Cross-Sectional Household Heterogeneity in Responses to Macroeconomic Shocks

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Abstract

Research into the effects of business cycles often focuses on aggregate macroeconomic consequences. This paper explores the heterogeneous effects of business cycles on households at different wealth and earnings potential levels. I perform a Bayesian estimation on a HANK model to identify business cycle forces. Then, I decompose the business cycle shocks and transmission channels driving changes in household decision rules using variance and historical decompositions. I find the factors causing changes in consumption decisions vary substantially across the income distribution and the factors causing changes in savings decisions vary substantially across the wealth distribution. In addition, I find fiscal determinants, including transfers, spending, and taxes, are most impactful for low income and low wealth households while supply-side and monetary determinants, including markups and the interest rate, are most impactful for high income and high wealth households.

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1 Introduction

The significant cross-sectional differences between households in the United States suggests business cycle fluctuations should have heterogeneous effects across households. At the same time, most macroeconomic research, both within representative agent and heterogeneous models, is interested in explaining changes in aggregates (Smets and Wouters 2007; Krusell and Smith 1998; Kaplan, Moll, and Violante 2018; Auclert 2019; McKay, Nakamura, and Steinsson 2016). I examine how business cycles affect households at different wealth and income levels. I also examine the important transmission channels for changes in behavior for different households. I find the factors causing changes in consumption decisions vary substantially across the income distribution and the factors causing changes in savings decisions vary substantially across the wealth distribution.

I analyze these effects within the framework of an estimated Heterogeneous Agent New Keynesian (HANK) model. HANK models add household heterogeneity to standard New Keynesian models that feature price and market frictions (Kaplan, Moll, and Violante 2018). The model features incomplete markets and uninsurable risks that give households a strong precautionary motive that plays an important role in the economy (McKay, Nakamura, and Steinsson 2016; Bayer et al. 2019). My model follows the standard with the HANK literature and features an idiosyncratic productivity process for households that determines their income (Kaplan, Moll, and Violante 2018; McKay, Nakamura, and Steinsson 2016).

Within the model, households decide how much to consume and save, which determines their movements along the wealth distribution. In response to changes in aggregate macroeconomic conditions and individual incomes, households can adjust their decisions. A shock can affect both consumption and savings if it causes households to reallocate their income from consuming to saving or vice versa. It could also affect only one decision if it changes household income and the household responds by varying only their saving or consumption choice while keeping the other one fixed.

To understand the effect of business cycles on the model, I perform a Bayesian estimation with US data from 1966 to 2019. The model includes seven macroeconomic shocks to the model: total factor productivity (TFP), price markups, wage markups, government spending, monetary policy, government transfers to households, and tax progressivity. The first five shocks are chosen from the representative agent literature as structural shocks to aggregates in the model (Smets and Wouters 2007). The tax progressivity shock is unique to heterogeneous agent models and applies non-uniformly across the distribution of households (Bayer, Born, and Luetticke 2024). The household transfer shock does the opposite, applying a uniform shock to the income of all households. This transfer shock is more impactful for lower-earning households, since the increase makes up a higher share of their income. My estimations suggest price and wage markups as well as tax progressivity and transfers play the most important role explaining the changes in aggregate outcomes during business cycles.

Given my estimates, I then examine the effect of business cycles on household decisions at different productivity and wealth levels. This goes one step farther than other Bayesian estimates of HANKs in the literature that typically focus on aggregates (Auclert, Rognlie, and Straub 2020; Acharya et al. 2023) or macro-level movements of the wealth distribution (Bayer, Born, and Luetticke 2024). I find that all seven of the shocks are important causal factors for business cycle driven changes in household decisions. Price and wage markups are especially important for household consumption decisions, with wage markup shocks affecting lower income households the most and price markup shocks affecting higher income households the most. Monetary policy is most important for explaining higher wealth households savings decisions while government spending, tax progressivity, and transfers are the main drivers of variation in savings decisions for lower wealth households.

Then, I expand the direct-indirect effects decomposition from Kaplan, Moll, and Violante (2018) to all factors that directly affect household decisions in my model: labor supply, wages, interest rates, transfers, and taxes. Using this decomposition, I analyze which macroeconomic factors that directly play into household decisions are the most important for households at different locations along the wealth and productivity distributions. I find that interest rates are most important for high income households' saving and consumption decisions. Labor supply and transfers are the primary determinants of low and middle income household consumption decisions and the interest rate has the largest effects on their savings decisions.

Finally, I use a historical decomposition to analyze the important factors over time. Similar to the variance decompositions, the historical decomposition points to price and wage markups through their labor supply and transfer effects being the key drivers of household consumption decisions, with price markups being more important only for higher income households. Savings decisions are most affected by interest rates, markups, and taxes. Due to the progressive tax scheme in the model and inclusion of a tax progressivity shock, the tax channel especially highlights differences in how households across the wealth and income distribution make decisions.

2 Literature Review

This paper adds to a growing body of work that adds household heterogeneity and market incompleteness to workhorse New Keynesian models that have been used to inform governmental policy for decades (Woodford 2003; Smets and Wouters 2007). Specifically, it contributes to work examining transmission channels and business cycle dynamics within these models.

HANK models have developed our understanding of the forces that affect the macroeconomy. Idiosyncratic household income risks give an additional motive for precautionary savings beyond the aggregate forces within representative agent models (McKay, Nakamura, and Steinsson 2016; Auclert, Rognlie, and Straub 2020; Acharya, Challe, and Dogra 2023). Heightened uncertainty from these risks explains parts of specific business cycle events, including the Great Recession (Bayer et al. 2019). Borrowing constrained households are more responsive to macroeconomic conditions, so their presence can exacerbate or dampen the consequences of macroeconomic shocks (Bilbiie 2020). After a monetary policy shock when heterogeneity is present, indirect, as opposed to direct, effects cause the aggregate household response to shocks (Kaplan, Moll, and Violante 2018). In this paper, I extend the direct-indirect decomposition from Kaplan, Moll, and Violante (2018) to all macroeconomic factors that directly effect household decisions.

Cross-sectional variation in marginal propensity to consume plays an important role in HANK models. Transfers have a trickle-up effect since poorer households have a larger marginal propensity to consume (Auclert, Rognlie, and Straub 2023). Wealthy households are self-insured against macroeconomic shocks, so the household response to the shock varies across the wealth distribution (Gornemann, Kuester, and Nakajima 2016). Shocks have unequal effects on households since earnings, balance sheet, and interest rate exposure are not evenly distributed (Auclert 2019). Heterogeneous changes in savings behavior creates a "redistribution channel" that affects aggregates (Auclert 2019). My analysis examines the transmission channels for changes in decisions for households across the wealth distribution. I focus on the heterogeneous household outcomes that are driven by the different exposure channels.

Bayesian estimates for business cycles are similar for HANKs and representative agent models (Smets and Wouters 2007; Bayer, Born, and Luetticke 2024). Investment, markups, and technology channels play the most important role in estimated business cycles (Auclert, Rognlie, and Straub 2020; Bayer, Born, and Luetticke 2024). Heterogeneous MPCs and precautionary motives drive economic outcomes in response to the estimated shocks (Auclert, Rognlie, and Straub 2020). The main obstacle to estimation is that the number of potential household states makes estimation slow. The estimation process in Bayer, Born, and Luetticke (2024) uses dimensionality reduction and parallelization to speed up the process and still takes days. Newer sequence-space methods make estimation much faster (Auclert et al. 2021). Therefore, I use a sequence-space method in this paper to estimate a series of shocks, including a novel estimate of a government transfer shock.

