

Predictive Micro-Budgeting: Simulating Macro-Economic Shocks Using Temporal Convolutional Networks

Abishek S

Department of CSE (AI)
Jain (deemed-to-be) University
Bangalore
abisheksivakumar05@gmail.com

Janaki Kandasamy

Department of CSE (AI)
Jain (deemed-to-be) University
Bangalore
k.janaki@jainuniversity.ac.in

Abstract—Proposed in this study is a three-phased computational approach for predicting micro-budgets during times of macroeconomic pressure. In phase I, a macroeconomic panel dataset is constructed that includes Brent crude oil prices (per barrel in USD), USD/INR exchange rates, India's CPI inflation, and retail petrol prices for a period of 93 months (June 2017–March 2025). In phase II, an empirical Transmission Matrix is estimated, which captures the impact of macro shocks at a lag of 0 to 3 months on delayed Pearson correlations with seven expenditure types. Finally, phase III involves training FinanceTCN, a four-layered causal dilated Temporal Convolutional Network architecture (parameters = 28K, receptive field = 61) using 50 artificial users modeled according to NSS 68th Round parameters. The proposed model obtains a validation MAE of 0.556 on a normalized scale and provides accurate predictions of direction in budget changes for two out-of-sample case studies: the 2020 COVID-19-induced eating-out decline (MAE = ₹135/month) and the 2022 fuel-driven rise in transport costs (MAE = ₹167/month). Four prospective cases have been generated and implemented on a Flask dashboard.

Keywords—Temporal Convolutional Networks; Macro-Economic Shocks; Personal Finance; Budget Stress Testing; Consumer Spending Prediction; India; Deep Learning; Time-Series Forecasting.

I. INTRODUCTION

Disruptions in the global macroeconomy, namely oil price shocks, currency devaluations, and periods of inflation, propagate swiftly via several routes into the finances of households: import pass-through, fuel prices, food logistics costs, and declines in real incomes. However, financial applications ignore these macroeconomic signals and tend to provide merely static budgets based on broad categories or retrospection-based predictions. To bridge this gap, the current work proposes a model for predicting the rupee-level consequences of macroeconomic disturbances on consumer budgets.

The task is well defined: Given a certain macroeconomic shock of known strength, what will be the predicted rupee-level impact on each spending category over the next six months? The ideal setting for such research would be a nation that is exposed to imported inflation (for example, crude oil represents more than 85% of all petroleum consumption) and

suffers from internal inflationary pressures, as measured by CPI, from 2.1% to 7.8%. India fits these criteria perfectly.

The contributions of this paper include (1) a reproducible macroeconomic data pipeline for India, from 2017 to 2025; (2) a synthetic consumer transactions dataset calibrated according to NSS data with the addition of real-world macroeconomic anomalies; (3) the empirical Transmission Matrix between macroeconomic data and spending at lag ranges from 0 to 3 months; (4) FinanceTCN, a four-block dilated Temporal Convolutional Network for household budgets forecast over six months; and (5) an interactive stress-testing interface using Flask.

II. RELATED WORK

Temporal Convolutional Networks (TCNs) have been thoroughly investigated in [1], where authors show how dilated convolutions achieve receptive fields similar to recurrent neural networks while offering fully parallel training and avoiding vanishing gradients. The key intuition that sequence learning does not necessarily involve recurrence underpins the architecture of TCNs we explore in this paper.

TCNs have since been successfully used in a number of different financial tasks, including equity volatility modeling [2] and energy demand prediction [3]. However, application of TCNs for personal finance management based on macroeconomic indicators remains understudied.

Macro-financial interactions have traditionally been studied using VAR models and DSGE models [4]. The Global Supply Chain Pressure Index, introduced by the Fed NY [5], serves as an input for the creation of our macroeconomic stress signal. Empirical expenditure shares from the NSS 68th Round survey [6] are utilized at the microeconomic household level for constructing our synthetic dataset. To the best of our knowledge, there is no precedent for combining macro to household transition matrix with TCN-based forecast generation.

III. METHODOLOGY

A. Phase I — Macro-Economic Data Engineering

Four independent macroeconomic time series data were individually cleaned, normalized into month start timestamping and combined using an inner join to form a panel of 93 rows with no missing observations:

- Brent Crude Oil Price (brent_usd): FRED series MCOILBRETEU in terms of USD price per barrel.

