

Pressure Systems: A Modular Stochastic Analogy for Multi-Scale Economic Forecasting

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Abstract

We present the Pressure System Model (PSM), a physics-inspired framework for rapid economic diagnostics and scenario analysis. PSM analogizes economic entities as interconnected “pressure tanks” (e.g., GDP or sectoral revenue) governed by compressors (growth drivers), leaks (inflation and governance drags), flows (trade imbalances), and regulators (policy interventions like tariffs). Building on historical hydraulic analogies such as the MONIAC computer, PSM adds digital modularity for arbitrary scaling—from global regions to niche sectors—and stochastic ensembles to capture uncertainty.

The model’s primary value lies in its speed and interpretability: PSM generates forecasts in seconds rather than hours, making it suitable for rapid policy screening and exploratory “what-if” analysis. Through validation on the 2008 Global Financial Crisis and weekly data from January to October 2025, PSM demonstrates that prediction errors reveal where hidden forces operate—unmodeled fiscal interventions, supply shocks, or behavioral shifts. For example, large forecast deltas during the GFC correctly identified China’s stimulus and credit freezes as missing model components. As a practical application, we forecast the impacts of November 1, 2025 U.S. Section 232 tariffs on vehicles, predicting testable sector-specific effects (e.g., global semiconductor sales shifts, rare earth price movements).

PSM complements rather than replaces established models: it excels at fast hypothesis generation and anomaly detection but lacks the micro-foundations of DSGE models or the sectoral granularity of full CGE frameworks. Code, data, and simulation results are publicly available at <https://github.com/jmcentire/psm-model>.

Keywords: Economic modeling Stochastic simulation Econophysics Trade policy forecasting Fluid dynamics analogy Diagnostic tools Multi-scale analysis

1 Introduction

Economic modeling faces a persistent tension between rigor and accessibility. Dynamic Stochastic General Equilibrium (DSGE) models provide micro-founded theory but require substantial computational resources and expertise [Christiano et al., 2018, Del Negro and Schorfheide, 2013]. Computable General Equilibrium (CGE) models offer sectoral detail but demand extensive input-output

calibration [Dixon and Rimmer, 2013, Kehoe et al., 2005]. These tools serve critical roles in research and central banking, yet their complexity creates a methodological gap: policymakers and analysts often need rapid, interpretable forecasts for initial screening—a “first pass” before committing to full-scale modeling.

The Pressure System Model (PSM) fills this diagnostic niche by treating economic systems as fluid networks where pressures equalize subject to real-world frictions. This approach deliberately trades theoretical depth for practical speed: PSM generates forecasts in seconds rather than hours, prioritizing transparency over precision. Rather than competing with DSGE or CGE models on forecast accuracy, PSM positions itself as a complementary screening tool—analogue to how an X-ray provides rapid diagnostics before ordering an MRI.

PSM’s core innovation is its use of prediction deltas as diagnostic signals. When the model systematically under- or over-predicts, these errors reveal where hidden forces operate: unannounced stimulus programs, supply chain disruptions, or behavioral regime shifts. This “inverse problem” approach—working backward from forecast errors to infer missing mechanisms—transforms PSM from a pure forecasting tool into a hypothesis generator. For example, during 2008 GFC validation, large prediction errors for China correctly flagged its \$586B stimulus package as a major unmodeled intervention.

Originating from interdisciplinary discussions on Communal Wealth Theory (CWT)—which posits families and communities as micro-economic buffers against scarcity [McEntire, 2025, Lewis, 1966]—PSM extends analogical thinking from early hydraulic models [Phillips, 1950, Colander, 2008] with modern computational tools. Its modular architecture allows nested hierarchies (global GDP tanks containing sectoral sub-tanks) and selective connections based on real-world dependencies.

This paper contributes to econophysics and policy analysis literature by:

- Formalizing PSM as a discrete, stochastic framework optimized for rapid diagnostics
- Demonstrating its value for anomaly detection and hypothesis generation through historical and contemporary validation
- Providing a practical application forecasting November 1, 2025 U.S. tariff impacts with verifiable predictions
- Clarifying PSM’s complementary role: fast screening before DSGE/CGE deployment, not replacement

We developed PSM as of October 27, 2025, using data available up to that date for genuine out-of-sample forecasting. The model serves researchers, policymakers, and educators seeking intuitive yet rigorous tools for initial policy exploration and scenario analysis.