3 Model

I model a discrete time, one-asset HANK with incomplete markets stemming from uninsurable, idiosyncratic income risks and nominal rigidities. The economy is composed of households, unions, firms, and a government. Within the model, there are shocks to total factor productivity (TFP) A_t, price markups ψ_t, wage markups ψ_t^W, government spending g_t, transfers to households η_t, tax progressivity τ_t^P, and monetary policy ξ_t.

The household sector features a continuum of dynamically optimizing heterogeneous households that choose to consume and save. Households earn income from their wages, firm profits, and government transfers. Household productivity levels evolve idiosyncratically over time, which they self-insure against by investing in a risk-free government bond.

The union sector includes a labor packer and a continuum of unions. The labor packer aggregates the labor provided by the unions, which choose a homogenous level of labor to be supplied by households to maximize aggregate utility. Unions are subject to quadratic wage adjustment costs paid in utils following Auclert, Bardóczy, and Rognlie (2023).

The firm sector comprises a representative perfectly competitive final goods firm and a continuum of monopolistically competitive intermediate goods firms. The final goods firm aggregates production from the intermediate goods firms, who produce differentiated goods using labor supplied by unions. Following Rotemberg (1982), intermediate goods firms face quadratic price adjustment costs, creating pricing frictions in the economy.

The government acts as the fiscal and monetary authority. As the fiscal authority, the government supplies a risk-free bond to households, spends exogenously, pays a lump-sum transfer amount to households, and imposes a progressive tax scheme to balance the budget. As the monetary authority, the government sets the interest rate according to a Taylor rule based on the levels of inflation and output.

In this section, I give the assumptions and key equations in the model. For a derivation of the equations and characterization of the model, see Appendix A.

3.1 Households

The model is populated by a unit continuum of infinitely lived households indexed $i \in [0,1]$. Each period, households provide the amount of labor $\ell_{i,t}$ decided by the union and choose to consume $c_{i,t}$ and hold $b_{i,t}$ of a risk-free government bond which has gross real returns R_t to maximize expected discounted utility. Households have constant relative risk aversion (CRRA) preferences given by

$$\max_{\{c_{i,t},\ell_{i,t},b_{i,t}\}_{t=0}^{\infty}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t \left[\frac{c_{i,t}^{1-\gamma}}{1-\gamma} - \phi \frac{\ell_{i,t}^{1+\chi}}{1+\chi} \right]$$

where β, γ, ϕ, and χ represent the intertemporal discount rate, risk aversion level, relative disutility of labor, and inverse Frisch elasticity of labor supply.

Household productivity $z_{i,t}$ evolves stochastically over time subject to the log-AR(1) process

$$\log z_{i,t} = \rho_z \log z_{i,t-1} + \epsilon_{z,i,t}, \quad \epsilon_{z,i,t} \sim \mathcal{N}(0, \sigma_z^2)$$

where ρ_z and σ_z^2 represent the persistence and variance of individual productivity shocks. Based on their productivity, labor supply, and the real wage W_t, households generate pre-tax labor income $W_t z_{i,t} \ell_{i,t}$. Additionally, dividends D_t and transfers η_t are evenly distributed across households from the profits of intermediate goods firms and exogenously by the government.

Following McKay, Nakamura, and Steinsson (2016), the government imposes a progressive tax on productivity. Since productivity is exogenous, this acts like a lump sum tax and does not distort household decisions. The tax scheme is given by $\tau_t^L z_{i,t}^{\tau_t^P}$ where τ_t^L and τ_t^P measure the level and progressivity of the tax scheme respectively. Therefore, $\tau_t^P < 1$ creates a regressive tax scheme, $\tau_t^P = 1$ creates a proportional tax scheme, and $\tau_t^P > 1$ creates a progressive tax scheme.

Combined, this results it the household budget constraint

$$b_{i,t} + c_{i,t} = R_t b_{i,t-1} + W_t z_{i,t} \ell_{i,t} + D_t + \eta_t - \tau_t^L z_{i,t}^{\tau_t^P}.$$

Households are also subject to the borrowing constraint $b_{i,t} \geq \underline{b}$ which enforces a no-Ponzi condition for all households.

Because productivity $z_{i,t}$ follows an exogenous law of motion that is time invariant, the distribution of household productivity $\Gamma_t^z(z)$ is also fully exogenous and follows a time invariant process. Assuming the initial distribution for $\Gamma_t^z(z)$ is equal to the ergodic distribution of the AR(1) process, the overall distribution stays constant over time, even as individual households change state within it.

Each period, household's choices depend on their states $z_{i,t}$ and $b_{i,t-1}$ entering the period. Given these states, households follow the decision rules

$$b_t(b_{i,t-1}, z_{i,t}) = b_{i,t}$$
$$c_t(b_{i,t-1}, z_{i,t}) = c_{i,t}.$$

Therefore, the distribution of household states $\Gamma_t(b, z)$ evolves according to

$$\Gamma_{t+1}(b', z') = \int_{\{(b,z):b_t(b,z)=b'\}} \Pr(z'|z) d\Gamma_t(b, z)$$

which says the density of households with savings b' and productivity z' is equal to the density of households that choose to save b' times the probability that their productivity ends up z'.

3.2 Unions

A single labor packer aggregates labor from a unit continuum of unions indexed $k \in [0, 1]$.

The labor packer aggregates labor supplied by each union $n_{k,t}$ into aggregate labot N_t according to the Dixit-Stiglitz aggregator

$$N_t = \left(\int_0^1 n_{k,t}^{\frac{1}{\psi_t^W}} \, dk \right)^{\psi_t^W}$$

where $\dfrac{\psi_t^W}{\psi_t^W - 1}$ represents the elasticity of substitution for labor provided by each union. Profit maximization for the union gets the demand for labor provided by each union k

$$n_{k,t} = N_t \left(\frac{w_{k,t}}{W_t} \right)^{\frac{\psi_t^W}{1-\psi_t^W}}$$

where $w_{k,t}$ is the real wage demanded by union k.

Unions choose a level of labor to demand uniformly from households $\ell_{k,t}$ and aggregates it according to

$$n_{k,t} = \int z \ell_{k,t} d\Gamma_t^z(z).$$

The uniform labor demand assumption follows Auclert, Bardóczy, and Rognlie (2023), and suggests that households supply the same level of labor to the union regardless of their productivity and wealth differences. This ignores household differences in willingness to work and does require that some households are required to work more than they would choose to (Gerke et al. 2024). Alternative approaches would allow unions to vary the quantity of labor demanded or wage for different households, but add substantial mathematical and computational complexity to the model (Gerke et al. 2024).

