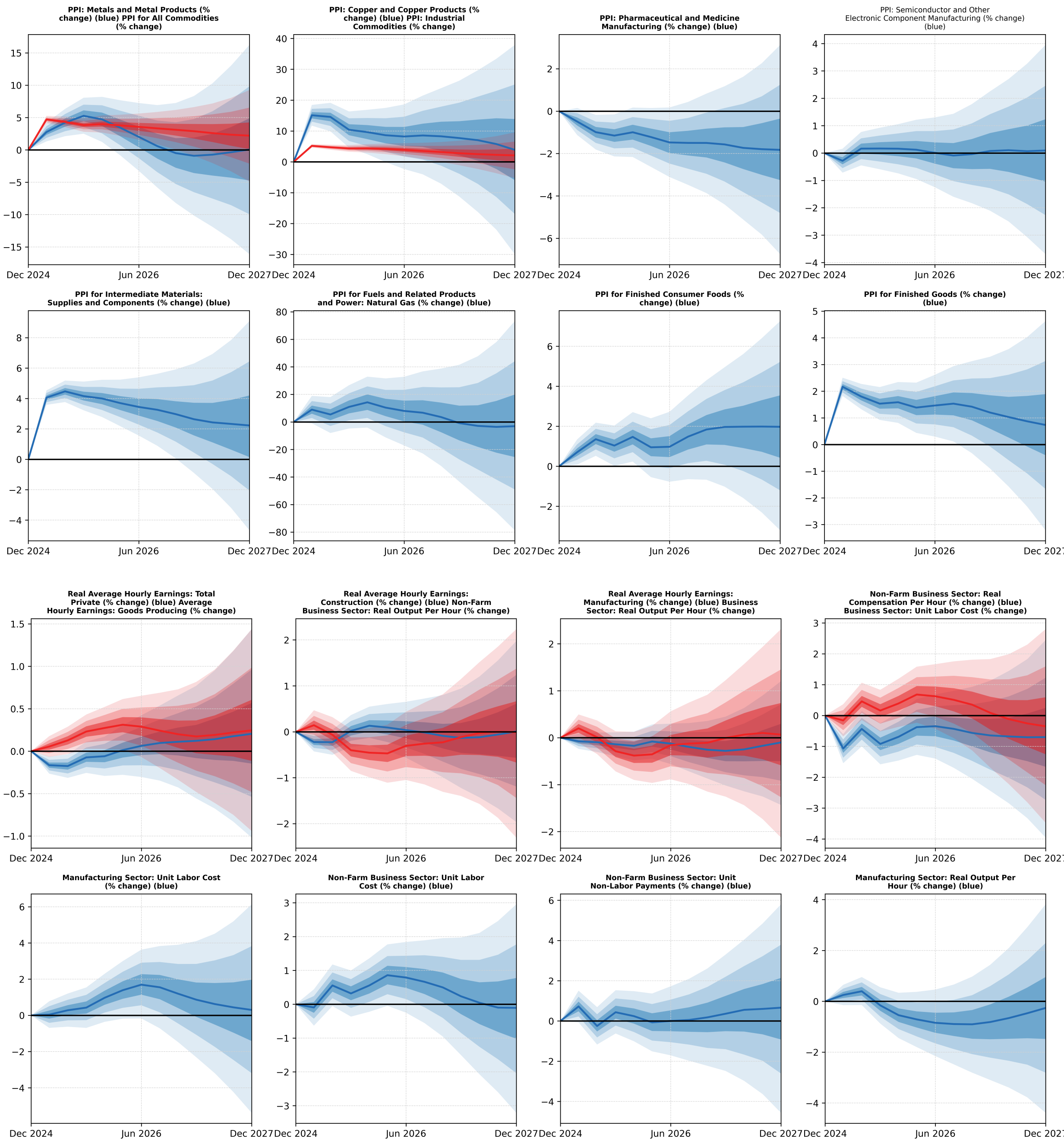


Figure 7b. Responses of various measures of PPI, earnings and productivity when the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports.