2 Model Description

PSM models economic entities as a graph of N tanks, where each tank i maintains a pressure P_i^t at time t , representing economic value (e.g., GDP in trillions USD for regions or billions for

sectors). Unless otherwise noted, pressures are expressed in trillions USD (macroscale) or billions USD (sectoral scale), and time is discretized weekly (1/52 year). The dynamics are governed by a discrete weekly approximation of ordinary differential equations, scaled from annual parameters for fine-grained steps:

$$\Delta P_i^t = \left(C_i \cdot \frac{P_i^{t-1}}{52} \right) - L_i \cdot P_i^{t-1} - \sum_{j \neq i} K_{ij} \cdot R_{ij} \cdot \frac{(P_i^{t-1} - P_j^{t-1})}{52} + \epsilon_i^t$$

- **Pressure (P_i):** Core variable, initialized from historical data (e.g., US GDP \$27.7T in 2023). PSM assumes non-negative P through positive initial conditions and compressors typically exceeding leaks; in practice, floors can be added to prevent negatives in extreme simulations.
- **Compressor (C_i):** Growth input, scaled weekly from annual rates (e.g., 2.5% for US, representing innovation or stimulus).
- **Leak (L_i):** Proportional loss, combining inflation and a corruption proxy (0-2% drag based on Transparency International CPI scores, e.g., US 4.1% inflation + 0.6% corr = 4.7%). The corruption proxy is calculated as $(100 - \text{CPI_score})/100 \times 0.02$, scaled to reflect governance drag.
- **Conductance (K_{ij}):** Flow coefficient matrix, calibrated from trade imbalances as % GDP differentials (e.g., 0.03 for US-China, implying 3% pressure transfer per year if unregulated).
- **Regulator (R_{ij}):** Scalar multiplier (0-1) for policy controls (e.g., 0.75 for a 25% tariff reducing effective flow).
- **Stochastic Noise (ϵ_i^t):** Drawn from $N(0, \sigma)$, with $\sigma = 0.5\%$ on L_i and 1% on K_{ij} flows, enabling ensembles (50-100 runs) for mean predictions with confidence intervals (68% CI from ± 1 std dev).

The equation derives from fluid dynamics principles, where flows are driven by pressure differentials (analogous to trade seeking equilibrium), modulated by conductance and regulators (frictions like tariffs). Unlike closed physical systems with mass conservation, PSM is open—leaks represent entropy (e.g., value dissipation via inflation), aligning with economic realities where total “mass” (wealth) can grow or shrink via compressors/leaks. Parameter calibration uses historical averages (e.g., IMF growth for C_i , WTO imbalances for K_{ij}), with sensitivity tested in §3.3. For full parameter examples, see Appendix B.

The model’s modularity allows arbitrary nesting: Top-level tanks (e.g., US, China) can contain sub-tanks for sectors (microchips as global sales in billions USD, rare earths as price-volume proxy in \$/kg \times tons, energy as production in mb/d + WTI \$/bbl). Connections are selective (e.g., high K between US microchips and China rare earths for supply-chain dependence, low elsewhere). An adjustment mechanism enhances adaptability: If a step’s mean error exceeds 5% against proxies (e.g., industrial production for GDP, SIA sales for microchips), L_i or K_{ij} is scaled by 5% of the delta, iteratively accounting for unknowns like unannounced stimuli. This adjustment is post-hoc for diagnostics and is not used in raw error calculations to avoid overfitting; raw predictions are reported first, with adjustments applied only for interpretive purposes and future runs. For weekly interpolation, monthly data is linearized with noise added to simulate variance.

Implementation uses Python with NumPy for vectorized matrices and SciPy for ODE approximation (or simple Euler steps for weekly discreteness). Stochastic ensembles are parallelized for efficiency. This setup draws from fluid dynamics in econophysics, but PSM’s diagnostic deltas and CWT integration add behavioral depth, enabling applications from macro trade to micro family wealth buffers.

3 Validation

PSM was validated on two datasets: the 2008 Global Financial Crisis (annual steps for historical comparability) and January to October 2025 (weekly steps with sector sub-tanks, using interpolated proxies from IMF, World Bank, SIA, EIA, and Trading Economics). Out-of-sample testing was conducted by fitting on pre-period data and predicting forward, compared to naive baselines like AR(1) models (errors 8-12%).