The union chooses $\ell_{k,t}$ to maximize household utility subject to quadratic adjustment $m_{k,t}^W$ costs

$$m_{k,t}^W = \frac{\psi_t^W}{\psi_t^W - 1} \frac{1}{2\kappa^W} \log \left(\frac{w_{k,t}}{\overline{\pi}^W w_{k,t-1}} \right)^2$$

which is paid in utils where κ^W denotes the responsiveness of wages to economic changes, $\pi_t^W = \frac{W_t}{W_{t-1}}$ is wage inflation, and the overline over a variable represents its steady state value. The aggregate utility maximization problem gets the wage Philips curve

$$\log\left(\frac{\pi_t^W}{\overline{\pi}^W}\right) = \kappa^W \left(\phi L_t^{1+\chi} - \frac{1}{\psi_t^W} W_t L_t \int z c_t(b,z)^{-\gamma} d\Gamma_t(b,z)\right) + \beta \log\left(\frac{\pi_{t+1}^W}{\overline{\pi}^W}\right)$$

where L_t is the amount of labor demanded from each household and $c_t(b,z)^{-\gamma}$ is a household's marginal utility of consumption.

3.3 Firms

The model is populated by a representative, competitive final goods firm and a unit continuum of intermediate goods firms indexed $j \in [0,1]$.

Like the labor packer, the final goods firm aggregates intermediate goods $y_{j,t}$ into output Y_t according to the Dixit-Stiglitz aggregator

$$Y_t = \left(\int_0^1 y_{j,t}^{\frac{1}{\psi_t}}\, dj\right)^{\psi_t}$$

where $\frac{\psi_t}{\psi_t - 1}$ represents the elasticity of substitution for intermediate goods. Profit maximization for the final goods firm gets the demand for intermediate good j

$$y_{j,t} = Y_t \left(\frac{p_{j,t}}{P_t}\right)^{\frac{\psi}{\psi-1}}$$

where $p_{j,t}$ is the price of intermediate good j and P_t is the overall price level of the economy given by

$$P_t = \left(\int_0^1 p_{j,t}^{\frac{1}{1-\psi_t}}\, dj\right)^{1-\psi_t}.$$

Intermediate goods firms use productive units of labor $n_{j,t}$ to produce their intermediate good according to

$$y_{j,t} = A_t n_{j,t}$$

where A_t represents the overall productivity level of the economy.

Intermediate goods firms also choose prices subject to quadratic adjustment costs $m_{j,t}$ à la Rotemberg (1982) given by

$$m_{j,t} = \frac{\psi_t}{\psi_t - 1}\frac{1}{2\kappa}\log\left(\frac{p_{j,t}}{\overline{\pi}p_{j,t-1}}\right)^2 Y_t$$

where $\pi = \dfrac{P_t}{P_{t-1}}$ is inflation and κ determines the responsiveness of inflation to changes in output. Compared to the alternative Calvo (1983) rule, the Rotemberg price frictions have a couple advantages. First, price frictions under a Rotemberg rule are more consistent with real data (Richter and Throckmorton 2016). Additionally, a Rotemberg rule has an analytically solvable Philips curve, which makes the model easier to solve. The Philips curve is

$$\log\left(\frac{\pi_t}{\overline{\pi}}\right) = \kappa\left(\frac{W_t}{A_t} - \frac{1}{\psi_t}\right) + R_{t+1}\frac{Y_{t+1}}{Y_t}\log\left(\frac{\pi_{t+1}}{\overline{\pi}}\right).$$

Finally, since intermediate goods firms are monopolistically competitive, they can make a profit. Profits will be paid out in the form of real dividends $d_{j,t}$ such that

$$d_{j,t} = \frac{p_{j,t}}{P_t}y_{i,t} - W_t n_{j,t} - m_{j,t}$$

where firms earn real revenue $\frac{p_{j,t}}{P_t}y_{i,t}$ and pay labor costs $W_t n_{j,t}$ and price adjustment costs. Aggregate dividends D_t are

$$D_t = \int_0^1 d_{j,t}dj.$$

3.4 Government

In the economy, the government acts as both the fiscal and monetary authority.

As the fiscal authority, the government spends an exogenous fraction g_t of output so that government spending G_t follows

$$G_t = g_t Y_t.$$

The government also offers the risk-free bond B_t and pays out transfers to households subject to the law of motion for bonds

$$B_t = \overline{B} + \rho_B \left(R_t B_{t-1} - \overline{RB} + G_t - \overline{G} + \eta_t - \overline{\eta}\right)$$

following Auclert, Rognlie, and Straub (2024) where ρ_B represents how quickly the government pays back non-steady state levels of debt. In the steady state, this means the government holds a constant stock of debt which it pays all the interest on every period. However, increases in transfers η_t, the interest rate R_t, or government spending G_t will be financed by taking on more debt and paying it back over time. To balance the budget, the government sets the tax level τ_L so that government spending equals government revenue

$$R_t B_{t-1} + G_t + \eta_t = \tau_t^L \int z^{\tau_t^P} d\Gamma_t^Z(z) + B_t.$$

As the monetary authority, the government sets the interest rate I_t according to the Taylor Rule

$$I_t = \overline{I} \hat{\pi}_t^{\omega_\pi} \hat{Y}_t^{\omega_Y} \xi_t$$

where ω_π and ω_Y represent the relative importance of inflation and output stabilization and ξ_t is the monetary policy shock. The Fisher relation means

$$R_t = \frac{I_{t-1}}{\pi_t}.$$

3.5 Equilibrium

For the economy to be in equilibrium, the labor, bond, and goods markets all need to clear. Labor market clearing requires unions to provide as much labor as firms demand so that

$$N_t = \int_0^1 n_{j,t} dj.$$

Bond market clearing requires the supply of bonds by the government to equal household savings

$$B_t = \int b_t(b, z) d\Gamma_t(b, z).$$

Finally, goods market clearing requires consumption, government spending, and price adjustment costs to equal output

$$Y_t = \int c_t(b, z) d\Gamma_t(b, z) + M_t + G_t$$

where $M_t = \int_0^1 m_{j,t} dj$.

Therefore, a solution to the model consists of sequences for prices $\{\pi_t, W_t, \pi_t^W, M_t, D_t, R_t, I_t, \tau_t^L\}_{t=0}^{\infty}$, household decision rules $\{b_t, c_t\}_{t=0}^{\infty}$ that solve the household utility maximization problem, the distribution of household states $\{\Gamma_t\}_{t=0}^{\infty}$ that evolves following the policy rules, and macroeconomic aggregates $\{Y_t, N_t, L_t, B_t, G_t\}_{t=0}^{\infty}$ all so that the labor, bond, and goods markets clear subject to exogenous, AR(1) processes for $\{A_t, \psi_t, \psi_t^W, g_t, \xi_t, \tau_t^P, \eta_t\}_{t=0}^{\infty}$.

3.6 Computational Methods

I solve the model in the sequence-space following Auclert et al. (2021). This method has significant computational advantages over standard state-space methods like Reiter (2009) or even dimensionality-reduced state-space methods like Bayer and Luetticke (2018) since it removes household states, of which there can be thousands, from the system used to solve the model.

The first step to solve the model is to find the steady state. I discretize the household asset and productivity levels into a grid. Household transitions between productivity levels are modeled using a Rouwenhorst process (Kopecky and Suen 2010). Following Reiter (2009), I add more asset gridpoints closer to the borrowing constraint $\underline{b}$ to address the nonlinearities in the decision rules near that point. I solve for household decision rules using the endogenous grid method (Carroll 2006). Then, following Young (2010), the distribution Γ_t is represented as a histogram at each of the asset-productivity gridpoints, which households travel between based on the savings decision rule.