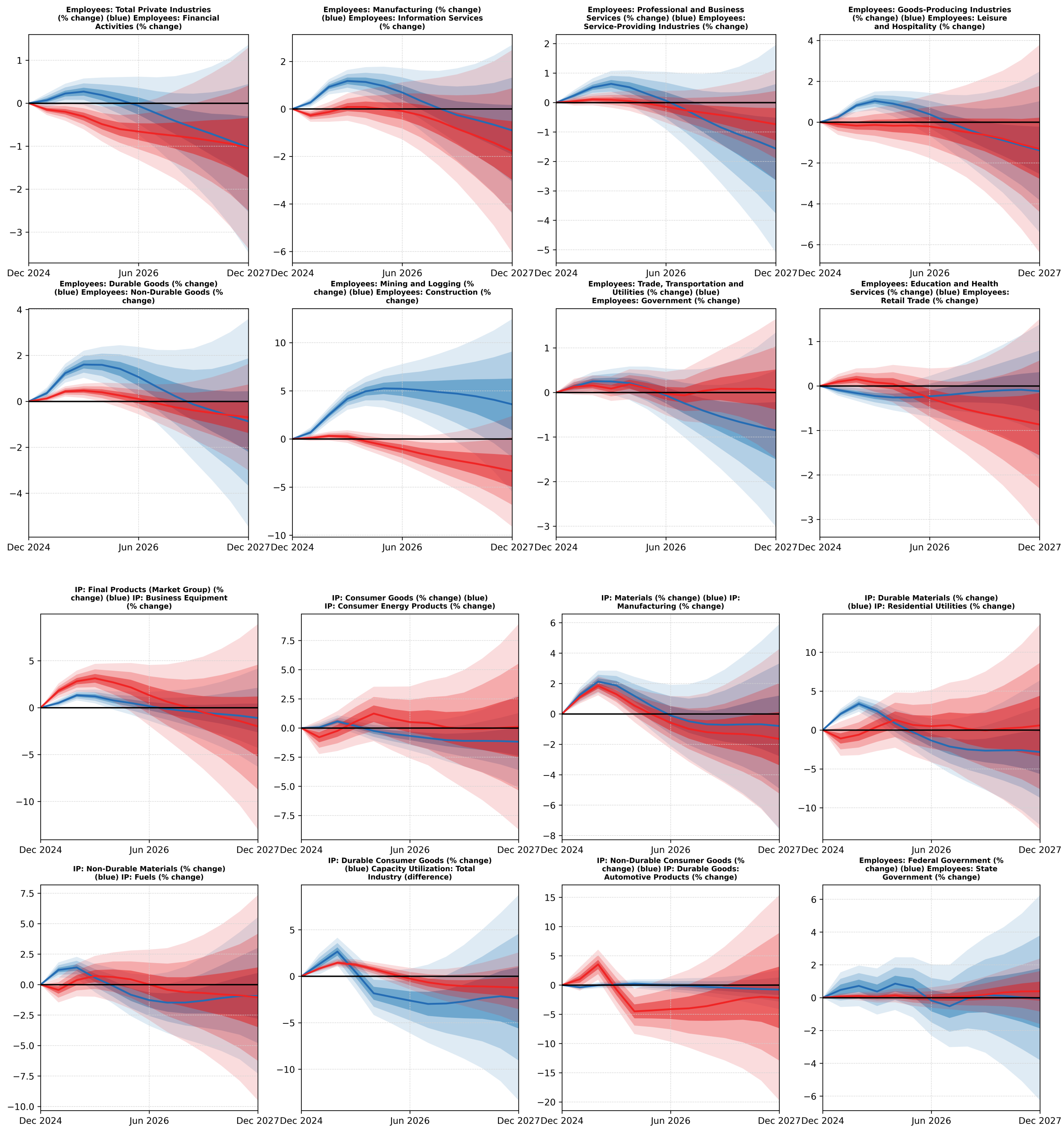


Figure 7c. Responses of various measures of employment and industrial production when the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports.

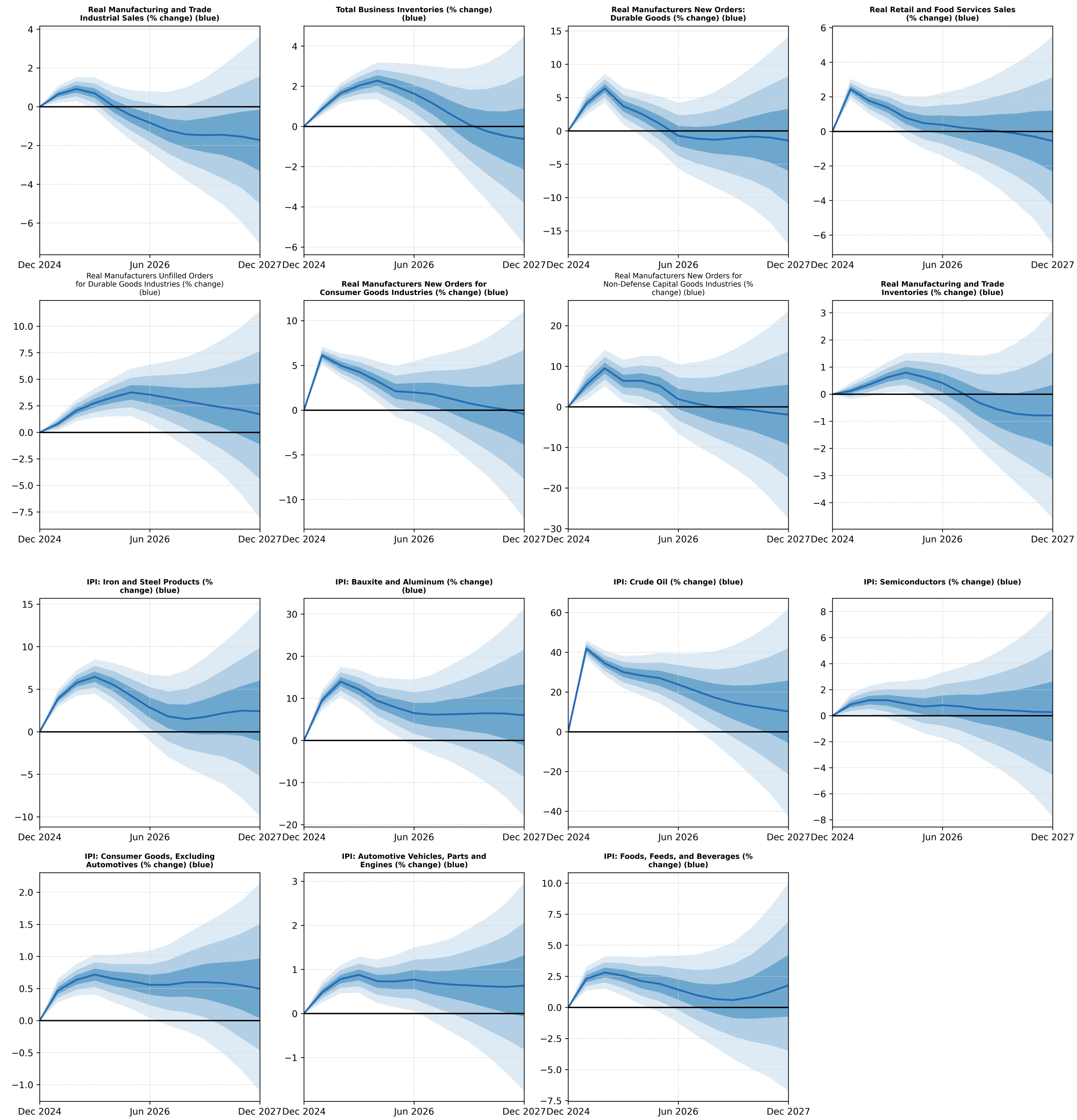


Figure 7d. Responses of various measures of inventories, orders and sales, and sectoral import price indices when the import price index rises in Q1-2025 by 8.61% after imposing a 20% tariff on all Chinese imports and 25% tariff on Mexican and Canadian imports.

