Generative Economic Modeling

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Using Nonlinear Structural Models for Forecasting

Nonlinearly solving large economic models remains hard
$\Rightarrow$ limiting use of structural models for **risk assessment & forecasting**

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Can we use **neural networks** with proven **conventional methods** we already know?
(cf. Heer & Maussner, 2024; Judd, 1998; Miranda & Fackler, 2004)

The Curse of Dimensionality Limits Economic Analysis

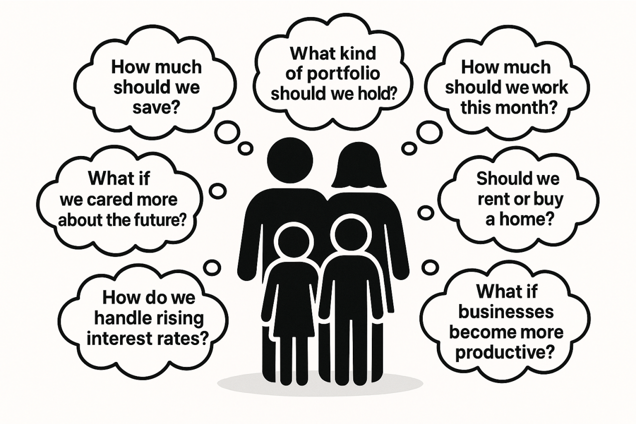

Figure 1: Full model

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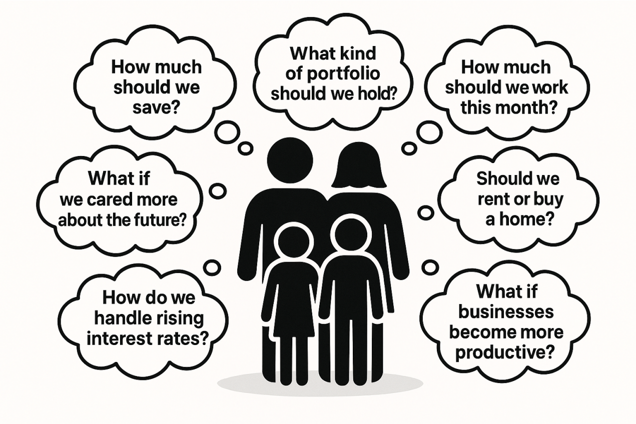

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- Full model is intractable

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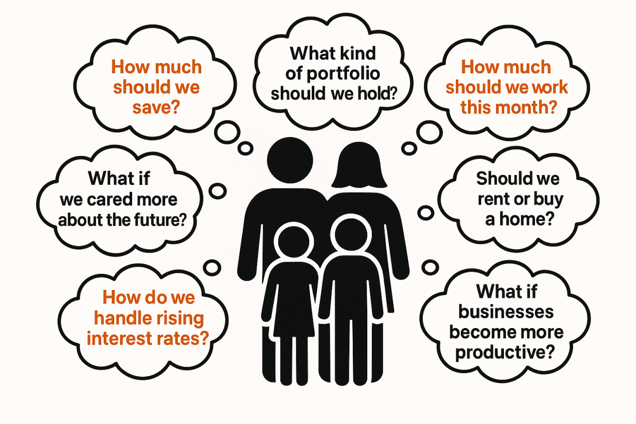

Figure 2: **Simplified** model

- Full model is intractable
- Forces researchers to focus on the key model components
- Conventional methods (VFI, PFI) work well for simplified models

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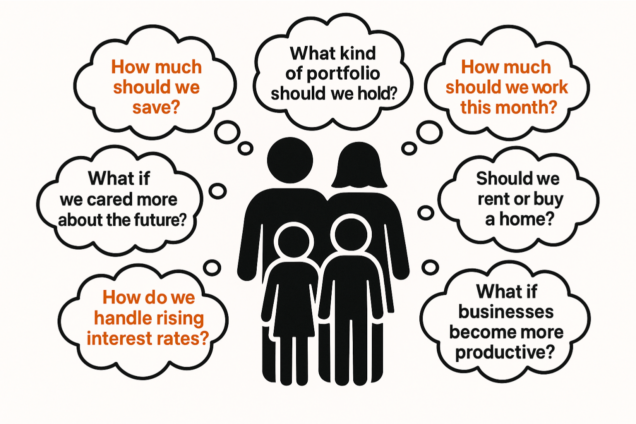

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- **Question:** Can many simplified models approximate the full model?