Shocks are modeled as linear perturbations around the steady state in the sequence space

Table 3.1: Computational Parameters

Parameter	Value	Description
n_b	501	Number of asset gridpoints
$\underline{b}$	0	Borrowing constraint
$\overline{b}$	50	Maximum asset gridpoint
n_z	7	Number of productivity gridpoints
T	500	Sequence space perturbation time horizon

(Auclert et al. 2021). I use the Python automatic differentiation library Jax to solve for derivatives of the aggregate conditions and the Fake News Algorithm with two-sided numerical differentiation to solve for derivatives of the heterogeneous agent block aggregates (Auclert et al. 2021). To model the effect of shocks on individual policy rules, I use the disaggregated Fake News derivative and aggregate economic conditions to solve for the linearized effect of the shock on households (Auclert et al. 2021).

The grid dimensions and sequence space truncation horizon are outlined in Table 3.1. In Appendix C, I test the effect of the truncation horizon on my results, showing that it has a negligible effect on my results.

4 Parameterization

I use a two-step procedure to parameterize the model at a quarterly frequency. First, I calibrate the micro-parameters and frictions within the model. Then, I use a Bayesian estimation of the shocks to decompose business cycle dynamics into each different shock channel. This "calibrate then estimate" approach is common in HANK literature since the method reuses the perturbation matrix instead of having to recompute it each draw, which is the most computationally difficult part of the solution process (Winberry 2018; Auclert, Rognlie, and Straub 2020; Auclert et al. 2021; Bayer, Born, and Luetticke 2024). Alternative approaches use parallelized estimation strategies and still can take days to estimate the full set of parameters in the model (Acharya et al. 2023).

Table 4.1: Model Parameters

Parameter	Value	Description	Target
Preferences			
β	0.945	Discount rate	2% annual interest rate
γ	4	Risk aversion	Kaplan, Moll, and Violante (2018)
$1/\chi$	1/2	Frisch elasticity	Chetty (2012)
ϕ	3.16	Disutility of labor	$\overline{N} = 1$
$\underline{b}$	0	Borrowing constraint	
Productivity			
ρ_z	0.963	Productivity persistence	Storesletten, Telmer, and Yaron (2004)
σ_z	0.134	Productivity STD	Cross-sectional STD of 0.5
Unions			
κ_W	0.1	Wage Philips Curve	
Firms			
κ	0.1	Philips Curve	
Government			
ρ_B	0.93	Debt persistence	Auclert, Rognlie, and Straub (2024)
$\overline{B}$	0.577	Govt. debt target	57.7% debt to GDP steady state
ω_π	1.5	Taylor inflation	
ω_Y	0	Taylor output	
$\overline{\pi}$	1	Inflation target	0% inflation steady state
Shock SS			
$\overline{A}$	1	TFP	
$\overline{\psi}$	1.2	Markup	20% markup
$\overline{\psi}^W$	1.2	Wage markup	20% markup
$\overline{g}$	0.202	Govt. spending	20.1% govt. spending
$\overline{\eta}$	0.081	Transfers	8.1% transfers
$\overline{\tau}^P$	1.18	Tax progressivity	Heathcote, Storesletten, and Violante (2017)
$\overline{\xi}$	1	Monetary shock	

4.1 Calibration

The calibrated model parameters are listed in Table 4.1. Risk aversion is set to 4, which is standard in HANK literature (Kaplan, Moll, and Violante 2018). I take Frisch elasticity of 0.5 from Chetty (2012). Household productivity transitions are based on Storesletten, Telmer, and Yaron (2004) to have persistence 0.963 and cross-sectional standard deviation of 0.5. The slope of the Philips Curve and the Taylor coefficients for inflation and output are set based on standard values in the literature. The government inflation target ensures a 0% inflation steady state. The values for TFP and monetary policy shocks have no effect in the steady state. The price and wage markups are set to give intermediate goods firms and unions a 20% markup in the steady state. Tax progressivity of 1.18 creates a progressive taxation scheme for the economy (Heathcote, Storesletten, and Violante 2017). The government debt persistence parameter is set to match Auclert, Rognlie, and Straub (2024).

The government debt target, government spending rate, and transfers are calibrated to match historical US averages for debt to GDP, government spending to GDP, and household transfers to GDP between 1966 and 2019. This process is explained in Appendix B.1. The values for the discount rate and the disutility of labor are calibrated within the model to match a 2% annual (0.5% quarterly) interest rate and full employment in the steady state ($\overline{N} = 1$).

4.2 Estimation Strategy

To estimate the shocks to the model, I assume they each follow a Gaussian AR(1) processes with a persistence parameter ρ and standard deviation σ. Then, I use the Bayesian estimation procedure from Auclert et al. (2021). This method uses the impulse response functions (IRFs) solved for in the sequence space to find the coveriences between endogenous variables in the model. Then, the likelihood is evaluated by comparing the covariances within the model to the coveriences found in the real data. Similar to other estimations of HANKs, I use a standard random-walk Metropolis-Hastings (RWMH) algorithm with 250,000 draws and a 50,000 draw burn-in (Auclert et al. 2021; Bayer, Born, and Luetticke 2024).

I estimate the persistence and standard deviation for each of the seven shocks on quarterly macroeconomic time-series for GDP, inflation, the federal funds rate, hours worked, consumption, government debt, and wages from 1966 to 2019. For inflation and the interest rate, I estimate on the difference from the mean. For GDP, employment, consumption, debt, and wages, I estimate on the difference from log-linear trend over time. The data series and detrending process are explained further in Appendix B.2. I do not include any microdata in the estimation process, which is a limitation of the paper. However, fitting to distributional microdata generally has a negligible effect on the overall estimates (Bayer, Born, and Luetticke 2024).[1] Due to the lack of microdata, the data used for the estimation do not directly link to the tax progressivity and transfer shocks in the model. Instead, these shocks are identified from their effect on consumption and savings (bonds) through the varying MPCs along the wealth distribution.

I assume weak prior distributions for each of the estimated parameters. The prior for the persistence of each shock is assumed to be a beta distribution with mean 0.5 and standard deviation 0.15. The prior for the standard deviation of each shock is assumed to be an inverse gamma distribution with mean 0.1 and standard deviation 2%.

4.3 Estimation Results

The estimation results are presented in Table 4.2. Impulse response functions for the estimated shocks can be found in Appendix E. I find wage markup shocks are the most persistent, with a ρ of 0.998. Price markup shocks have a ρ of 0.984, making them also very persistent. Shocks to TFP, tax progressivity, household transfers, and government spending are also found to be fairly persistent, with ρ estimates of 0.952, 0.907, 0.842, and 0.854 respectively. Shocks to monetary policy are the least persistent, with a ρ estimate of 0.633. The estimated standard deviation σ is highest for transfer shocks (2.455%), tax progressivity shocks (1.820%), and wage markup shocks (1.759%). Comparatively, the standard deviations of shocks to government spending, price markups, and monetary policy are found to be small with values of 0.652%, 0.554%, and 0.444%. TFP has the smallest average shock size with an estimated standard deviation of 0.153%.