Table 1 summarizes the average elasticities or responses of variables in the three pricing sectors - PCE, CPI, and PCE over the course of a year Q2-2024 to Q2-2025. In other words, rather than examining the immediate median response, say at Q2-2025, the tabular values capture the average growth rate of each variable over the four quarters after import price index rises. This is pertinent because certain variables may may be sticky in the short run and rise with a lag after a few quarters, while others may immediately adjust to multiple shocks, and reverse course thereafter. Averaging the quarterly elasticities smooths out the quarterly information, capturing the annual responsiveness sustained during a year across the sectors. Broadly, all goods categories respond more strongly than services, while total services, and its components such as health care, housing and utilities are less elastic over a year. From the producer's point of view, upstream commodities such as fuels, copper and copper products, and all metals are highly sensitive.

Personal Consumption Expenditure		**Consumer Price Index – Urban**		**Producer Price Index**	
Variable	**Elasticity**	**Variable**	**Elasticity**	**Variable**	**Elasticity**
Non-Durable Goods	1.98	Transportation	3.09	Copper and Copper Products	10.81
Goods	1.53	Commodities	1.70	Fuels and Related Products	10.27
Transportation Services	1.09	All Items Less Shelter	1.23	Metals and Metal Products	4.41
Furnishings & Durable Household Equipment	0.78	All Items Less Medical Care	0.88	Industrial Commodities	4.41
Food & Beverages Purchased for Off-Premises Consumption	0.75	Durables	0.38	Intermediate Materials & Supplies	4.08
Recreational Goods and Vehicles	0.63	Apparel	0.37	All Commodities	3.99
Durable Goods	0.58	Services	0.24	Finished Consumer Goods	1.92
Clothing and Footwear	0.46	Owners' Equivalent Rent of Residences	0.00	Finished Goods	1.58
Motor Vehicles and Parts	0.38	Medical Care	–0.13	Finished Consumer Foods	1.20
Services: Household Consumption Expenditures	0.30			Semiconductor & Other Electronic Components	0.15
Services	0.29			Pharmaceutical & Medicine Mfg.	–1.09
Recreation Services	0.29				
Health Care	0.28				
Housing and Utilities	0.22				
Financial Services and Insurance	0.14				

Table 1. Median elasticities of PCE, CPI-U, and PPI subcomponents, averaged over the quarterly median responses from Q2 2025 to Q2 2026 (year-over-year growth rates). Within each pricing category, items are ordered from most to least responsive.

7. Beyond the Trade-Weighted Dollar Index: A COVID-Volatility BVAR Approach to Building a Forex Trade Index

In 2022, the US dollar heavily appreciated against those of major developed and emerging markets, accelerating both the broad and narrow real effect of the exchange rate of the US to reach their apex levels since the 1980s. Crucially, movements in exchange rates influence domestic economic activity via the financial and real channels. On the real side, trade captured by increased net exports boosts the domestic real economy when the US dollar depreciates, whereas, on the financial side, changes in exchange rates alter valuations and adjust balance sheet, shifting the amount of risk that investors take while transacting with financial and real assets. Unlike the real channel, the appreciated US dollar spurs foreign investment locally as balance sheets strengthen, boosting the real activity.

Likewise, trade-weighted dollar indices such as the real and nominal broad dollar index and nominal emerging market economies US dollar index spiked. Also known as the broad index, the trade-weighted dollar index measures the value of the US dollar relative to that of other currencies in the world. This helps to evaluate the overall impact of fluctuations in the US dollar on international trade, and there are two approaches to defining it - using the nominal exchanges, and real exchange rates. In the former, the Fed computes them by taking the geometric mean of the bilateral exchange rates of the currencies of its major trading partners, where it assigns weight using trade data - imports and exports of goods and services of each country w.r.t the US. So, the model gives the largest weight to Euro Area with the largest bilateral trade with the US at 16.5 percent (as of 2017), followed by China, totaling 26 countries in their index. Alternatively, the index based on real exchange rates adjusts for a measure of the inflation rate - the consumer price index of the individual countries relative to that of the US. The formula for the nominal trade-weighted dollar index, also known as the Nominal Broad Index is

$$I_t = I_{t-1} \times \prod_{j=1}^{N_t} \left(\frac{e_{j,t}}{e_{j,t-1}} \right)^{w_{j,t}}$$

where, I_t is the value of the index at time t,

- N_t is the number of currencies included in the index at time t,
- $e_{j,t}$ is the amount of currency j needed to buy one USD at time t,
- $w_{j,t}$ is the weight assigned to currency j based on the trade share at time t.

Rewriting in logs returns a weighted average of log changes in bilateral exchange rates:

$$\log(I_t) - \log(I_{t-1}) = \sum_{j=1}^{N_t} w_{j,t} \left[\log(e_{j,t}) - \log(e_{j,t-1})\right]$$

A few downsides of this geometric mean approach to constructing the index is as follows. First, it assumes that the model is dynamically homogeneous - all variables respond at the same time when a currency appreciates or depreciates, disregarding the phenomenon that certain currencies react slower or faster than others to changes in shocks. In reality, the central banks of some countries like China tightly manage their currencies; and others float and respond immediately such as the pound and euro. Shocks may be persistent and may propagate with a delay due to interest rate differentials, changing trade flows and capital account channels. Second, because the index isn't modeled, it doesn't respond to changes in the US federal funds rate, global risks, trade policy shocks. Third, the index assumes that exchange rates move independently, whereas in reality, many currencies co-move (example, USD to Australian Dollar, and USD to New Zealand Dollar)

To allow the variables to respond heterogeneously across times to any financial and economic shocks, I fit a large BVAR model with ninety-nine variables comprising of macroeconomic variables, financial intermediation variables, bilateral exchange rates, import and export price indices, trade balance of goods on a balance of payment basis, and trade data on US imports and exports of goods with seventeen major trading partners - China, Canada, Mexico, Japan, U.K., South Korea, India, Switzerland, Taiwan, Australia, Malaysia, Thailand, Indonesia, Sweden, Hong Kong, Brazil, and Israel. The complete list of trade variables and the transformations applied are in Appendix A3. I follow the methods of Crump et al. (2021) who construct a financial conditions index. Recall the BVAR(p):

$$y_t = \alpha + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \eta_t \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma)$$

Let the vector of orthogonal structural shocks be $u_t \sim N(0, I_{n\times n})$, where $E[u_t u_t'] = 0$.