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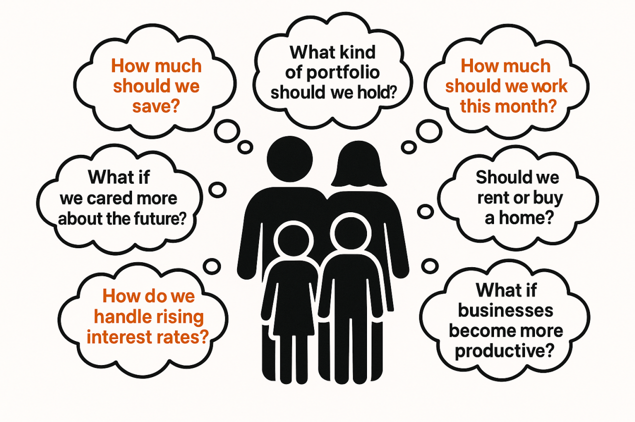

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$\Rightarrow$ **Generative Economic Modeling:**

Conventional Methods + Deep Learning

Recasting model solution as simulation and learning

1. **Solving Simplified Models**
    - Solve simplified models nested within the full model
    - Solve each with standard numerical methods

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2. **Simulating Synthetic Data**
   - Simulate data from each simplified model
   - Combine into a unified training set

Generative Economic Modeling: Bridging Traditional Methods & Deep Learning

Recasting model solution as simulation and learning

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   - Solve each with standard numerical methods
2. **Simulating Synthetic Data**
   - Simulate data from each simplified model
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3. **Neural Network Approximation**
   - Train a neural network on the combined dataset
   - The trained network generalizes to the full model

Results and Roadmap for the Talk

- **Practical demonstrations** across Asset Pricing and RBC model variants
  - Globally solving the full model vs. solving with generative economic modeling
  - Prediction errors comparable to training NN on the full model
  - Euler equation errors comparable to other methods
- **Application** to a Heterogeneous Agent New Keynesian (**HANK**) model
  - Understand transmission of financial shocks with heterogeneous agents
  - Interaction of multiple aggregate shocks with precautionary behavior

Generative Economic Modeling

Generative Economic Modeling in One Slide

- **Goal:** Solve model with variables $\mathbb{X}_t$, shocks ν_t, and parameters Θ

$$\mathbb{X}_t = f(\mathbb{X}_{t-1}, \nu_t \mid \Theta)$$

Challenge: numerical solution for $f(\cdot)$ is subject to the curse of dimensionality

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- **Solution:** Use a **simplified model** $\tilde{f}^i$:

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- **Generative Economic Modeling:** Generate full model from simplified models
  - Solve various simplified models $\tilde{f}^i$ with $i \in \{a, b, c, ...\}$
  - Simulate data $\bar{\mathbb{D}}$ from collection of simplified models
  - Train $\bar{f}_{DNN}$ to approximate f through generative ability of neural network

$$f(\cdot) \approx \bar{f}_{DNN} = \arg\min_{\bar{W}} \mathbb{L}(\bar{W} \mid \bar{\mathbb{D}})$$

Proof of Concept

Analytical asset pricing model as a benchmark

Analytical tractable asset pricing model of Canzoneri, Cumby, and Diba (2007):

$$q_t = \beta \mathbb{E}_t \Big[\exp\big(- \pi_{t+1} - \gamma \Delta c_{t+1} \big) \Big]$$