These estimates generally line up with both representative agent and HANK literature. My estimated TFP persistence and standard deviation is nearly identical to Bayer, Born, and Luetticke (2024). Similarly, the estimates for government spending and the interest rate mostly line up with Bayer, Born, and Luetticke (2024) and Smets and Wouters (2007). I estimate a similarly sized but slightly more persistent price markup shock than Bayer, Born, and Luetticke (2024). The estimated wage markup shock is both bigger and more persistent than Smets and Wouters (2007) and Bayer, Born, and Luetticke (2024). The differences in markup shocks could be explained by recent trends

1. Iao and Selvakumar (2024) finds a smaller error band for estimates using microdata, but the parameter estimates themselves are very similar.

Table 4.2: Estimation Results

Parameter		**Prior**			**Posterior**			
Shock	Statistic	Distribution	Mean	Std. Dev.	Mode	Mean	5%	95%
TFP	ρ	Beta	0.50	0.15	0.953	0.952	0.934	0.969
	σ	Inv. Gamma	0.20	2.00	0.152	0.153	0.142	0.166
Markup	ρ	Beta	0.50	0.15	0.986	0.984	0.971	0.993
	σ	Inv. Gamma	0.20	2.00	0.549	0.554	0.507	0.607
Wage Markup	ρ	Beta	0.50	0.15	0.998	0.998	0.998	0.998
	σ	Inv. Gamma	0.20	2.00	1.753	1.759	1.619	1.912
Govt. Spend	ρ	Beta	0.50	0.15	0.857	0.854	0.806	0.904
	σ	Inv. Gamma	0.20	2.00	0.647	0.652	0.576	0.705
Mon. Pol.	ρ	Beta	0.50	0.15	0.633	0.629	0.576	0.678
	σ	Inv. Gamma	0.20	2.00	0.440	0.444	0.409	0.483
Tax Prog.	ρ	Beta	0.50	0.15	0.907	0.907	0.876	0.936
	σ	Inv. Gamma	0.20	2.00	1.828	1.820	1.476	2.213
Transfers	ρ	Beta	0.50	0.15	0.849	0.842	0.781	0.909
	σ	Inv. Gamma	0.20	2.00	2.374	2.455	2.087	2.844

of increasing markups within the later estimation window I use (De Loecker, Eeckhout, and Unger 2020). My estimated tax progressivity shock is more persistent and larger than that of Bayer, Born, and Luetticke (2024), although they use a different taxation scheme that should expect a different parameter estimate. An estimation of a household transfer shock is, to my knowledge, novel.

The credible intervals for the estimates are high compared to other literature (Smets and Wouters 2007; Bayer, Born, and Luetticke 2024). This is common when estimating a one-asset, as opposed to two-asset, model (Auclert et al. 2021). This does add uncertainty to my analysis, however the parameters are all well identified with means of the RWMH process near the posterior modes and credible intervals that, despite being larger than those in other liturature, are still reasonably narrow. Appendix D features plots of the recursive means (Figure D.1), posterior distributions (Figure D.2), and posterior covariances (Figure D.3) which all suggest good convergence.

5 Business Cycles

5.1 Aggregate Outcomes

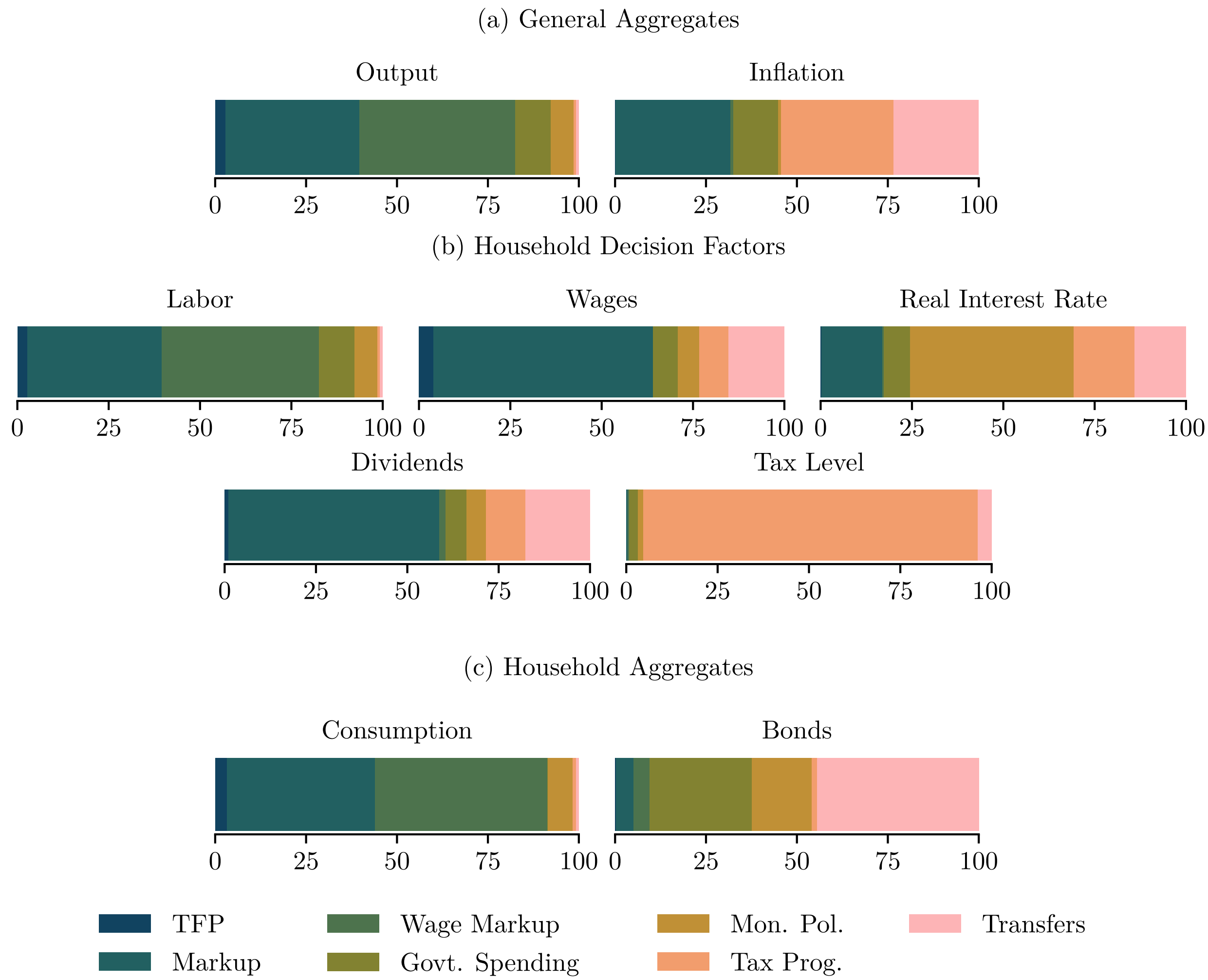
Using the estimated shock parameters, I examine the role of each shock within business cycles. Figure 5.1 features a forecast error variance decomposition for key aggregates in the model.[2] Panel 5.1a describes how output and inflation are affected by different business cycle shocks. Compared to other literature, I find TFP plays a smaller role in my model, especially in explaining output variance (Smets and Wouters 2007; Bayer, Born, and Luetticke 2024). I find that price and wage markups are important business cycle drivers in the model, and play a much larger role explaining changes in output than seen in Bayer, Born, and Luetticke (2024). This difference is likely explained by the lack of a capital sector in the economy causing changes in firm behavior to be explained by price, not production, factors. Consistent with other estimates, supply-side factors (TFP and price/wage markups) account for about 80% of output volatility, suggesting my estimated TFP, price markup, and wage markup shocks act as general supply side shocks, including the investment shock seen in Bayer, Born, and Luetticke (2024). Government spending, tax progressivity, and transfers have an important effect on prices (inflation) in the model but not output.