The reduced form shocks from above are a linear combination of structural shocks as follows:

$$\epsilon_t = B u_t$$

where B is a lower triangular structural impact matrix that saves the contemporaneous responses to shocks such that $BB' = \Sigma$.

I partition the variables into 3 blocks, arranging the variables in the order - macro, trade, and financials. Macro variable, such as the federal funds rate influence exchange rates contemporaneously, but the opposite is not true. For example, a rise in the federal funds rate makes the dollar-denominated assets more attractive, and foreign investors seek more US dollars to invest locally, appreciating the currency, while making the exports expensive to foreign buyers, weakening the competitiveness of US goods in global markets. Consequently, changing domestic macroeconomic conditions have repercussions in the foreign exchange and trade market, influencing the dollar indices. So, I recursively identify the structural shocks, assuming that the variables earlier affect those ordered later contemporaneously.

$$y_t = \begin{bmatrix} y_t^{\text{macro}} \\ y_t^{\text{trade}} \\ y_t^{\text{fin}} \end{bmatrix}$$

To build the index from the large BVAR model, I isolate a specific set of structural "trade" shocks by zeroing out the columns of the Cholesky factor that correspond to the other blocks, namely macro and financial variables. The partitioned variance-covariance matrix is

$$\Sigma = \begin{bmatrix} \Sigma_{\text{mac, mac}} & \Sigma_{\text{mac, tra}} & \Sigma_{\text{mac, fin}} \\ \Sigma_{\text{tra, mac}} & \Sigma_{\text{tra, tra}} & \Sigma_{\text{tra, fin}} \\ \Sigma_{\text{fin, mac}} & \Sigma_{\text{fin, tra}} & \Sigma_{\text{fin, fin}} \end{bmatrix}$$

where, each element of Σ_{ij} describes how variable i responds to shock j.

I assume that trade shocks are uncorrelated with macro and financial shocks, and set all macroeconomic and financial shocks to zero.

$$\Sigma_{\text{tra, tra}} \neq 0 \quad \text{and} \quad \Sigma_{i,j} = 0 \quad \forall\, i, j \in \{\text{macro, fin, trade}\}, \quad \text{for all other elements}$$

I define the restricted structural covariance matrix as:

$$\hat{\Sigma} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \Sigma_{\text{tra, tra}} & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$u_t^{\text{macro}} = u_t^{\text{fin}} = 0$$

$$u_t^{\text{tra}} \sim \mathcal{N}\left(0, I_{n-n_{\text{fin}}}\right)$$

where, $n - n_{\text{fin}}$ is the total number of trade variables

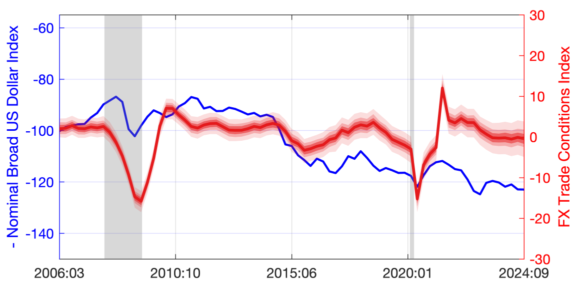
This isolates the pure effects of trade shocks, and propagates only the trade shocks through the system. To create the Forex Trade Index, I simulate the counterfactual history of industrial production growth given the known paths of the trade variables and the first five observations of macro and financial variables. So, the new index is the conditional forecast of industrial production index and can be structurally interpreted, reflecting how trade conditions affect the real economy.

Conditioning on structural shocks, I contrast the Forex Trade Index generated from the large BVAR model with the real and nominal broad dollar indices[1], respectively, in Figure 15. Shown in double axes, where the

[1]The real broad dollar index is available from January 2006 onwards as the Fed adjusted the index by weighting countries by the total bilateral trade, removed Venezuela, and included Vietnam in its calculation. On the other hand, the series on trade-weighted dollar index is available till January 1, 2021, and was subsequently supplanted by the nominal broad US dollar

right side represents the values for the BVAR Forex Trade Index, and the left side represents the values for the dollar indices generated by the Fed, I multiplied these by -1. The Forex Trade Index is more volatile than the other two indices, as also evidenced by the deep plunge during the 2008 GFC, and 2020 COVID-19 pandemic crises. Yet they are overall correlated and move in tandem with the other indices.

Stark differences emerge in the paths of dollar indices and the model-generated Forex Trade Index as they don't overlap. This is because they capture different information and serve different purposes. Note that the Broad Dollar Indices utilize only observed exchange rates with weights adjusted yearly and are devoid of any propagation effects or transmission channels, making it more suited to track the dollar's purchasing power or competitiveness in the global landscape. Alternatively, the BVAR models how trade shocks affect macro outcomes, includes heterogeneous dynamics, and account for the lead-lag relationships. Thereby, the BVAR Forex Trade Index is apt to measure the impact of trade shocks on the real economy.