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VAR(1) for variables $y_t = [\pi_t, \Delta c_t]'$ with shocks $\epsilon_t = [\epsilon_t^a, \epsilon_t^\zeta, \epsilon_t^\mu]'$:

$$y_t = A y_{t-1} + \eta \epsilon_t$$

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Analytical solution as expression of conditional mean and variance:

$$q_t = \beta \exp\Big(- (a_{11} + \gamma a_{21})\, \pi_t \; - \; (a_{12} + \gamma a_{22})\, \Delta c_t + \tfrac{1}{2} \big[\underbrace{(\eta_{11} + \gamma \eta_{21})^2}_{\epsilon_t^a} + \underbrace{(\eta_{12} + \gamma \eta_{22})^2}_{\epsilon_t^\zeta} + \underbrace{(\eta_{13} + \gamma \eta_{23})^2}_{\epsilon_t^\mu} \big] \Big)$$

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Assume the model would be **too complicated to solve**

Solving satellite versions of the model instead of the full model

Solving simplified **satellite models** without one shock:

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$$
\begin{aligned}
q_t^{\backslash a} = \beta \exp\Big(&-(a_{11} + \gamma a_{21})\,\pi_t - (a_{12} + \gamma a_{22})\,\Delta c_t \\
&+ \tfrac{1}{2}\big[(\eta_{12} + \gamma \eta_{22})^2 + (\eta_{13} + \gamma \eta_{23})^2 \big]\Big) \\
q_t^{\backslash \zeta} = \beta \exp\Big(&-(a_{11} + \gamma a_{21})\,\pi_t - (a_{12} + \gamma a_{22})\,\Delta c_t \\
&+ \tfrac{1}{2}\big[(\eta_{11} + \gamma \eta_{21})^2 + (\eta_{13} + \gamma \eta_{23})^2 \big]\Big) \\
q_t^{\backslash \mu} = \beta \exp\Big(&-(a_{11} + \gamma a_{21})\,\pi_t - (a_{12} + \gamma a_{22})\,\Delta c_t \\
&+ \tfrac{1}{2}\big[(\eta_{11} + \gamma \eta_{21})^2 + (\eta_{12} + \gamma \eta_{22})^2 \big]\Big)
\end{aligned}
$$

Solving satellite versions of the model instead of the full model

Solving simplified **satellite models** without one shock:

$$q_t^{\setminus a} = \beta \exp\Big(-(a_{11} + \gamma a_{21})\,\pi_t \;-\; (a_{12} + \gamma a_{22})\,\Delta c_t$$
$$+\tfrac{1}{2}\big[\qquad\qquad (\eta_{12} + \gamma\eta_{22})^2 + (\eta_{13} + \gamma\eta_{23})^2\big]\Big)$$

$$q_t^{\setminus \zeta} = \beta \exp\Big(-(a_{11} + \gamma a_{21})\,\pi_t \;-\; (a_{12} + \gamma a_{22})\,\Delta c_t$$
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$$q_t^{\setminus \mu} = \beta \exp\Big(-(a_{11} + \gamma a_{21})\,\pi_t \;-\; (a_{12} + \gamma a_{22})\,\Delta c_t$$
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- coefficients on π_t and Δc_t learned from each partial dataset

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- coefficients on π_t and Δc_t learned from each partial dataset
- coefficients from shocks learned as shift from partial datasets with shock

Solving **Asset-Pricing** model:

1. Solving (sub)models

$$q_t^{\backslash a} = \dots$$
$$q_t^{\backslash \zeta} = \dots$$
$$q_t^{\backslash \mu} = \dots$$

Illustrating Generative Economic Modeling

Step-by-Step

Solving **Asset-Pricing** model:

1. Solving (sub)models
2. Simulating data

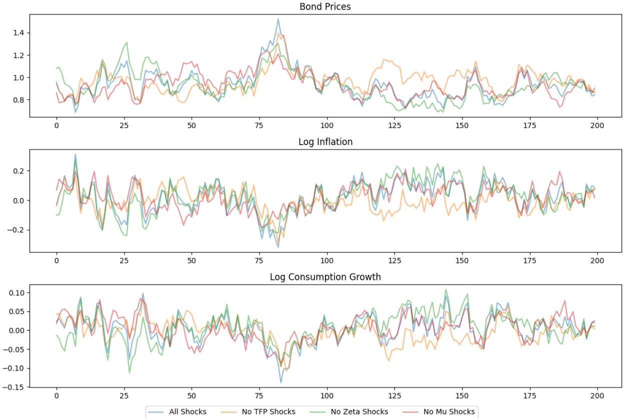

Figure 4: Simulation of economies with different combinations of aggregate shocks

Solving **Asset-Pricing** model:

1. Solving (sub)models
2. Simulating data and combining into one dataset

q_t	π_t	Δc_t	ϵ_t^a	ϵ_t^ζ	ϵ_t^μ
0.99	-0.02	-0.01	-0.12	1.04	0.0
1.06	-0.04	0.02	1.63	1.85	0.0
⋮		⋮		⋮	
1.01	-0.08	0.02	-0.12	0.0	-1.73
0.99	-0.03	-0.01	1.63	0.0	0.45
⋮		⋮		⋮	
1.06	-0.11	0.01	0.0	-1.0	-1.72
0.94	-0.01	-0.07	0.0	-0.39	-0.86

Table 1: Simulation snapshots from combined dataset for q_t, π_t, Δc_t, ϵ_t^a ϵ_t^ζ, and ϵ_t^μ

Illustrating Generative Economic Modeling

Step-by-Step

Solving **Asset-Pricing** model:

1. Solving (sub)models
2. Simulating data and combining into one dataset
3. Training the neural network

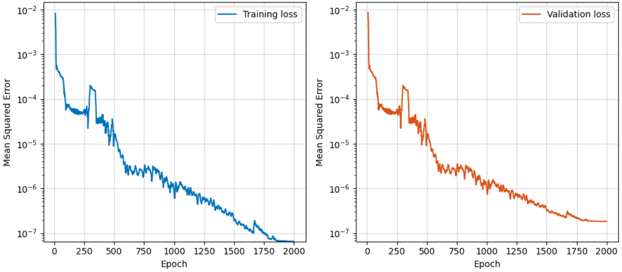

Figure 5: Loss function from training the NN

Solving **Asset-Pricing** model:

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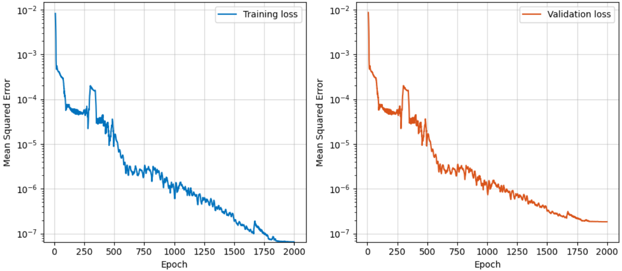
Evaluate against **NNs** trained on data **generated by true model**

NN Specification | Evaluation Criteria



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Evaluating Generative Economic Modeling: Predicted values vs. actual values

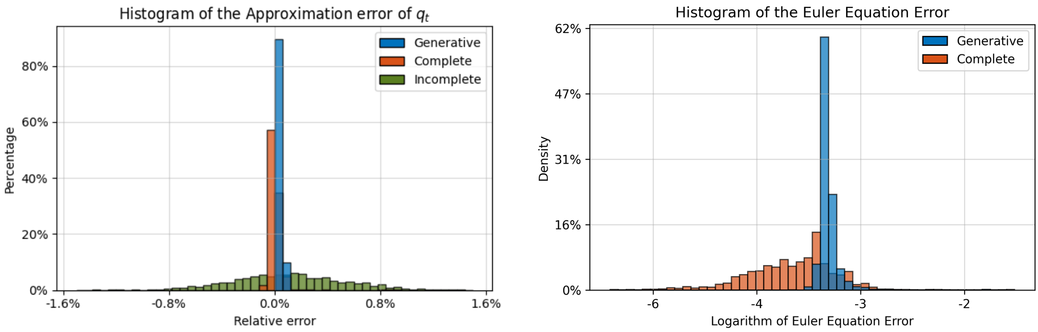

Figure 6: Prediction error distribution and Euler Equation Errors

- **Generative**: extrapolates with a NN trained on simulated data from submodels
- **Complete**: Train a NN on simulated data from true model