Panel 5.1b explores how business cycles affect the factors that directly impact household decisions. Variance in the amount of labor supplied by each household is mostly explained by price and wage markups. Price markups also play an important role determining the wages and dividends paid out to households. Monetary policy shocks explain the largest share of interest rate variance, and tax progressivity shocks explain almost all variance in the tax level. Altogether, TFP and government spending shocks have a relatively small effect on the factors that impact households. Therefore, price markups affect households income and labor supply while wage markups only significantly impact the amount of labor households supply. Monetary policy primarily affects the interest rate and tax progressivity primarily affects the tax level. Government transfers have a small but non-negligible effect across the board.

A variance decomposition of household aggregates is presented in Panel 5.1c. Price and wage

2. See Appendix F for how the forecast error variance decomposition was calculated.

Figure 5.1: Variance Decomposition: Aggregates



Notes: Forecast error variance decomposition calculated at a 4 quarter time horizon.

markups have the largest impacts on consumption, suggesting the union's labor supply choice, wages, and dividends are important factors to the household's consumption decisions. In contrast, household bond holdings are mostly affected by government spending, monetary policy, and transfers. Since government spending, the interest rate, and transfers play into the government bond law of motion, this suggests household reactions to the supply side of the market is most important explaining variation in aggregate household savings.

5.2 Decision Rules

Next, I examine the business cycle factors that drive changes in household behavior at different points along the income and wealth distribution. I focus on the 10th, 50th, and 90th percentiles on the productivity distribution. Since labor is supplied homogeneously across households, these represent low, middle, and high income households. On the wealth distribution, I look at the 0th, 50th, 90th, and 99th percentiles. Over 40% of the households in the model hold 0 savings, so the decision rules for the 0th percentile apply to a significant portion of households. The 50th, 90th and 99th percentiles represent households that have small, medium, and large savings respectively. I look at the decision rules at fixed points on the wealth distribution. This means the analysis does not apply to specific individuals in the model, who can move along the distribution, or account for shifts in the distribution changing the threshold for wealth percentiles.

Table 5.1 gives information about the decision rules and income sources at these productivity and wealth levels in the steady state. Both consumption and savings, as expected, are increasing with both productivity and wealth. Consumption increases more between income than wealth shares while savings increases more between wealth than income shares. This suggests higher wealth households exhibit significant consumption smoothing over time attempting to save more to be able to maintain slightly higher levels of consumption, however higher income households count on having a more sustained income to be able to consumption smooth. Despite this, within the model there exists precautionary saving from high income households to protect against idiosyncratic income shocks since, unlike low and middle income households, high income households at all but the highest wealth levels are net savers and end the period with more assets than they start with.

Households at different points along the income and wealth distribution get their budget each period from different sources. For low income households, transfers and, at higher wealth levels, interest rates contribute significantly to their budget. In contrast, higher income households get a significantly larger share from their wages. Because of the progressive tax structure, higher income households contribute a significantly higher share of their income to taxes. For a more detailed breakdown, see Appendix G for surface plots of household decision rules (Figure G.1) and income sources (Figure G.2) at all wealth and productivity levels.

Table 5.1: Household Steady State Behavior

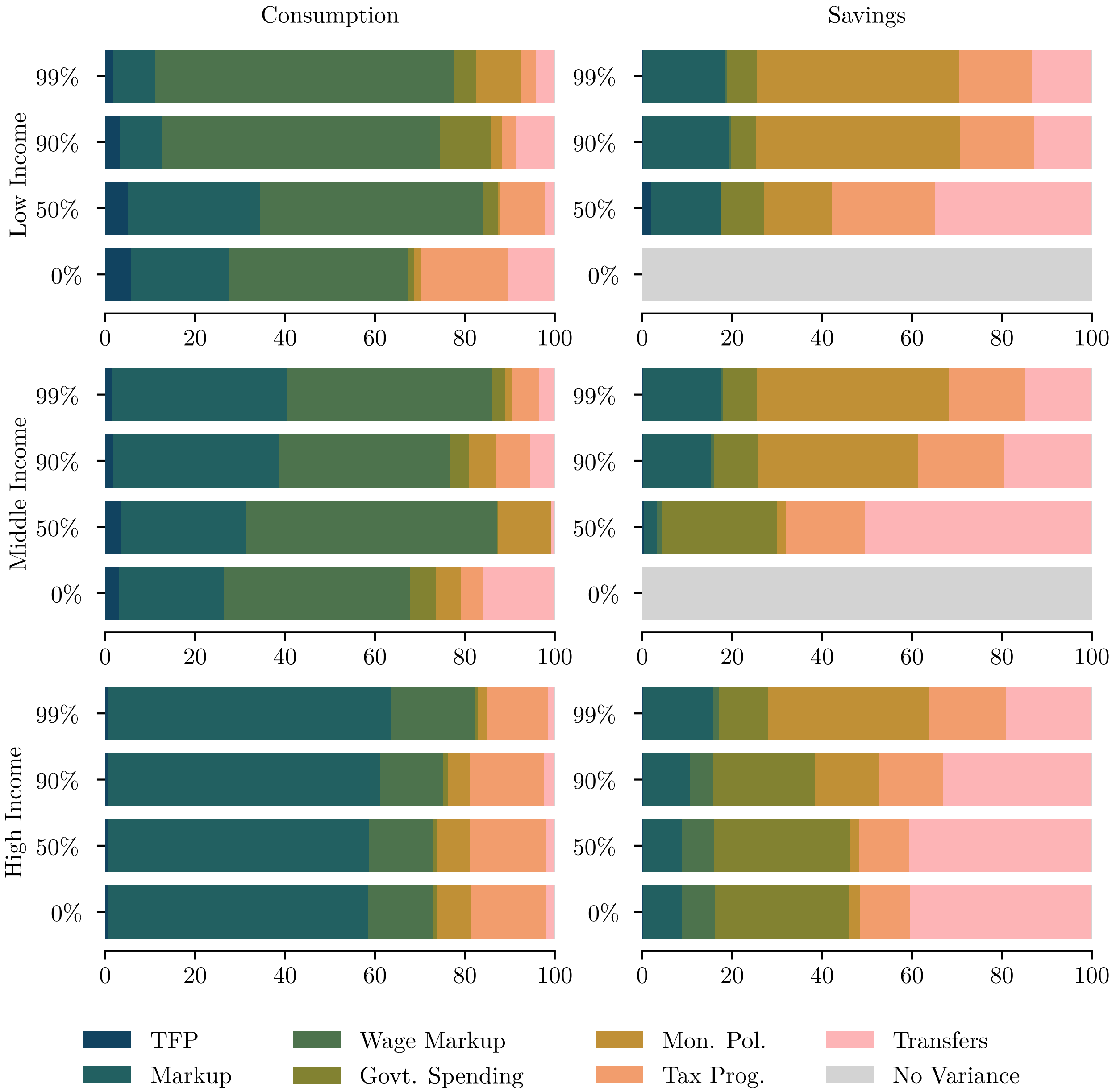
	Low Income (10%)				Middle Income (50%)				High Income (90%)			
	0%	50%	90%	99%	0%	50%	90%	99%	0%	50%	90%	99%
States												
Productivity	0.444	0.444	0.444	0.444	1.000	1.000	1.000	1.000	2.252	2.252	2.252	2.252
Assets	0.000	0.040	1.874	5.896	0.000	0.040	1.874	5.896	0.000	0.040	1.874	5.896
Decisions												
Consumption	0.483	0.507	0.696	0.896	0.744	0.754	0.898	1.079	1.109	1.111	1.200	1.352
Savings	0.000	0.016	1.670	5.512	0.000	0.030	1.730	5.591	0.173	0.211	1.965	5.855
Income												
Wages	0.327	0.327	0.327	0.327	0.737	0.737	0.737	0.737	1.660	1.660	1.660	1.660
	(67.79)	(62.60)	(13.83)	(5.11)	(99.00)	(93.95)	(28.05)	(11.05)	(129.54)	(125.62)	(52.45)	(23.03)
Interest	0.000	0.040	1.883	5.926	0.000	0.040	1.883	5.926	0.000	0.040	1.883	5.926
	(0.00)	(7.66)	(79.60)	(92.47)	(0.00)	(5.10)	(71.67)	(88.83)	(0.00)	(3.03)	(59.51)	(82.22)
Transfers	0.248	0.248	0.248	0.248	0.248	0.248	0.248	0.248	0.248	0.248	0.248	0.248
	(51.30)	(47.37)	(10.47)	(3.86)	(33.27)	(31.57)	(9.42)	(3.71)	(19.33)	(18.74)	(7.83)	(3.44)
Taxes	-0.092	-0.092	-0.092	-0.092	-0.240	-0.240	-0.240	-0.240	-0.626	-0.626	-0.626	-0.626
	(19.09)	(17.63)	(3.89)	(1.44)	(32.27)	(30.62)	(9.14)	(3.60)	(48.86)	(47.38)	(19.79)	(8.69)
Total	0.483	0.523	2.366	6.408	0.744	0.785	2.628	6.670	1.282	1.326	3.165	7.207
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)