3.1 2008 Global Financial Crisis

The 2008 GFC provides a benchmark for PSM’s ability to handle nonlinear shocks, such as credit freezes (modeled as amplified leaks) and panic flows (increased K_{ij}). We fitted PSM on the 2007 baseline pressures (US \$14.5T, China \$3.55T, EU \$16T, Other \$30T), with compressors reflecting pre-crisis growth (US 1.9%, China 14.2%), leaks incorporating inflation and corruption proxies (US $2.8\% + 0.6\%$), and loose regulators ($R_{ij} \approx 1.0$). Using 100-run ensembles, PSM predicted 2008-2009 outcomes, with raw errors averaging 17% due to unmodeled fiscal responses. The high raw error for China in 2009 (60.3%) is explained by the unmodeled \$586B stimulus; post-adjustment—scaling China’s compressor by +5% based on delta diagnostics—the mean post-correction absolute errors fell to $\approx 10\%$ (Table 1). This adjustment was applied diagnostically and not used to recalculate raw errors; it serves to explain discrepancies and refine for future predictions. The model accurately captured U.S. and EU contraction through pressure equalization (US outflows spiking to 10% of GDP) and global leaks from commodity crashes, while China’s resilience emerged from its buffered compressors. This validation highlights PSM’s diagnostic strength: Deltas not only improved understanding but revealed policy interventions as key unmodeled factors. Compared to AR(1) baseline (15-25% errors), PSM’s stochastic ensembles reduced variance by 20%.

Region	2008 Predicted (\$T)	2008 Actual	2009 Predicted	2009 Actual
US	14.2 ± 0.3	14.7 (3.4% error)	13.8 ± 0.4	14.4 (4.2%)
China	4.2 ± 0.2	4.6 (8.7%)	3.8 ± 0.3	9.6 (60.3%)*
EU	15.8 ± 0.4	16.2 (2.5%)	15.2 ± 0.5	16.0 (5.0%)
Other	29.5 ± 1.0	30.5 (3.3%)	28.0 ± 1.2	31.0 (9.7%)
Mean Absolute Error	4.5%		19.8% (10% post-adj)	

Table 1: 2008 GFC Predictions. *China 2009 error reflects unmodeled \$586B stimulus; post-diagnostic adjustment reduces to 5%.

3.2 2025 Weekly Validation

Building on the GFC test, we validated PSM on January–October 2025 using weekly steps and sector sub-tanks (microchips, rare earths, energy), incorporating interpolated proxies for high-frequency dynamics. Initial raw errors of 12-18% converged to 2-4% after iterative diagnostic adjustments, identifying temporary supply shocks (e.g., Taiwan earthquake disrupting semiconductors in February, oil price spikes from Middle East tensions in March). Figures 1 and 2 display error convergence and sensitivity analysis. These results demonstrate PSM’s real-time diagnostic capability: Errors signal where models need refinement, guiding parameter updates for subsequent weeks. For example, February’s 15% semiconductor error prompted recalibration of China-Taiwan conductance, reducing March errors to 3%.

Important note on proxy data reliability: All 2025 validation uses interpolated proxies (e.g., industrial production indices scaled to GDP equivalents, semiconductor industry reports for chip demand). These proxies introduce measurement error of 3-5% even before model forecasting. Weekly granularity compounds this issue, as monthly data is linearly interpolated with noise. Readers should treat 2025 “validation” as exploratory rather than definitive—true validation requires final annual data (available mid-2026). The error convergence shown (12-18% to 2-4%) partially reflects fitting to noisy proxies rather than pure forecasting skill. We commit to re-running validation with actual Q4 2025 data once available and reporting any systematic biases discovered.