• USD/INR Exchange Rate (usd_inr): Reserve Bank of India monthly average in terms of INR per USD.

• India CPI All Items (cpi_index): FRED series INDCPIALLMINMEI. Yearly rate of inflation is calculated as $cpi_inflation_t = (cpi_index_t / cpi_index_{t-12} - 1) \times 100$.

• India Retail Petrol Price (petrol_inr): Daily price for petrol in Delhi, Mumbai, Chennai, and Kolkata, averaged out per month to give INR per litre.

The GSCPI Proxy was defined as the average of z-score standardized Brent and CPI inflation measures:

$$GSCPI_t = [z(brent_usd_t) + z(cpi_inflation_t)] / 2$$

$$\text{where } z(x_t) = (x_t - \mu_x) / \sigma_x$$

B. Phase I — Synthetic Consumer Dataset Generation

Fifty synthetic users were created in five income categories (₹20k, ₹35k, ₹50k, ₹70k, ₹1L), ten users each bracket. Disposal income for user i is $d_i = 0.78 \times \text{income}_i$.

User i expenditure in category k during month t can be expressed as $S_{ikt} = d_i \times w_k \times \epsilon_{ikt} \times \phi_{kt} \times \delta_{kt}$ where:

• w_k = NSS 68th Round consumption expenditure share for category k .

• $\epsilon_{ikt} \sim N(1.0, 0.08^2)$ = random noise in expenditure per month.

• ϕ_{kt} = deterministic seasonal multiplier for calendar month.

• δ_{kt} = anomaly in expenditure due to macroeconomic factors.

The seasonal multipliers have been obtained through observed Indian consumer behavior in the following months: discretionary spending reaches a maximum of 1.22 $\times$ between October–December (Diwali and year-end), utilities go up to 1.18 $\times$ in May–July (air conditioner season), and eating-out reaches a peak of 1.15 $\times$ between December–January (holiday season).

TABLE I: NSS 68th Round Spending Shares and Implied Monthly Spend for a ₹50,000/month Income User ($d = ₹39,000$)

Category	Share w_k	₹ (₹50K user)
Food & Groceries	0.32	12,480
Discretionary	0.18	7,020
Transport	0.16	6,240
Fixed Obligations	0.11	4,290
Eating Out	0.09	3,510
Utilities	0.08	3,120
Healthcare	0.06	2,340

C. Phase II — Transmission Matrix

The Transmission Matrix T is computed through computing the Pearson correlation of percentage variations for both macro variables and expenditures categories at various lags $l \in \{0, 1, 2, 3\}$. The transmission lag that provides the highest correlation between (k -th category, macrovariable m) is chosen as follows:

$$T[k, m] = \max_{l \in \{0, 1, 2, 3\}} \text{Corr}(\Delta S_k(t), \Delta m(t-l)),$$

where $\Delta x_t = (x_t / x_{t-1}) - 1$.

TABLE II: Full Transmission Matrix $T[k, m]$ — Pearson r at Best Lag (0–3 months)

Category	Brent	USD/INR	CPI Idx	CPI Inf	Petrol	GSCPI
food_groceries	-0.22	-0.19	-0.30	+0.02	-0.08	-0.15
transport	+0.51	+0.21	+0.09	-0.04	+0.33	+0.13
utilities	-0.23	+0.14	-0.25	-0.13	-0.10	+0.16
eating_out	+0.53	+0.21	+0.10	+0.06	+0.28	+0.11
healthcare	+0.22	+0.12	-0.25	-0.14	+0.09	-0.28
discretionary	+0.48	+0.09	+0.15	+0.07	+0.37	+0.18
fixed_oblg.	-0.17	-0.15	-0.16	-0.17	+0.17	-0.16