Notes: After-tax income share in parenthesis. Column percentiles correspond to the 0th, 50th, 90th, and 99th wealth percentiles.

Within business cycles, the shock determinants of household behavior exhibit significant variability across the wealth and income distribution. Figure 5.2 gives a forecast error variance decomposition for household decision rules for consumption and savings at different productivity and wealth levels. Appendix G also features IRFs for each decision rule in response to each shock at all income and wealth levels.

In Figure 5.2, changes in consumption for low income households are best explained by wage markup shocks while changes in consumption for high income households are best explained by price markup shocks. Given the decompositions for household decision determinants in Figure 5.1c, low income households are highly responsive to changes in the labor supply decided by the unions while higher income households respond more to changes in the level of wages and dividends. Interestingly, tax progressivity and transfers have more significant effects on the decision rules for household consumption at all wealth and income levels than on aggregate consumption. This suggests the consumption effects of tax progressivity and transfers for different households cancel each other out, making the shocks less important in aggregate. This emphasizes the heterogeneous effects that macroeconomic shocks can have on different households and the importance of understanding the disaggregated effects of macroeconomic events.

Figure 5.2: Variance Decomposition: Household Decision Rules



Notes: Forecast error variance decomposition calculated at a 4 quarter time horizon. Subplot y-axis is the household position on the wealth distribution.

The variance decompositions of household savings decisions also vary across the wealth and income distributions. Low and middle income households that hold no wealth never choose to save, so they have no variance explained within the model. Monetary policy shocks affect already high wealth households far more than any other group, suggesting the effect of interest rate hikes can be explained more through income effects, which only affect households that already hold wealth, than households choosing to save because of the higher potential gains, which would affect all households. Government spending and transfer shocks explain the most variance for high income households, suggesting increases in government spending and transfers, which the government funds through offering more bonds to households, are primarily funded by higher income households, though transfers are also important to middle and low income households with median wealth levels. Again, tax progressivity shocks play a more significant role explaining individual rather than aggregate savings, meaning household responses to the shocks cancel each other out.

Similar to the steady states in Table 5.1, variance decompositions of household consumption vary more between income levels than wealth levels while variance decompositions for household savings vary more between wealth levels than income levels. This means heterogeneity in household decisions depends on the distribution of households states and the decision being made, suggesting more complex models where households make more decisions could exhibit more complex types of heterogeneity.

6 Endogenous Effects

Except for tax progressivity and government transfers, household behavior within the model is not a direct response to shocks, but rather a response to the macroeconomic consequences of the shock. In this section, I decompose the variance in household decisions into the different direct channels that affect households. Within the framework of my estimated HANK, this analysis pinpoints the most important macroeconomic factors for different types of households.

6.1 Direct Effects Decomposition

I expand the direct-indirect decomposition for monetary policy shocks from Kaplan, Moll, and Violante (2018) to the full set of shocks and direct household effects within my model. Household conditions depend on the union's labor supply choice L, wages W, the interest rate R, dividends D, household transfers η, the tax level τ^L, and tax progressivity τ^P. Therefore, I can decompose the vector $d\mathbf{C}$ representing the linearized impulse response function (IRF) for consumption as

$$d\mathbf{C} = \frac{\partial \mathbf{C}}{\partial \mathbf{L}} d\mathbf{L} + \frac{\partial \mathbf{C}}{\partial \mathbf{W}} d\mathbf{W} + \frac{\partial \mathbf{C}}{\partial \mathbf{R}} d\mathbf{R} + \frac{\partial \mathbf{C}}{\partial \mathbf{D}} d\mathbf{D} + \frac{\partial \mathbf{C}}{\partial \boldsymbol{\eta}} d\boldsymbol{\eta} + \frac{\partial \mathbf{C}}{\partial \boldsymbol{\tau}^P} d\boldsymbol{\tau}^P + \frac{\partial \mathbf{C}}{\partial \boldsymbol{\tau}^L} d\boldsymbol{\tau}^L$$

where $\frac{\partial \mathbf{C}}{\partial \mathbf{X}}$ is the direct effect of X on consumption and $d\mathbf{X}$ is the IRF for X. For my analysis, I combine dividends and direct transfers since both are evenly distributed transfers to all households. I also combine the tax level and tax progressivity since tax level variation is almost entirely explained by changes in tax progressivity (Figure 5.1b). Denoting transfers T and taxes τ, this means

$$d\mathbf{C} = \underbrace{\frac{\partial \mathbf{C}}{\partial \mathbf{L}} d\mathbf{L}}_{\text{Labor effects}} + \underbrace{\frac{\partial \mathbf{C}}{\partial \mathbf{W}} d\mathbf{W}}_{\text{Wage effects}} + \underbrace{\frac{\partial \mathbf{C}}{\partial \mathbf{R}} d\mathbf{R}}_{\text{Interest effects}} + \underbrace{\frac{\partial \mathbf{C}}{\partial \mathbf{T}} d\mathbf{T}}_{\text{Transfer effects}} + \underbrace{\frac{\partial \mathbf{C}}{\partial \boldsymbol{\tau}} d\boldsymbol{\tau}}_{\text{Tax effects}} .$$