Accuracy of the prediction

Model	$\log_{10}$(MSE)	$\log_{10}$(MAE)	$\log_{10}$(EEE)
Asset Price	-4.85	-3.22	-3.15
Analytical RBC			
Nonlinear RBC			
Krusell-Smith			
Global HANK			

Table 2: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Euler Equation Error (EEE) of different models

Proof of Concept using an Extended Stochastic RBC Model

RBC Model variants with increasing complexity

1. Baseline: tractable, analytically solvable RBC variant
2. Medium-scale: includes nonlinearities in capital adjustment cost friction
3. Heterogeneous agents: partial insurance against income risk

Evaluating Generative Economic Modeling: Heterogeneous Agent Model

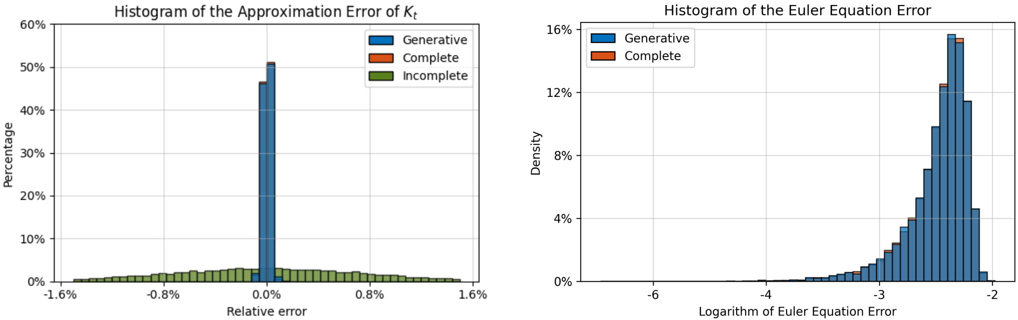

Figure 8: Graphical evaluation of model fit:

Prediction error distribution and Euler Equation Errors

Errors for individual policy functions

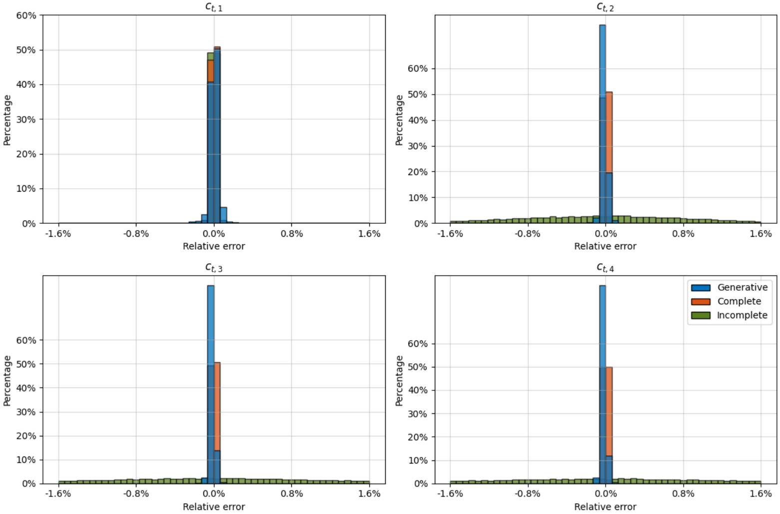

Figure 9: Comparison of error distributions for consumption function at individual grid points

Numerical Accuracy of GEM Approximations

Model	$\log_{10}$(MSE)	$\log_{10}$(MAE)	$\log_{10}$(EEE)
Asset Price	-4.85	-3.22	-3.15
Analytical RBC	-6.08	-3.47	-3.96
Nonlinear RBC	-3.30	-2.05	-2.46
Krusell-Smith	-7.10	-4.00	-2.09
Global HANK			