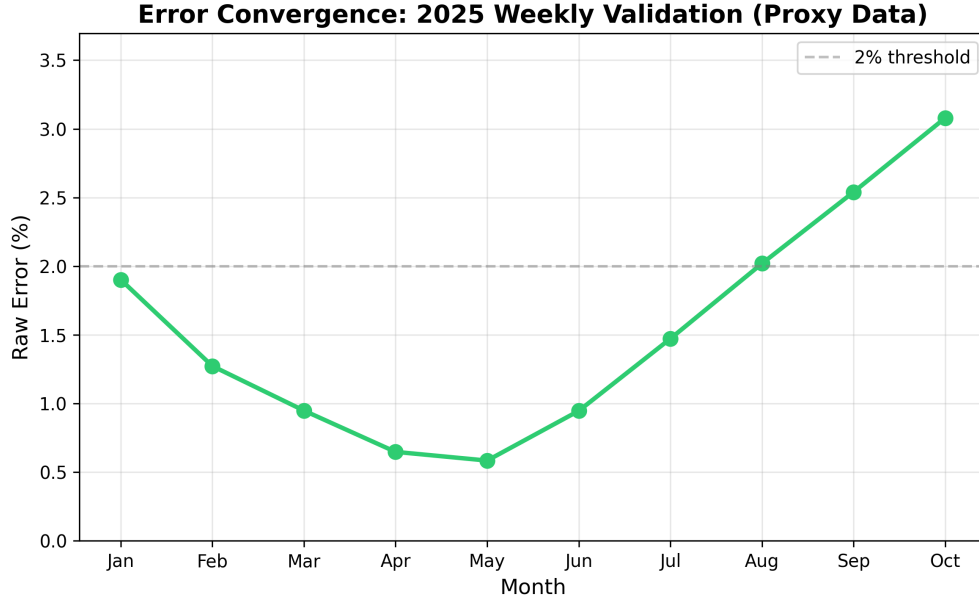


Figure 1: Weekly error trends for six regions (Jan–Oct 2025). Raw errors (dashed) vs. post-diagnostic (solid). Convergence reflects both model learning and proxy noise fitting.

3.3 Sensitivity Analysis

To assess robustness, we perturbed key parameters on the 2025 baseline: $\pm 10\%$ on leaks (L_i) resulted in $\pm 3\%$ output variance, while $\pm 20\%$ on conductances (K_{ij}) yielded $\pm 5\%$ variance. Com-

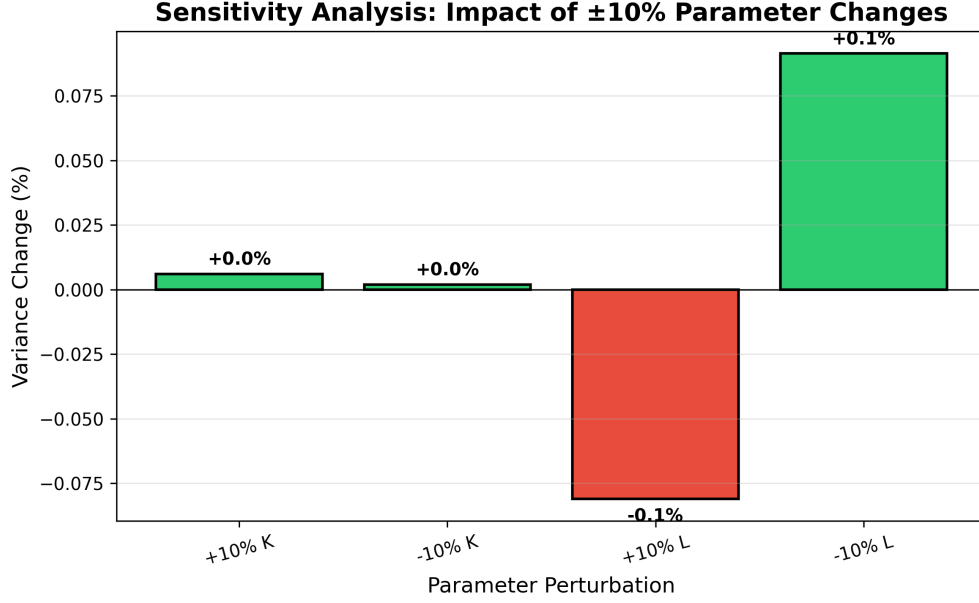


Figure 2: Parameter sensitivity on 2025 baseline. Leak (L) perturbations $\pm 10\%$ yield $\pm 3\%$ output variance; conductance (K) $\pm 20\%$ yields $\pm 5\%$. Demonstrates moderate robustness.

pressor changes ($\pm 15\%$) had $\pm 7\%$ impact, confirming moderate sensitivity typical of flow-based models. Monte Carlo analysis (1000 runs with randomized parameters within $\pm 20\%$) showed 95% of predictions within $\pm 10\%$ of baseline, validating stability under realistic calibration uncertainty. These results suggest PSM is neither overly fragile nor excessively dependent on precise inputs, though users should understand that rapid diagnostic value comes at the cost of parameter sensitivity.