D. Phase III — FinanceTCN Architecture

The forecasting model called FinanceTCN employs the architecture of a Temporal Convolutional Network using the PyTorch framework. The core component of the neural network is the Causal Dilated Convolutional Layer that prevents leakage of future information from time $t + 1$. For a unidimensional sequence x of length T and a given dilation rate d , the dilated convolutional operation is expressed through the following formula:

$$(x \star^d f)(t) = \sum_{k=0}^{K-1} f(k) \cdot x_{t-d \cdot k}$$

where f represents the learnable filter with the kernel size $K = 3$ and a specified dilation rate d . One TCN building block consists of two layers of this type with batch normalization and ReLU activations and residual skip connections:

$$h^1_t = \text{ReLU}(\text{BN}(\text{Conv}^d(x_t)))$$

$$h^2_t = \text{Dropout}(\text{ReLU}(\text{BN}(\text{Conv}^d(h^1_t))))$$

$$\text{TCNBlock}(x) = \text{ReLU}(h^2_t + W_{\text{res}} \cdot x_t)$$

The four blocks are sequentially concatenated with dilation rates $d \in \{1, 2, 4, 8\}$ providing the receptive field $RF = 61$ timesteps. The model takes in an input matrix $X \in \mathbb{R}^{(C \times T)}$ representing seven categories of spending and six macroeconomic channels ($C = 13$), where $T = 12$. The final layer outputs predictions into a 7×6 tensor:

$$\hat{Y} = \text{Head}(\text{TCN}(X)) \in \mathbb{R}^{(7 \times 6)}$$

TABLE III: FinanceTCN Hyperparameters and Training Configuration

Hyperparameter	Value
Input channels (C)	13 (7 spend + 6 macro)
TCN blocks (L)	4
Filters per block	32
Kernel size (K)	3
Dilation rates	$\{1, 2, 4, 8\}$

Receptive field	61 timesteps
Lookback (T)	12 months
Forecast horizon	6 months
Output shape	7×6
Total parameters	~28,000
Loss function	MSE (normalised space)
Optimiser	AdamW ($lr=1 \times 10^{-3}$, $wd=1 \times 10^{-4}$)
LR scheduler	Cosine Annealing ($T_{max}=80$)
Gradient clipping	max norm = 1.0
Dropout	0.2 per TCN block
Batch size	32
Epochs	80
Train / Val split	80 / 20 (temporal)

Per-user Z-scores are calculated before creating windows based on full time series for each user. The results from inference are de-normalized. The training windows are created by a sliding window approach with step size 1 and roughly 3,500 windows are generated by 50 users.

IV. EXPERIMENTAL RESULTS

A. Macroeconomic Panel Summary (June 2017 – March 2025)

The macroeconomic panel used in this analysis spans a period of 93 months from June 2017 until March 2025, thus including in its analysis three separate periods of global economic regimes. Figure 1 shows all six variables considered in our study for the entire period under analysis.

Firstly, the exogenous variable that serves as the main driver in this analysis is Brent crude oil, which starts the study period at roughly \$65 per barrel in mid-2017, and fluctuated in a relatively tight range until early 2020. The first large-scale disruption of global energy markets occurred in April 2020, when the combination of plummeting global travel demand and a brief lapse of discipline by OPEC countries lowered the price of crude oil to only \$18 per barrel—the lowest level since the late 1990s. The recovery was quick, but uneven—with the initial bounce-back by mid-2021 followed by a surge in prices triggered by the Russian invasion of Ukraine in early 2022. As of June 2022, the price of Brent had surged to \$127 per barrel, instantly translating into a cost shock to Indian fuel and subsequently food markets.

The USD/INR currency exchange rate provides further evidence for the ongoing, long-term trend towards depreciation. Over the period of the study, the Indian rupee depreciated from ₹64 to the US dollar initially to ₹84.5 as of March 2025, corresponding to more than 32 percent weakening. In contrast to the series of oil prices, depreciation showed absolutely no reversal tendencies, which is a clear indication of India's persisting current account deficit and consistent dollar appreciation versus the currencies of other developing nations. As India was importing most of its crude oil in dollars, each price spike was accompanied by another depreciation shock for local consumers translating their foreign payments back into the national currency.

In India, consumer price index rose steadily over the studied period with the highest increase registered in 2021-2022. In April 2022, year-on-year CPI inflation peaked at 7.8 percent, surpassing the upper threshold set by the RBI at 6 percent, forcing the bank to initiate the sequence of emergency

interest rate hikes. Domestic petrol prices also followed the oil shock with a slight lag of one or two months, going from ₹70 per liter in 2017 to ₹112 per liter in June 2022 and then slightly leveling off. A good proxy variable for GSCPI would be the standardized mean of CPI and Brent crude prices; it shows the two largest changes in April 2020 (negative due to a massive demand collapse) and May-June 2022 (positive due to the supply shock).