Table 3: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Euler Equation Error (EEE) of different models

- Generative Economic Modeling yields accurate approximations across models
- Euler Equation Error (EEE) remains competitive with benchmark

Global solution of a HANK model with financial frictions

HANK Model with Financial Frictions - Nonlinearity Meets Amplification

- **Firms**
  - Face monopolistic competition and price adjustment costs
  - Produce using labor, subject to TFP shocks and a **cash-in-advance constraint**

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- **Government**
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  - Sets the nominal interest rate via a Taylor rule
- **Why is this model interesting?**
  - Features **125 million state combinations** - global solution typically infeasible
  - **Amplification** of financial shocks **through heterogeneity**
  - Heterogeneity relevant for **optimal policy?**

Accuracy of Solution of Financial HANK model

Model	$\log_{10}$(MSE)	$\log_{10}$(MAE)	$\log_{10}$(EEE)
Asset Price	-4.85	-3.22	-3.15
Analytical RBC	-6.08	-3.47	-3.96
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Krusell-Smith	-7.10	-4.00	-2.09
Global HANK			0.55

Table 4: Mean Squared Error (MSE), Mean Absolute Error (MAE), absolute and relative to baseline; and Euler Equation Error (EEE)

- Accuracy in line with other models

Scenario Analysis: Financial Shocks Trigger Nonlinear Recessions

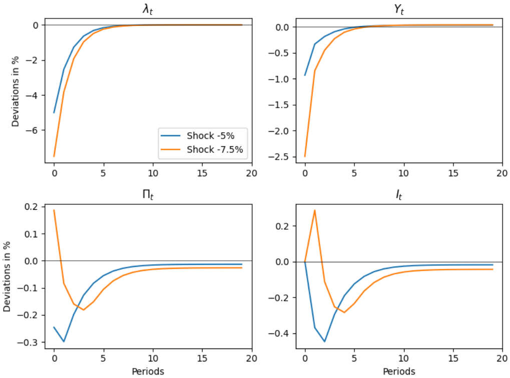

Figure 10: Generalized impulse responses to a financial shock of varying size

Acts as a supply shock:

- Financial shock limits firms' ability to finance inputs ⇒ output falls
- Inflation rises, pushing up nominal and real rates ⇒ demand contracts further

Global solution needed for the constraint:

- Economy's response is **nonlinear** in the size of the financial shock

Core Steps of GEM:

1. Solve a collection of **simplified models**
2. Simulate **synthetic data** from each specification
3. Train a **neural network** on the aggregated dataset

Takeaways for applied use:

- **Extends** existing solution methods – no new toolkit required
- Builds directly on established **conventional methods**
- Neural networks used **only for training** on simulated data

Thank you!

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Appendix

Overlap of simplified models

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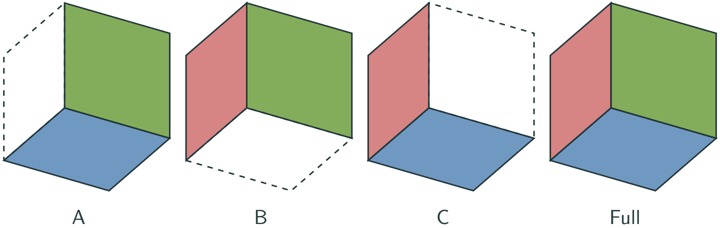

Figure 12: Graphical illustration for $n_\nu = 3$ and $n_{\tilde{\nu}} = 2$

- Model with shocks ν of length n_ν, simplified models with shocks $\tilde{\nu}$ of length $n_{\tilde{\nu}}$

$$\binom{n_\nu}{n_{\tilde{\nu}}} = \frac{n_\nu!}{n_{\tilde{\nu}}!(n_\nu - n_{\tilde{\nu}})!}$$