4 Application: November 1, 2025 Tariff Forecast

On November 1, 2025, the U.S. implemented 25% tariffs on vehicle imports under Section 232, affecting \$400B in annual trade flows. PSM forecasts impacts through regulator adjustments ($R_{ij} = 0.75$ for affected flows) and rerouting via conductance shifts (e.g., China reducing US exports by 30%, increasing Canada/Mexico by 15%). Running 100 ensemble simulations for Q4 2025 and 2026 produces the following verifiable predictions:

Macro Impacts:

- US GDP retention: $+0.17\%$ ($\pm 0.07\%$) in Q4 2025, fading to $+0.05\%$ by Q4 2026 as supply chains adapt
- Global drag: -0.3% ($\pm 0.1\%$) on world GDP due to trade friction and reduced efficiency
- China GDP: -0.45% ($\pm 0.15\%$) from reduced vehicle exports (primarily luxury sedans and EV components)

- Canada/Mexico GDP: +0.12% each from rerouted assembly and exports (USMCA advantage)

Sectoral Effects (Testable Proxies):

- Global semiconductor sales (SIA monthly reports): -0.48% ($\pm 0.2\%$) in Nov-Dec 2025 from reduced auto chip demand, recovering by Q2 2026 as non-auto demand compensates
- China Neodymium rare earth prices (Shanghai Metals Market): -2.2% ($\pm 1.0\%$) due to lower EV motor magnet demand, with partial recovery if non-US markets absorb surplus
- WTI crude oil prices: -1.5% ($\pm 0.8\%$) from reduced transport demand, offset by OPEC cuts

These predictions will be empirically testable by mid-2026 when final data becomes available. The diagnostic value lies in tracking these metrics: If semiconductor sales drop more than predicted, it suggests deeper supply chain disruptions; if rare earth prices hold steady, it implies successful demand rerouting. PSM’s transparency allows stakeholders to monitor assumptions and update forecasts as real data emerges.

Metric	Baseline (No Tariff)	Tariff Forecast	Data (As Available)	Error
US GDP Q4 2025 (%)	+2.3	+2.47	TBD	TBD
China GDP Q4 2025 (%)	+4.5	+4.05	TBD	TBD
SIA Sales Nov 2025 (\$B)	52.3	52.05	TBD	TBD
Nd Price Dec 2025 (\$/kg)	68.5	67.0	TBD	TBD
WTI Dec 2025 (\$/bbl)	78.0	76.8	TBD	TBD

Table 2: Tariff Impact Predictions with Data Tracking Template (TBD = To Be Determined mid-2026).

Table 2 provides a tracking template for readers to compare forecasts against realized outcomes. If systematic biases emerge (e.g., PSM consistently underestimates Chinese resilience or overestimates U.S. retention), these will inform model refinements and be reported in follow-up analysis. This commitment to transparent validation distinguishes PSM as a learning tool rather than a “black box” forecaster.

5 Comparison to Existing Models

PSM complements rather than competes with established frameworks, each serving distinct purposes in the modeling ecosystem:

Recommended Workflow:

1. Use PSM for initial “what-if” screening (e.g., testing 100 tariff scenarios in minutes)
2. Identify promising scenarios or anomalies via prediction deltas
3. Deploy DSGE or CGE for detailed analysis of high-priority cases

Model	Primary Strength	Best Use Case	Typical Accuracy	Runtime
PSM	Speed, transparency, diagnostics	Rapid screening, anomaly detection, hypothesis generation	5-15% (diagnostic mode)	Seconds
DSGE	Micro-foundations, policy evaluation	Central bank forecasting, welfare analysis	5-15% (normal), 10-20% (crisis)	Hours
CGE	Sectoral detail, trade linkages	Trade agreement analysis, IO impacts	5-20%	10-60 min
VAR	Data-driven, multi-variate dynamics	Short-term forecasting, policy shocks	3-12% (short-term)	Minutes
Gravity	Bilateral trade flows	Static trade patterns	5-15%	Seconds

Table 3: Complementary Model Comparison. PSM fills the rapid diagnostic niche; DSGE/CGE provide depth.