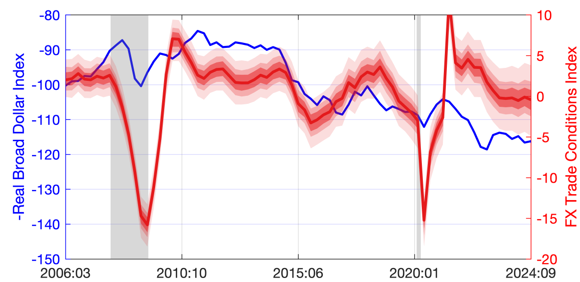


Figure 8. Comparison of the model-constructed foreign exchange dollar index with the nominal broad dollar index (left), and real broad dollar index (right). The red shaded regions around the BVAR generated index are the coverage intervals at 90, 80, and 70 percentiles, depicting uncertainty around the counterfactual median paths.

8. Conclusion

In this chapter, I dived deep into the interplay between international economic indicators, financial intermediation, and business cycles in the US. Using a large BVAR with COVID-Volatility, I document new stylized facts on the cyclical nature of capital flow, and trade variables. Building on these facts, I probe into the aggregate and sectoral effects of tariffs through a novel mechanism - changes in import price index. To extrapolate the effects of tariffs, I recursively identified a cost-push shock by conditioning on the hike in import price index, while affixing macro aggregates on impact. This enables us to structurally interpret the scenario, revealing stagflationary responses of macroeconomic variables that are consistent with historical episodes and existing DSGE based forecasts. Other application questions that are outside the scope of this paper but are worth exploring are as follows. Do higher tariffs in the aggregate economy or targeted to a

index.

sector feed into labor demand and wages, exhibiting wage-price spiral in certain industries such as leisure and hospitality, manufacturing and construction? Can shocks in one category spill over into other sectors? In other other words, if durable goods inflation spikes, do the historical correlations show evidence of changes in services inflation down the line? From a methodological standpoint, one promising direction will be to blend sign and zero restrictions, as shown in Rubio-Ramirez and Waggoner (2018), to precisely disentangle the tariff shocks from other supply or demand disturbances. Another way to identify can be to use exogenous tariff events or announcements as instruments for structural shocks, akin to Narrative VARs. Additionally, we could model spillover effects of initial and retaliatory tariffs across the world economy using a Global Bayesian VAR (G-BVAR). It can consist of a multi-country VAR with data on domestic and foreign variables, or weighted averages of foreign variables, that captures how countries' macroeconomies are interdependent. Such a model can capture the spillover effects of tariffs from the US to the top trading US partners, and gauge feedback loops - how shocks to the US IPI affects foreign measures of inflation, output, employment, trade balances and capital flows.

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Appendix

A1. Description of Quarterly Macro, Financial, and Internactional Economic Variables

Series Name	Units	Transformation	isFinancial	Prior
Real Gross Domestic Product	Billions of Chained 2017 Dollars	100×log	0	RW
Real Personal Consumption Expenditures	Billions of Chained 2017 Dollars	100×log	0	RW
Real Disposable Personal Income	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Private Non-Residential Fixed Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Real Government Consumption Expenditures and Gross Investment	Billions of Chained 2017 Dollars	100×log	0	RW
Industrial Production Index	Index 2017=100	100×log	0	RW
Capacity Utilization: Manufacturing	Percent of Capacity	Raw	0	RW
Housing Starts	Thousands of Units	100×log	0	RW
All Employees, Total Nonfarm	Thousands of Persons	100×log	0	RW
Civilian Unemployment Rate	Percent	Raw	0	RW
Business Sector: Real Compensation Per Hour	Index 2017=100	100×log	0	RW
GDP Deflator	Index 2017=100	100×log	0	RW
PCE: Chain-Type Price Index	Index 2017=100	100×log	0	RW
PCE Excluding Food and Energy	Index 2017=100	100×log	0	RW
CPI: All Items	Index 1982–1984=100	100×log	0	RW
CPI-Urban: All Items Less Food and Energy	Index	100×log	0	RW
Crude Oil, spliced WTI and Cushing	Dollars per Barrel	100×log	1	RW
10-Year Treasury Note Yield	Percent	Raw	1	RW
1-Year Treasury Bond Yield	Percent	Raw	1	RW
5-Year Treasury Bond Yield	Percent	Raw	1	RW
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw	1	RW
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw	1	RW
Real Exports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
Real Imports of Goods and Services	Billions of Chained 2017 Dollars	100×log	0	RW
S&P 500 Index	Index	100×log	1	RW
CBOE Volatility Index: VIX	Index	100×log	1	WN
University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	100×log	0	RW
Real M1 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real M2 Stock	Billions of 1982-84 Dollars	100×log	1	RW
Real Commercial and Industrial Loans	Billions of 2017 US Dollars	100×log	1	RW
Real Consumer Loans at All Commercial Banks	Billions of 2017 US Dollars	100×log	1	RW
Real Real Estate Loans	Billions of 2017 US Dollars	100×log	1	RW
Total Consumer Credit Outstanding	Billions of 2017 Dollars	100×log	1	RW
Total Real Non Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Real Revolving Credit Owned and Securitized	Billions of 2017 Dollars	100×log	1	RW
Total Consumer Loans and Leases Outstanding Owned and Securitized by Finance Companies	Millions of Dollars	100×log	1	RW
Federal Funds Rate	Percent	Raw	0	RW
30-Year Fixed Rate Mortgage Average	Percent	Raw	1	RW
Debt Securities and Loans; Liabilities (All Sectors)	Billions of Dollars	100×log	1	RW
Import Price Index: All Commodities	Index 2000=100	100×log	0	RW
Export Price Index: All Commodities	Index 2000=100	100×log	0	RW
Federal Debt Held by Foreign and International Investors	Millions of Dollars	100×log	1	RW
Treasury Securities Held by Foreign Official Institutions	Millions of Dollars	100×log	1	RW
10-Year Govt. Bond Yield, UK	Percent	Raw	1	RW
10-Year Govt. Bond Yield, Germany	Percent	Raw	1	RW