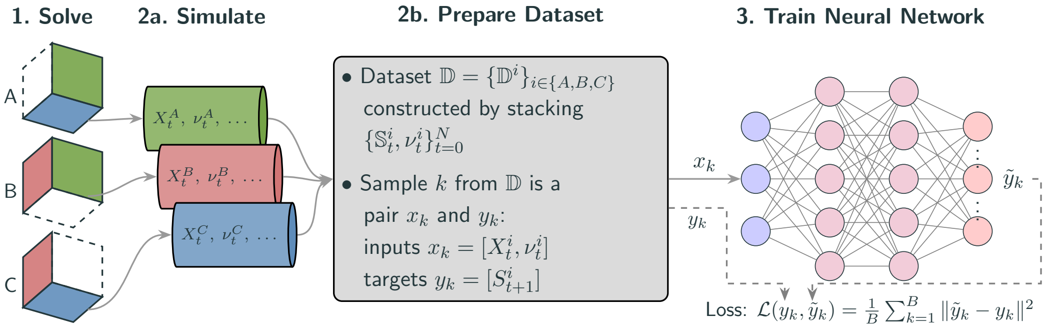

Figure 13: Flow chart of the generative economic modeling method

Training Setup and Evaluation Criteria

Back

Train one NN on the full model and another on the combined simulated data.

- **Training Setup:**
    - Network architecture: 5 hidden layers, each with 128 neurons
    - Activation function: CELU
    - Optimizer: AdamW, minimizing mean squared error (MSE)
    - Learning rate: cosine annealing schedule, decaying from 10^{-3} to 10^{-7}

- **Evaluation Metric: Euler Equation Error (EEE)**

$$EEE = u'(\underbrace{\bar{f}^{c}_{DNN}(\mathbb{X}_t, \nu_t|\Theta)}_{c_t}) - \beta \mathbb{E}_t \left[\underbrace{\bar{f}^{R}_{DNN}(\mathbb{X}_{t+1}, \nu_{t+1}|\Theta)}_{R_{t+1}} u'(\underbrace{\bar{f}^{c}_{DNN}(\mathbb{X}_{t+1}, \nu_{t+1}|\Theta)}_{c_{t+1}}) \right]$$

Proposition

If all households are ex-ante and ex-post identical, depreciation is deterministic and full, $\delta(u_t) = 1$, capacity utilization is fixed at $u_t = 1$, there are no capital adjustment costs $\phi = 0$, the discount factor shock is inactive $\sigma_\zeta^2 = 0$, and per period felicity is of King, Plosser, and Rebelo (1988) (KPR)-form given by $u(C_t, N_t) = \ln C_t - \omega \frac{N_t^{1+\gamma}}{1+\gamma}$. Then the policy functions of the representative household are

$$N_t(\mu_t) = \left[\frac{\mu(1-\tau^L)(1-\alpha)}{\mu_t \omega (1+\tau^C)(\mu - (1-\tau^K)\alpha\beta)} \right]^{\frac{1}{1+\gamma}}, \quad (1)$$

$$C_t(K_t, A_t, Z_t, \mu_t) = \left(1 - \frac{\alpha\beta}{\mu_t}\right) Y_t\left(K_t, A_t, Z_t, N_t(\mu_t)\right), \quad (2)$$

and $$K_{t+1}(K_t, A_t, Z_t, \mu_t) = \frac{\alpha\beta}{\mu_t} Y_t\left(K_t, A_t, Z_t, N_t(\mu_t)\right), \quad (3)$$

where $Y_t(K_t, A_t, Z_t, N_t(\mu_t))$ denotes the Cobb-Douglas production function. Given the policy functions of the household, the prices in the economy can be determined by the first-order conditions of the firm.