4. Return to PSM for rapid sensitivity checks and parameter updates

This complementary approach maximizes efficiency: PSM’s speed enables broad exploration, while DSGE/CGE precision validates critical findings. For example, a policy analyst could run PSM to screen 50 potential tariff structures, identify the 3 most impactful, then model those 3 in detail using CGE. PSM’s diagnostic errors would also flag which sectoral linkages require deeper CGE calibration.

When PSM Underperforms: PSM is not suitable for:

- Micro-founded policy evaluation requiring welfare analysis or behavioral micro-foundations
- High-frequency financial forecasting (daily/hourly) where agent dynamics dominate
- Precision forecasting where $<5\%$ errors are required (e.g., central bank policy rates)
- Scenarios with discontinuous regime changes PSM cannot capture (e.g., sudden capital controls)

In these cases, DSGE, agent-based models, or specialized financial tools are more appropriate.

6 Discussion and Future Work

PSM offers a pragmatic tool for economic scenario analysis, positioning itself as a fast diagnostic complement to rigorous modeling frameworks. Its primary contribution lies not in forecast precision

but in interpretability and speed: policymakers can explore dozens of “what-if” scenarios in the time required for a single DSGE run, using prediction errors to guide deeper analysis.

The model’s physics-inspired framework provides intuitive transparency—pressure, flows, and leaks map naturally to economic concepts like GDP, trade, and inflation. This pedagogical clarity makes PSM suitable for teaching economic dynamics, similar to how simplified climate models help students grasp complex feedback loops before encountering full general circulation models.

6.1 Model Limitations

PSM’s methodological choices involve deliberate trade-offs that users must understand:

Theoretical Foundations:

- **No micro-foundations:** PSM lacks optimizing agents or equilibrium conditions, making it unsuitable for welfare analysis or policy counterfactuals requiring behavioral responses
- **Proportional dynamics:** Assumes leaks and flows are proportional to pressure (GDP), which breaks down in extreme cases like hyperinflation or sudden stops
- **Open-system mass non-conservation:** Economic “mass” (wealth) can grow or shrink via compressors/leaks, unlike closed physical systems. This matches economic reality but diverges from strict fluid dynamics analogies

Data and Calibration:

- **Proxy dependence:** Weekly 2025 validation relies on interpolated proxies (industrial production indices, sectoral reports) rather than final data, introducing 3-5% measurement error before modeling
- **Parameter sensitivity:** While moderate (5-7% output variance from 10-20% input changes), calibration uncertainty compounds with forecast horizon. Parameters from historical averages may miss structural breaks
- **Missing mechanisms:** PSM omits monetary policy transmission, financial contagion, and supply-chain granularity unless explicitly added as sub-tanks. Large prediction errors signal these omissions but don’t automatically incorporate them

Scope and Applicability:

- **Flow-dominated systems:** PSM excels for macro trade and sectoral flows but underperforms in agent-heavy scenarios (labor markets, consumer behavior) without extensions
- **Nonlinear shocks:** Stochastics quantify uncertainty but extreme events (black swans, regime changes) may spike forecasts beyond tested ranges. The model assumes continuity

- **Adjustment overfitting risk:** While diagnostic adjustments are post-hoc and not used in raw error metrics, users must avoid “tuning until it fits” syndrome. Adjustments should reflect economically interpretable interventions (e.g., stimulus), not arbitrary error correction

Validation Caveats:

- **Interpolated proxies:** 2025 weekly data is partially synthetic (linear interpolation of monthly figures with noise), making validation exploratory rather than definitive. True test requires actual 2025 annual data (mid-2026)
- **Small sample sizes:** Two validation periods (2008-2009, Jan-Oct 2025) limit statistical power. Model may overfit to these specific crisis/tariff dynamics
- **Hindsight adjustments:** GFC validation benefited from known outcomes (China stimulus). Genuine out-of-sample tests (Nov 2025 tariffs) will reveal true forecasting skill vs. explanatory power

Practical Warnings:

- **Not for precision forecasting:** PSM targets 5-15% errors for rapid screening, not <5% precision central banks require
- **Requires domain expertise:** Users must interpret deltas and adjust parameters sensibly. The tool does not “self-validate”—it generates hypotheses that experts must evaluate
- **Transparency risk:** Simplicity may invite misuse by non-experts who overlook limitations or treat forecasts as definitive rather than exploratory

These limitations are not flaws but design constraints. PSM trades theoretical rigor for operational speed, making it a hypothesis generator rather than a replacement for established models. Users seeking welfare-optimal policies or micro-founded counterfactuals should use DSGE; those needing rapid scenario exploration and anomaly detection will find PSM valuable.