A2. Description of 127 Sector-Specific Variables

Series Name	Units	Transformation
Capacity Utilization: Manufacturing	Percent of Capacity	Raw
Non-Farm Business Sector: Real output	Index 2017=100	100×log
Business Sector: Real Output	Index 2017=100	100×log
Capacity Utilization: Total Industry	Percent of Capacity	Raw
Manufacturing Sector: Real Output	Index 2017=100	100×log
IP: Final Products (Market Group)	Index 2017=100	100×log
IP: Consumer Goods	Index 2017=100	100×log
IP: Materials	Index 2017=100	100×log
IP: Durable Materials	Index 2017=100	100×log
IP: Non-Durable Materials	Index 2017=100	100×log
IP: Durable Consumer Goods	Index 2017=100	100×log
IP: Durable Goods: Automotive Products	Index 2017=100	100×log
IP: Non-Durable Consumer Goods	Index 2017=100	100×log
IP: Business Equipment	Index 2017=100	100×log
IP: Consumer Energy Products	Index 2017=100	100×log
IP: Manufacturing	Index 2017=100	100×log
IP: Residential Utilities	Index 2017=100	100×log
IP: Fuels	Index 2017=100	100×log
Employees: Total Private Industries	Thousands of Persons	100×log
Employees: Manufacturing	Thousands of Persons	100×log
Employees: Service-Providing Industries	Thousands of Persons	100×log
Employees: Goods-Producing Industries	Thousands of Persons	100×log
Employees: Durable Goods	Thousands of Persons	100×log
Employees: Non-Durable Goods	Thousands of Persons	100×log
Employees: Construction	Thousands of Persons	100×log
Employees: Education and Health Services	Thousands of Persons	100×log
Employees: Financial Activities	Thousands of Persons	100×log
Employees: Information Services	Thousands of Persons	100×log
Employees: Professional and Business Services	Thousands of Persons	100×log
Employees: Leisure and Hospitality	Thousands of Persons	100×log
Employees: Other Services	Thousands of Persons	100×log
Employees: Mining and Logging	Thousands of Persons	100×log
Employees: Trade, Transportation and Utilities	Thousands of Persons	100×log
Employees: Government	Thousands of Persons	100×log
Employees: Retail Trade	Thousands of Persons	100×log
Employees: Wholesale Trade	Thousands of Persons	100×log
Employees: Federal Government	Thousands of Persons	100×log
Employees: State Government	Thousands of Persons	100×log
Employees: Local Government	Thousands of Persons	100×log
Real Manufacturing and Trade Industrial Sales	Millions of Chained 2017 Dollars	100×log

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Series Name	**Units**	**Transformation**
Real Retail and Food Services Sales	Millions of Chained 2017 Dollars	100×log
Real Manufacturers New Orders: Durable Goods	Millions of 2017 Dollars	100×log
Real Manufacturers New Orders for Consumer Goods Industries	Millions of 2017 Dollars	100×log
Real Manufacturers Unfilled Orders for Durable Goods Industries	Millions of 2017 Dollars	100×log
Real Manufacturers New Orders for Non-Defense Capital Goods Industries	Millions of 2017 Dollars	100×log
Real Manufacturing and Trade Inventories	Millions of 2017 Dollars	100×log
Total Business Inventories	Millions of 2017 Dollars	100×log
Total Business: Inventories to Sales Ratio	Ratio	100×log
PCE: Goods	Index 2017=100	100×log
PCE: Durable Goods	Index 2017=100	100×log
PCE: Services	Index 2017=100	100×log
PCE: Non-Durable Goods	Index 2017=100	100×log
PCE: Services: Household Consumption Expenditures	Index 2017=100	100×log
PCE: Motor Vehicles and Parts	Index 2017=100	100×log
PCE: Furnishings and Durable Household Equipment	Index 2017=100	100×log
PCE: Recreational Goods and Vehicles	Index 2017=100	100×log
PCE: Other Durable Goods	Index 2017=100	100×log
PCE: Food and Beverages Purchased for Off-Premises Consumption	Index 2017=100	100×log
PCE: Clothing and Footwear	Index 2017=100	100×log
PCE: Gasoline and Other Energy Products	Index 2017=100	100×log
PCE: Other Non-Durable Goods	Index 2017=100	100×log
PCE: Housing and Utilities	Index 2017=100	100×log
PCE: Health Care	Index 2017=100	100×log
PCE: Transportation Services	Index 2017=100	100×log
PCE: Recreation Services	Index 2017=100	100×log
PCE: Food Services and Accomodations	Index 2017=100	100×log
PCE: Financial Services and Insurance	Index 2017=100	100×log
PCE: Other Services	Index 2017=100	100×log
CPI-Urban: Apparel	Index 1982-84=100	100×log
CPI-Urban: Transportation	Index 1982-84=100	100×log
CPI-Urban: Medical Care	Index 1982-84=100	100×log
CPI-Urban: Commodities	Index 1982-84=100	100×log
CPI-Urban: Durables	Index 1982-84=100	100×log
CPI-Urban: Services	Index 1982-84=100	100×log
CPI-Urban: All Items Less Shelter	Index 1982-84=100	100×log
CPI-Urban: All Items Less Medical Care	Index 1982-84=100	100×log
CPI-Urban: Owners Equivalent Rent of Residences	Index 1982-84=100	100×log