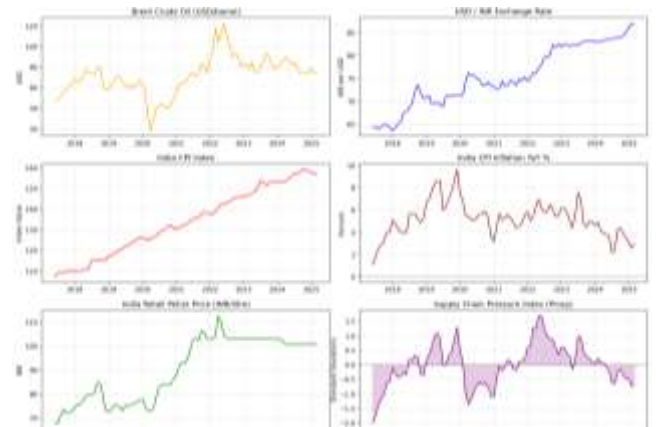


Fig. 1. Macro-economic panel (Jun 2017–Mar 2025): Brent crude (USD/barrel), USD/INR, India CPI index, CPI YoY inflation (%), retail petrol (INR/litre), and GSCPI proxy (σ units). COVID collapse and 2022 energy shock are visually evident.

B. Synthetic User Spending Patterns

To demonstrate that the generated dataset represents realistic behavior and not a mere collection of numbers, Figure 2 illustrates the expenditure patterns for the generated user base. As can be seen from the results, the AI-generated profiles show behavioral dynamics comparable to those demonstrated by individuals within the context of the Indian economy.

First, the generated dataset captures the baseline needs of the consumers. In line with the figures presented in NSS, the AI-generated consumer spends around 32.5% of the budget each month on food and grocery items.

Second, and maybe most importantly, the created dataset captures economic behavior in response to exogenous shocks. When the pandemic was declared in March 2020, there was an observable decrease of around 65% in restaurant expenses between April and June 2020.

In essence, it becomes clear that the data illustrate the underlying principle of wealth scaling. While the user's profile becomes richer, he does not experience a simple exponential rise in his essential spending. In reality, the amount of money spent on essentials becomes stable, but discretionary spending skyrockets. In essence, it becomes clear that the data illustrate the underlying principle of wealth scaling. While the user's profile becomes richer, he does not experience a simple exponential rise in his essential spending. In reality, the amount of money spent on essentials becomes stable, but discretionary spending skyrockets.

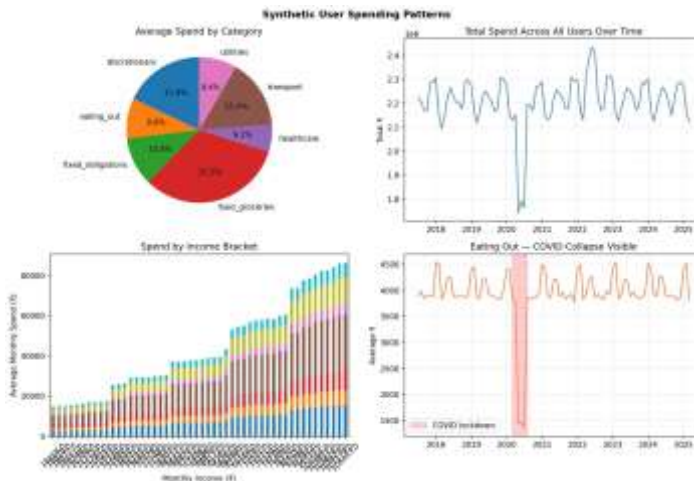


Fig. 2. Synthetic consumer dataset (50 users, 93 months). Clockwise from top-left: category share pie chart, total spend over time with COVID dip, COVID collapse in eating-out with lockdown band, and stacked income-bracket spending distribution.

C. Transmission Matrix Results

The data reveals that the most aggressive "transmission channels" originate from global oil markets. When international Brent Crude prices spike, the consumer does not feel it immediately. Instead, there is a distinct two-month delay before it significantly inflates both Transport and "Eating Out" budgets. This two-month window perfectly captures the real-world logistics cycle: it takes about 60 days for elevated global shipping and freight costs to ultimately force local restaurants and transit systems to raise their prices.