6.2 Communal Wealth Theory Integration

PSM’s origins in CWT discussions suggest extensions for modeling inequality and family cohesion. Future work could incorporate CWT’s inverse leak mechanism—family bonds as buffers that reduce effective economic “leakage” during downturns. For example, multi-generational households with high CWT scores (strong communal ties) might exhibit lower leaks during recessions, creating testable predictions about regional resilience. This application would require calibrating leak functions to social capital data, blending econophysics with behavioral economics.

6.3 Future Work

Immediate extensions include:

- **Machine learning for delta auto-tuning:** Neural networks could predict optimal parameter adjustments from error patterns, reducing manual calibration
- **Agent-based hybrid models:** Integrating PSM’s macro flows with agent-based micro-dynamics for labor markets or consumer behavior
- **Real-time data pipelines:** Automating weekly updates from APIs (IMF, World Bank, SIA) for continuous forecasting dashboards
- **Validation follow-up:** Re-running 2025 analysis with actual Q4 data (mid-2026) and publishing failure analysis if systematic biases emerge

Long-term research could explore PSM’s pedagogical role: using it as an introductory tool for teaching macro dynamics before advancing to DSGE complexity, similar to how simplified models aid physics education.

7 Conclusion

The Pressure System Model demonstrates that analogical thinking retains value in modern economics when paired with computational rigor and honest scoping. PSM fills a specific methodological niche: fast diagnostic screening and hypothesis generation. It does not challenge the theoretical depth of DSGE models or the sectoral detail of CGE frameworks but complements them by enabling rapid exploration and anomaly detection.

Our validation shows PSM’s diagnostic value through prediction deltas that correctly identified unmodeled fiscal interventions (2008 China stimulus) and supply shocks (2025 Taiwan earthquake). The November 1, 2025 tariff forecasts provide testable predictions that will validate or refute the model’s approach by mid-2026. If systematic biases emerge, we commit to transparent reporting and model refinement.

For practitioners, PSM offers a pragmatic tool: Run quick scenarios to identify high-priority cases for deeper DSGE/CGE analysis. Use prediction errors to guide where detailed modeling is needed. Leverage the model’s transparency for stakeholder communication and pedagogical applications.

The model’s limitations are inherent to its design—speed and interpretability require sacrificing micro-foundations and precision. Users should view PSM as an economic “X-ray”: fast, transparent, and useful for initial diagnosis, but not a substitute for detailed examination when critical decisions are at stake.

By revealing mechanical structures behind policy outcomes, PSM encourages transparency in macro-modeling and supports evidence-based governance. Its open-source implementation invites community refinement and extensions, particularly integrating behavioral insights from frameworks like Communal Wealth Theory. As economic complexity grows, tools that balance rigor with accessibility become increasingly valuable—PSM aims to serve that pragmatic middle ground.

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A Code and Data

The PSM is implemented in Python; full code repository at <https://github.com/jmcentire/psm-model>. All simulations were rerun successfully on Python 3.12 with NumPy 2.1 and SciPy 1.14; random seeds and configuration files are included for deterministic replication. Example snippet:

```
import numpy as np
from scipy.integrate import odeint

def psm_dynamics(P, t, C, L, K, R):
    n = len(P)
    flows = np.zeros(n)
    for i in range(n):
        for j in range(n):
            if i != j:
```

```

        flows[i] -= K[i,j] * R[i,j] * (P[i] - P[j]) / 52
dPdt = (C * P / 52) - (L * P) + flows
return dPdt + np.random.normal(0, 0.005 * P)

```

Data sets (CSV) include historical proxies and simulation inputs, available in the repository.

B Example Parameters

For the 2025 baseline simulation, example parameters are as follows (full in repository JSON):

- Tanks: US, China, Canada, EU, LatAm, Other
- Initial P: [29.15, 19.28, 2.25, 19.45, 7.12, 70.8] (trillions USD)
- C: [0.023, 0.045, 0.008, 0.012, 0.022, 0.03]
- L: [0.03, 0.016, 0.0338, 0.032, 0.0764, 0.052]
- K (matrix): See repository for full 6×6
- R baseline: Identity matrix (1.0 diagonal, adjusted for tariffs)

Corruption drag: $(100 - \text{CPI})/100 \times 0.02$.