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Series Name	**Units**	**Transformation**
PPI for Finished Goods	Index 1982=100	100×log
PPI for All Commodities	Index 1982=100	100×log
PPI for Finished Consumer Goods	Index 1982=100	100×log
PPI for Finished Consumer Foods	Index 1982=100	100×log
PPI: Industrial Commodities	Index 1982=100	100×log
PPI for Intermediate Materials: Supplies and Components	Index 1982=100	100×log
PPI for Fuels and Related Products and Power: Natural Gas	Index 1982=100	100×log
PPI for Fuels and Related Products and Power: Crude Petroleum	Index 1982=100	100×log
PPI: Crude Materials for Further Processing	Index 1982=100	100×log
PPI: Commodities: Primary Non-Ferrous Metals	Index 1982=100	100×log
Real Average Hourly Earnings: Total Private	Dollars Per Hour	100×log
Real Average Hourly Earnings: Construction	Dollars Per Hour	100×log
Real Average Hourly Earnings: Manufacturing	Dollars Per Hour	100×log
Non-Farm Business Sector: Real Compensation Per Hour	Index 2017=100	100×log
Manufacturing Sector: Real Output Per Hour	Index 2017=100	100×log
Non-Farm Business Sector: Real Output Per Hour	Index 2017=100	100×log
Business Sector: Real Output Per Hour	Index 2017=100	100×log
Business Sector: Unit Labor Cost	Index 2017=100	100×log
Manufacturing Sector: Unit Labor Cost	Index 2017=100	100×log
Non-Farm Business Sector: Unit Labor Cost	Index 2017=100	100×log
Non-Farm Business Sector: Unit Non-Labor Payments	Index 2017=100	100×log
Average Hourly Earnings: Goods Producing	Index 2017=100	100×log
10-Year Treasury Note Yield	Percent	Raw
1 Year Treasury Note Yield	Percent	Raw
5 Year Treasury Note Yield	Percent	Raw
Moody Seasoned Aaa Corporate Bond Yield	Percent	Raw
Moody Seasoned Baa Corporate Bond Yield	Percent	Raw
Real Exports of Goods and Services	Billions of Chained 2017 Dollars	100×log
Real Imports of Goods and Services	Billions of Chained 2017 Dollars	100×log
S&P 500 Index	Index	100×log
CBOE Volatility Index: VIX	Index	100×log
University of Michigan: Consumer Sentiment	Index 1st Quarter 1966=100	100×log
30-Year Fixed Rate Mortgage Average	Percent	Raw
Import Price Index: All Commodities	Index 2000=100	100×log
Export Price Index: All Commodities	Index 2000=100	100×log
Imports of Automotive Vehicles, Engines and Parts	Billions of US Dollars	100×log
Imports of Foods, Feeds, and Beverages	Billions of US Dollars	100×log
IP: Pharmaceutical and Medicine	Index 2017=100	100×log
IP: Semiconductor and Other Electronic Components	Index 2017=100	100×log

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Series Name	**Units**	**Transformation**
PPI: Metals and Metal Products	Index 1982=100	100×log
PPI: Copper and Copper Products	Index 1982=100	100×log
PPI: Pharmaceutical and Medicine Manufacturing	Index Dec 1984=100	100×log
PPI: Semiconductor and Other Electronic Component Manufacturing	Index Dec 1984=100	100×log
IPI: Iron and Steel Products	Index 2000=Index	100×log
IPI: Bauxite and Aluminum	Index 2000=Index	100×log
IPI: Crude Oil	Index 2000=Index	100×log
IPI: Semiconductors	Index 2000=Index	100×log
IPI: Consumer Goods, Excluding Automotives	Index 2000=Index	100×log
IPI: Automotive Vehicles, Parts and Engines	Index 2000=Index	100×log
IPI: Foods, Feeds, and Beverages	Index 2000=Index	100×log

A3. Description of Global Trade and Exchange Rate Variables

The large COVID-Volatility BVAR model uses the following variables in addition to the financial and macro variables listed in Appendix A2.

Series Name	**Units**	**Transformation**	**isTrade**	**Prior**
Exports to Indonesia	Millions of Dollars	100×log	1	RW
Exports to Thailand	Millions of Dollars	100×log	1	RW
US Exports to China	Millions of Dollars	100×log	1	RW
Exports to U.K	Millions of Dollars	100×log	1	RW
Exports to Japan	Millions of Dollars	100×log	1	RW
Exports to Canada	Millions of Dollars	100×log	1	RW
Exports to Mexico	Millions of Dollars	100×log	1	RW
Exports to Germany	Millions of Dollars	100×log	1	RW
Exports to India	Millions of Dollars	100×log	1	RW
Exports to France	Millions of Dollars	100×log	1	RW
Exports to Switzerland	Millions of Dollars	100×log	1	RW
Exports to Singapore	Millions of Dollars	100×log	1	RW
Exports to Australia	Millions of Dollars	100×log	1	RW
Exports to Malaysia	Millions of Dollars	100×log	1	RW
Exports to Saudi Arabia	Millions of Dollars	100×log	1	RW
Exports to Sweden	Millions of Dollars	100×log	1	RW
Imports from Thailand	Millions of Dollars	100×log	1	RW
Imports from Mexico	Millions of Dollars	100×log	1	RW
Imports from Japan	Millions of Dollars	100×log	1	RW
Imports from Canada	Millions of Dollars	100×log	1	RW
Imports from China	Millions of Dollars	100×log	1	RW
Imports from Germany	Millions of Dollars	100×log	1	RW
Imports from India	Millions of Dollars	100×log	1	RW
Imports from France	Millions of Dollars	100×log	1	RW
Imports from Switzerland	Millions of Dollars	100×log	1	RW
Imports from UK	Millions of Dollars	100×log	1	RW
Imports from Singapore	Millions of Dollars	100×log	1	RW
Imports from Australia	Millions of Dollars	100×log	1	RW
Imports from Malaysia	Millions of Dollars	100×log	1	RW
Imports from Indonesia	Millions of Dollars	100×log	1	RW
Imports from Saudi Arabia	Millions of Dollars	100×log	1	RW
Imports from Sweden	Millions of Dollars	100×log	1	RW
USD to 1 U.K. Pound Sterling	USD	100×log	1	RW
Japanese Yen to 1 USD	Japanese Yen	100×log	1	RW
Canadian Dollar to 1 USD	Canadian Dollar	100×log	1	RW
Chinese Yuan Renminbi to 1 USD	Chinese Yuan Renminbi	100×log	1	RW
Indian Rupee to 1 USD	Indian Rupee	100×log	1	RW
Swiss Francs to 1 USD	Swiss Francs	100×log	1	RW
Singapore Dollar to 1 USD	Singapore Dollar	100×log	1	RW
USD to 1 Australian Dollar	USD	100×log	1	RW