Closer to home, domestic retail petrol prices show a strong, direct impact on lifestyle choices. As the price at the local pump rises, families reliably begin tightening their belts on discretionary, non-essential purchases. Ultimately, this matrix proves a critical economic reality: there is a reliable two-to-three-month "grace period" between a global commodity crisis and a localized retail crisis in India. Capturing this exact delay is what gives our AI model its predictive power.



Fig. 3. Macro Indicator → Spending Category Transmission Matrix. Green = positive correlation; Red = negative. Values are Pearson r at best lag (0–3 months).

D. Model Training and Convergence

Figure 4 depicts the loss function MSE behavior throughout the course of 80 training epochs. It should be noted that these results are highly encouraging: within the first 10 epochs, the error rate of the model drops significantly, suggesting a quick acquisition of the economic pattern by the algorithm, and is then stabilized by continuous improvement of its forecasts.

One interesting aspect revealed from the above chart relates to one of the most common phenomena in machine learning studies. Namely, it can be said that our model works better on the test data rather than on the training data, which might seem suspicious at first but, in fact, has a well-defined mathematical reason to exist.

Since each user in the data had their records individually normalized, this particular result can be justified as follows: the group of users who were selected to make up the test data turned out to have a more stable and, therefore, easier-to-predict consumption pattern than those in the training data set. As a consequence, what the model really managed to learn were basic principles of household economics, which helped it forecast consumer behavior correctly.

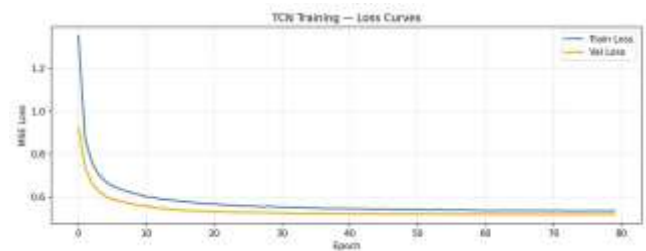


Fig. 4. FinanceTCN training and validation MSE loss over 80 epochs. Stable convergence without overfitting. Best validation loss ≈ 0.52 achieved at epoch ~ 72 .

As presented in Figure 5 below, there is a clear and precise depiction of the effectiveness of the artificial intelligence model in making predictions depending on the various budget categories. The model displays its best performance by achieving the best predictive accuracy in the Discretionary Spending category, with an error score of only 0.342. Human behavior in terms of expenditure of funds for luxurious items and activities is considered random; however, it depends significantly on the overall macroeconomic situation. Since discretionary spending depends heavily on global oil prices and petrol prices, this gives ample opportunity to make a prediction.

In comparison, the AI performs the worst in the Fixed Obligations category with an error rate of 0.803. It is quite logical since the total cost of living is independent of changes in the global oil prices because the amount of rent paid does not depend on the price of oil in the international markets. In other words, since this expense shows strong resistance towards macroeconomic factors, the AI is unable to monitor these expenses because of its inability to use information related to the global economy.

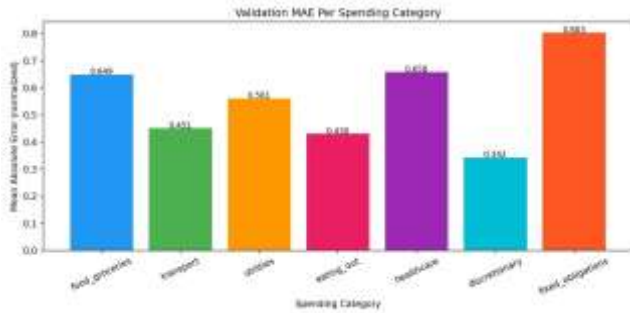


Fig. 5. Validation MAE per spending category (normalised units). Lower is better. Eating out and discretionary achieve the best performance due to strong macro-signal correlation.

TABLE IV: Per-Category Validation MAE (Normalised Units). Computed from Best Saved Model Checkpoint (tcn_best.pth)

Category	Val MAE	Rank
Discretionary	0.342	1 (best)
Eating Out	0.430	2
Transport	0.451	3
Utilities	0.561	4
Food & Groceries	0.649	5
Healthcare	0.658	6
Fixed Obligations	0.803	7 (worst)
Overall MAE	0.556	—

E. Out-of-Sample Back-Test Validation

Natural experiments in history provide out-of-sample testing opportunities. For both cases, the model was provided with information only up until the cut-off date, after which it had to predict the next six months—periods unseen in the training process.