Generative Economic Modeling with Analytical Solution: Errors

Back

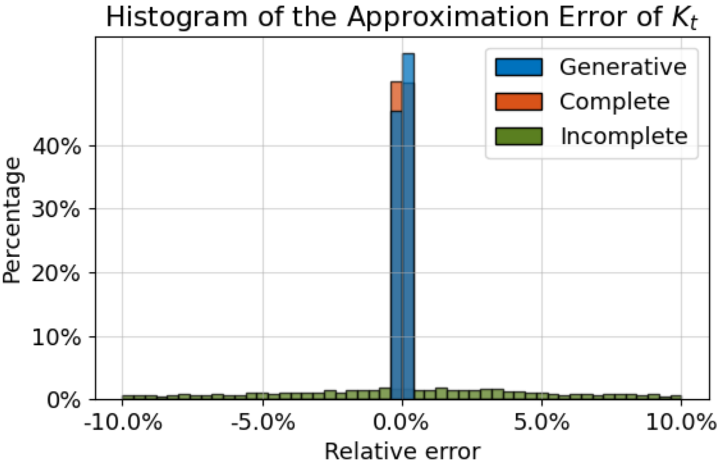

Figure 15: Error distribution of surrogate model for analytical model

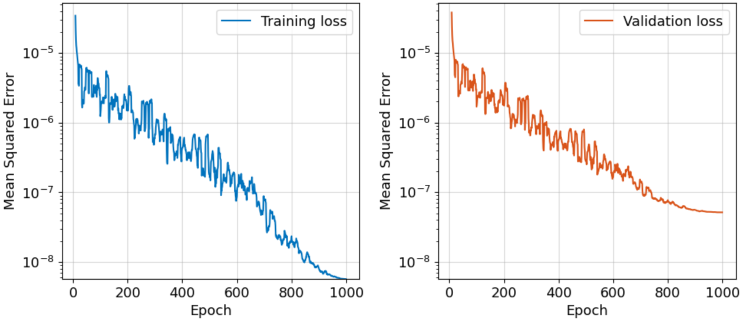

Figure 16: Loss in training and validation data over iterations

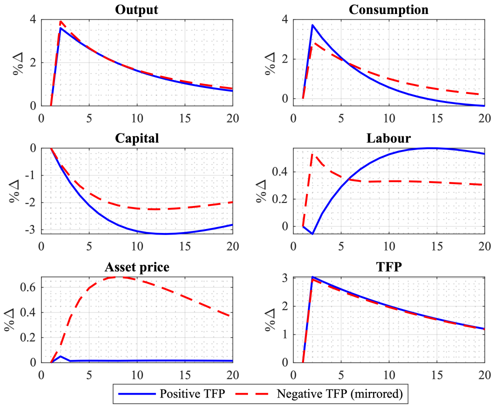

Figure 17: IRFs and Nonlinear Propagation of the TFP Shock

- Nonlinear medium-sized RBC with state-dependent capital adjustment costs
- Model is solved with global solution method (time iteration)
- Generalized IRFs illustrate nonlinear effect of capital adjustment costs

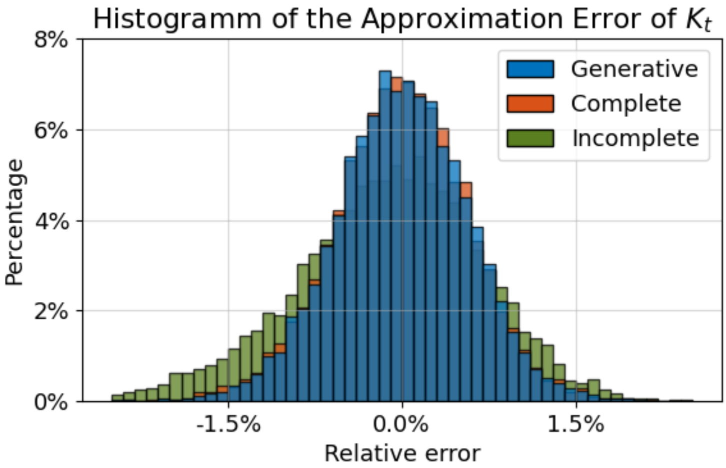

Figure 19: Error distribution of surrogate model for nonlinear Rep. Agent