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Series Name	**Units**	**Transformation**	**isTrade**	**Prior**
Malaysian Ringgit to 1 USD	Malaysian Ringgit	100×log	1	RW
Thai Baht to 1 USD	Thai Baht	100×log	1	RW
Swedish Kronor to 1 USD	Swedish Kronor	100×log	1	RW
Mexican Peso to 1 USD	Mexican Peso	100×log	1	RW
Indonesian Rupiah to 1 USD	Indonesian Rupiah	100×log	1	RW
New Israeli Sheqel to 1 USD	New Israeli Sheqel	100×log	1	RW
Saudi Riyal to 1 USD	Saudi Riyal	100×log	1	RW
Chilean Peso to 1 USD	Chilean Peso	100×log	1	RW
Colombian Peso to 1 USD	Colombian Peso	100×log	1	RW
USD to 1 New Zealand Dollar	USD	100×log	1	RW
Taiwan Dollar to 1 USD	Taiwan Dollar	100×log	1	RW
South Korean Won to 1 USD	South Korean Won	100×log	1	RW
Hong Kong Dollar to 1 USD	Hong Kong Dollar	100×log	1	RW

A4. Derivation: How do Tariffs Affect Import Price Index?

The import price index (IPI), developed by the Bureau of Labor Statistics, is a variation of Laspeyres price index that aggregates the import prices of all commodities. Tariffs influence the IPI through the following relationship:

$$IPI_t = \left(\frac{\sum_i p_{i,t} q_{i,0}}{\sum_i p_{i,0} q_{i,0}} \right) \times 100$$

where:

- $p_{i,t}$ = price of commodity i at time t,
- $q_{i,0}$ = quantity of imports of commodity i in the base year,
- $p_{i,0}$ = price of commodity i in the base year 2000.

This is a fixed-base quantity index.

To model the effects of tariffs at the country level, introduce the (commodity, country) pair (i, j).

$$IPI_t = \left(\frac{\sum_{i,j} p_{i,j,t} q_{i,j,0}}{\sum_{i,j} p_{i,j,0} q_{i,j,0}} \right) \times 100$$

where:

- $p_{i,j,t}$ = price of commodity i from country j at time t,
- $q_{i,j,0}$ = quantity of imports of commodity i from country j in the base year,
- $p_{i,j,0}$ = price of commodity i from country j in the base year.

Since base-year prices and quantities are fixed:

$$\frac{1}{100} \sum_{i,j} p_{i,j,0} q_{i,j,0} = D \quad \text{(constant)}$$

Thus,

$$IPI_t \propto \sum_{i,j} p_{i,j,t} q_{i,j,0}$$

When we impose tariff, the import price adjusts according to:

$$p_{i,j,t}^{\text{new}} = p_{i,j,t}^{\text{old}} \left(1 + T_{j,t}\lambda\right)$$

where:

- $T_{j,t}$ = tariff rate on country j at time t,
- λ = pass-through rate of tariffs to import prices.

The new import price index is:

$$IPI_t^{\text{new}} = \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{new}} q_{i,j,0}$$

Substitute the tariff-adjusted price.

$$= \frac{1}{D} \sum_{i,j} \left[p_{i,j,t}^{\text{old}}(1 + T_{j,t}\lambda)\right] q_{i,j,0}$$

$$= \frac{1}{D} \sum_{i,j} \left[p_{i,j,t}^{\text{old}} q_{i,j,0} + p_{i,j,t}^{\text{old}} T_{j,t}\lambda q_{i,j,0}\right]$$

$$IPI_t^{\text{new}} = \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} q_{i,j,0} + \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} T_{j,t}\lambda q_{i,j,0}$$

The change in the import price index is

$$\Delta IPI_t = IPI_t^{\text{new}} - IPI_t^{\text{old}}$$

Substitute:

$$= \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} q_{i,j,0} + \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} T_{j,t}\lambda q_{i,j,0} - \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} q_{i,j,0}$$

The first terms cancel out.

$$\therefore \Delta IPI_t = \frac{1}{D} \sum_{i,j} p_{i,j,t}^{\text{old}} T_{j,t}\lambda q_{i,j,0}$$

$$= \frac{100\lambda}{\sum_{i,j} p_{i,j,0} q_{i,j,0}} \sum_{i,j} p_{i,j,t}^{\text{old}} T_{j,t} q_{i,j,0}$$

$$= 100\lambda \frac{\sum_j T_{j,t} \sum_i p_{i,j,t}^{\text{old}} q_{i,j,0}}{\sum_{i,j} p_{i,j,0} q_{i,j,0}}$$

Where, for each country j, we sum over commodities i:

$$\Rightarrow \Delta IPI_t = 100\lambda \sum_j T_{j,t} \left(\frac{\sum_i p^{\text{old}}_{i,j,0} q_{i,j,0}}{\sum_{i,j} p_{i,j,0} q_{i,j,0}} \right)$$

$$\approx 100\lambda \sum_j T_{j,t} \left(\frac{\sum_i p^{\text{old}}_{i,j,0} q_{i,j,t}}{\sum_{i,j} p_{i,j,0} q_{i,j,t}} \right)$$

Define the base-year import share for country j as

$$w_{j,t} = \frac{\sum_i p^{\text{old}}_{i,j,0} q_{i,j,t}}{\sum_{i,j} p_{i,j,0} q_{i,j,t}}$$

Thus,

$$\therefore \Delta IPI_t \approx \left(\sum_j \lambda T_{j,t} w_{j,t} \right) \times 100$$

For a single country j, the contribution to the change in the import price index at time t is

$$\boxed{\Delta IPI_{j,t} = \left(\lambda T_{j,t} w_{j,t}\right) \times 100}$$