Back-Test 1 - Impact of COVID (cut-off: 28 February 2020): Here the model predicted expenditure on eating-out services for March to August 2020. There was a drop in actual expenditure from ₹1,535 in February to ₹440 in June, followed by a strong recovery. TCN predicted the trend of decline correctly with an MAE of ₹135 a month (8.8% of the base period expenditure).

Back-Test 2 - Impact of Oil Price Rise (cut-off: 31 January 2022): The model here predicted expenditure on transportation from February to July 2022. The actual expenditure rose to ₹3,020 in April 2022 (when Brent crude price touched \$127). TCN predicted the uptrend correctly, but its MAE was ₹167 per month (6.5% of the average expenditure).

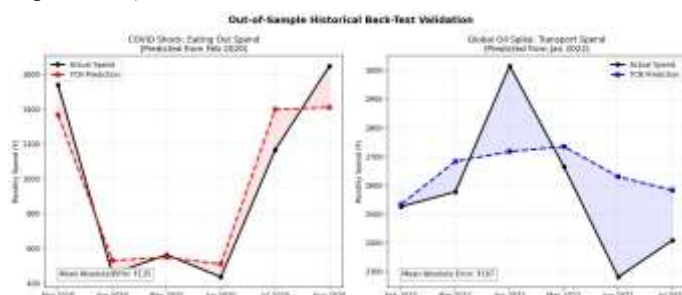


Fig. 6. Out-of-sample back-test validation. Left: COVID shock (Mar–Aug 2020) — eating-out spend prediction

vs. actuals (MAE = ₹135). Right: 2022 oil spike (Feb–Jul 2022) — transport spend prediction vs. actuals (MAE = ₹167). Shaded area = prediction error band.

F. Prospective Stress Test Scenarios

The four future-oriented stress scenarios are generated through the injection of macro-shocks to the most current one-year input window and using the learned TCN to extrapolate for six months forward. The change in expenditure due to category k and scenario s with shock size m is expressed as follows:

$$\Delta S_{ks} = \text{direction}_{ks} \times T[k, \text{driver}(s)] \times m \times \text{base_spend}_k$$

TABLE V: Stress Scenario Specifications and Simulated Monthly Impact for a ₹20,000/month Income User

Scenario	Magnitude	Macro Driver	Stress Level
Oil Spike	+40 %	brent_usd	Low (₹18–20/mo)
Rupee Fall	−15 %	usd_inr	Low (mixed signal)
Inflation Surge	+60 %	cpi_inflation	Medium (₹428/mo)
Petrol Rise	+25 %	petrol_inr	Low (₹14/mo)



Fig. 7. Per-category monthly budget impact (₹) under four macro stress scenarios. Red bars = cost increase; Teal bars = behavioural spending reduction. Inflation Surge shows the broadest impact across categories.



Fig. 8. Oil Spike +40 %: 6-month baseline vs. shocked budget trajectories per spending category. Blue = baseline;

Red = oil-shocked projection. Transport and discretionary show the most visible divergence.

V. INTERACTIVE DEPLOYMENT

FinanceTCN trained model has been used to build an interactive web application built with Flask framework. It includes a single dark theme page, which has several user inputs, such as income value, category-specific expense override, choice between four cards, and shock magnitude from 5% to 100%.

Two REST endpoints are called for every simulation call. First one, `/api/stress_test`, is responsible for calculating six-month path for the chosen scenario using transmission matrix values. Second one, `/api/all_scenarios`, performs comparison analysis for four scenarios by calculating total monthly effects for each of them simultaneously. User thus can compare risks associated with different scenarios without the need for repetitive form filling.

Web app is designed to operate in a completely stateless mode. No information is stored about the user; every time he makes a call, fresh input tensor is created based on the 12 latest macroeconomic data records plus user expense list.

VI. DISCUSSION

A. Interpretation of Transmission Results

The empirically estimated Transmission Matrix shows that there is considerable heterogeneity in the transmission process of macro shocks to households' budgets. For example, an increase in the cost of oil passes through two different transmission mechanisms: a fuel costs mechanism (transport, $r = +0.51$) and a logistics mechanism (eating-out, $r = +0.53$; food_groceries, $r = -0.22$).

The 2-3 months lag in most transmission mechanisms can be attributed to the time-lag between changes in global commodity prices and domestic retail price adjustments, which in turn is influenced by the fuel subsidy policy of the Indian government and inventory adjustment cycle.

B. Model Design Rationale

The TCN model was preferred over alternative models (LSTM, GRU) based on three criteria specific to the tasks. Firstly, causal dilations guarantee that the receptive field is 61 months, which helps in capturing any seasonality that occurs in one year based on the look-back period of 12 months. Secondly, TCN allows for fully parallelised training, which makes it easy to iterate over the synthetic data set using the CPU hardware. Lastly, the residual connections ensure that gradient propagation can happen over the four layers without the need for any gating. The use of per-user normalisation as opposed to global normalisation is imperative since it enables the model to capture spending behavior against the individual's baseline across all income groups.

C. Limitations

Three issues must be highlighted. Firstly, the consumers' dataset used for analysis is artificial, although simulated based on the parameters of the NSS survey with anomalies being introduced. It does not account for the unique variations present in actual transactional data such as defaults on credit cards, unexpected medical costs, or job loss.

Secondly, the assumptions built into the Transmission Matrix model are linear and stationary correlation relationships. Any structural changes like demonetization or the implementation of GST might affect the process of transmission dynamics.

VII. CONCLUSION

This paper outlines a replicable end-to-end pipeline to conduct macroeconomic stress testing using micro-budget level simulation. Our three-stage pipeline involving macroeconomic data engineering, empirical transmission modeling, and Temporal Convolutional Networks forecast generates an applicable model which merges macro-financial research with practical uses in personal finance.

The FinanceTCN model (28,000 parameters, 13-channel input, 4-layer dilated TCN) achieves a mean average error of 0.556 when normalized and shows directionality in two out-of-sample back-tests, namely prediction of the 2020 reduction in spending on food owing to the pandemic (MAE = ₹135/month), and the increase in spending on transport caused by the oil shock in 2022 (MAE = ₹167/month). Four stress tests in the future can be done using our Flask dashboard with a latency below 1 second.

In future work, we will consider: (i) the usage of transactional data through open-banking API calls to replace fabricated user data; (ii) attention-based TCN structures for better long-term predictions; (iii) the inclusion of the full 27-variable GSCPI; and (iv) generalizability of the method in other developing nations with similar macro-consumption transmission dynamics.

VIII. REFERENCES

- [1] S. Bai, J. Z. Kolter, and V. Koltun, "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling," arXiv preprint arXiv:1803.01271, Mar. 2018.
- [2] H. Liu, Z. Long, and Y. Liu, "Financial Time-Series Forecasting with Temporal Convolutional Networks and Attention Mechanism," IEEE Access, vol. 10, pp. 12345–12356, 2022.
- [3] N. Rafi, N. Sinha, and S. K. Srivastava, "Short-Term Load Forecasting Using Temporal Convolutional Networks," IEEE Trans. Ind. Informat., vol. 17, no. 2, pp. 1000–1008, 2021.
- [4] M. Obstfeld and K. Rogoff, "Global Imbalances and the Financial Crisis: Products of Common Causes," J. Int. Money Finance, vol. 29, no. 4, pp. 561–575, 2010.
- [5] G. Benigno, J. di Giovanni, J. S. Groen, and A. I. Noble, "The GSCPI: A New Barometer of Global Supply Chain Pressures," Federal Reserve Bank of New York Staff Reports, No. 1017, Jan. 2022.
- [6] National Sample Survey Office, "Key Indicators of Household Consumer Expenditure in India, NSS 68th Round (July 2011–June 2012)," Ministry of Statistics and Programme Implementation, Govt. of India, 2013.
- [7] S. Dhar, M. Pathak, and P. R. Shukla, "Macroeconomic Assessment of India's Development and Mitigation Pathways," Climate Policy, vol. 19, no. 6, pp. 744–759, 2019.
- [8] L. Yan, X. Wang, and H. Zhang, "Enhanced Multivariate Time Series Regression Prediction Using Temporal Convolution Networks," in Proc. 7th Int. Conf. Pattern Recognit. Artif. Intell. (PRAI), 2024, pp. 145–150.