Then, denoting $\frac{\partial \mathbf{C}}{\partial \mathbf{X}} d\mathbf{X}$ as $d\mathbf{C}_X$, variance in consumption within the model can be explained as

$$\begin{aligned}
\operatorname{Var}(d\mathbf{C}) = {} & \operatorname{Var}(d\mathbf{C}_L) + \operatorname{Var}(d\mathbf{C}_W) + \operatorname{Var}(d\mathbf{C}_R) + \operatorname{Var}(d\mathbf{C}_T) + \operatorname{Var}(d\mathbf{C}_\tau) \\
& + 2\operatorname{Cov}(d\mathbf{C}_L, d\mathbf{C}_W) + 2\operatorname{Cov}(d\mathbf{C}_L, d\mathbf{C}_R) + 2\operatorname{Cov}(d\mathbf{C}_L, d\mathbf{C}_T) + 2\operatorname{Cov}(d\mathbf{C}_L, d\mathbf{C}_\tau) \\
& + 2\operatorname{Cov}(d\mathbf{C}_W, d\mathbf{C}_R) + 2\operatorname{Cov}(d\mathbf{C}_W, d\mathbf{C}_T) + 2\operatorname{Cov}(d\mathbf{C}_W, d\mathbf{C}_\tau) \\
& + 2\operatorname{Cov}(d\mathbf{C}_R, d\mathbf{C}_T) + 2\operatorname{Cov}(d\mathbf{C}_R, d\mathbf{C}_\tau) \\
& + 2\operatorname{Cov}(d\mathbf{C}_T, d\mathbf{C}_\tau) .
\end{aligned}$$

Unlike the variance decompositions in Section 5, this features covariance terms. This is because the shocks to the model decomposed in Section 5 are assumed to be orthogonal to each other, while direct effects within the model are not. Positive covariance between terms within the decomposition implies comovement between the decomposed effects that complement each other. Negative covariance implies comovement between decomposed effects that, in part, cancel each other out. Substituting in any other household variable for consumption, including the policy rules at specific states, results in an identical decomposition.

Table 6.1: Direct Effects Decomposition: Consumption

	Total	**Low Income**				**Middle Income**				**High Income**			
		0th	50th	90th	99th	0th	50th	90th	99th	0th	50th	90th	99th
Variance Components $\times$100													
Var(L)	0.58	0.14	0.13	0.15	0.18	0.70	0.52	0.45	0.47	1.29	1.28	1.20	1.17
	(72.4)	(129.7)	(1,062.9)	(71.2)	(146.0)	(904.8)	(78.2)	(26.0)	(41.5)	(14.0)	(14.0)	(14.5)	(20.6)
Var(W)	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.02	0.04	0.03	0.03	0.06	0.09
	(0.0)	(2.7)	(22.7)	(2.1)	(14.7)	(18.5)	(0.6)	(1.0)	(3.6)	(0.3)	(0.3)	(0.7)	(1.5)
Var(R)	0.25	0.00	0.02	0.19	0.10	0.00	0.24	0.72	0.33	2.53	2.54	2.22	1.08
	(30.9)	(0.0)	(150.2)	(93.9)	(78.2)	(0.0)	(35.5)	(42.1)	(29.4)	(27.6)	(27.7)	(26.8)	(18.9)
Var(T)	0.09	0.08	0.06	0.09	0.14	0.08	0.06	0.12	0.15	0.13	0.13	0.16	0.17
	(11.9)	(79.0)	(474.3)	(46.0)	(108.1)	(108.6)	(8.5)	(6.8)	(13.2)	(1.4)	(1.4)	(1.9)	(2.9)
Var(τ)	0.00	0.13	0.09	0.01	0.00	0.04	0.01	0.00	0.00	0.25	0.25	0.21	0.18
	(0.6)	(117.6)	(760.7)	(6.4)	(3.2)	(52.3)	(1.7)	(0.1)	(0.2)	(2.8)	(2.7)	(2.5)	(3.1)
Covariance Components $\times$100													
Cov(L,W)	0.01	-0.02	-0.02	0.02	0.06	-0.10	-0.04	0.08	0.14	0.19	0.20	0.26	0.32
	(0.7)	(-17.8)	(-154.3)	(11.9)	(46.2)	(-124.6)	(-6.3)	(4.9)	(12.1)	(2.1)	(2.1)	(3.2)	(5.6)
Cov(L,R)	0.36	0.00	0.05	0.15	0.03	0.00	0.35	0.55	0.33	1.79	1.79	1.61	1.06
	(44.8)	(0.0)	(384.0)	(73.4)	(24.5)	(0.0)	(52.0)	(32.0)	(28.9)	(19.5)	(19.5)	(19.4)	(18.6)
Cov(L,T)	-0.23	-0.11	-0.09	-0.12	-0.16	-0.24	-0.17	-0.23	-0.26	-0.41	-0.41	-0.43	-0.44
	(-29.1)	(-99.0)	(-701.9)	(-57.2)	(-125.6)	(-306.6)	(-25.8)	(-13.3)	(-23.4)	(-4.5)	(-4.5)	(-5.2)	(-7.8)
Cov(L,τ)	-0.03	-0.13	-0.11	-0.04	-0.03	-0.15	-0.06	0.02	0.03	0.57	0.57	0.50	0.45
	(-3.9)	(-122.7)	(-890.9)	(-20.9)	(-21.0)	(-198.7)	(-9.7)	(0.9)	(2.7)	(6.2)	(6.2)	(6.1)	(7.9)
Cov(W,R)	0.00	0.00	-0.01	0.02	0.01	0.00	-0.03	0.10	0.09	0.26	0.27	0.35	0.28
	(0.4)	(0.0)	(-55.3)	(11.2)	(5.9)	(0.0)	(-4.4)	(5.8)	(8.0)	(2.8)	(2.9)	(4.2)	(4.9)
Cov(W,T)	-0.00	0.01	0.01	-0.02	-0.05	0.03	0.01	-0.04	-0.08	-0.06	-0.06	-0.10	-0.12
	(-0.3)	(12.8)	(101.5)	(-9.7)	(-39.8)	(39.8)	(2.1)	(-2.5)	(-6.8)	(-0.7)	(-0.7)	(-1.2)	(-2.1)
Cov(W,τ)	-0.00	0.02	0.02	-0.01	-0.01	0.02	0.01	0.00	0.01	0.09	0.09	0.11	0.12
	(-0.0)	(16.4)	(129.6)	(-3.3)	(-6.5)	(24.3)	(0.9)	(0.2)	(0.8)	(0.9)	(0.9)	(1.3)	(2.1)
Cov(R,T)	-0.15	0.00	-0.03	-0.12	-0.03	0.00	-0.12	-0.28	-0.18	-0.57	-0.57	-0.58	-0.40
	(-18.6)	(0.0)	(-264.6)	(-58.6)	(-20.6)	(0.0)	(-17.3)	(-16.3)	(-16.3)	(-6.2)	(-6.2)	(-7.0)	(-7.0)
Cov(R,τ)	-0.03	0.00	-0.04	-0.05	-0.01	0.00	-0.05	0.01	0.02	0.79	0.79	0.67	0.41
	(-3.5)	(0.0)	(-333.5)	(-23.4)	(-6.2)	(0.0)	(-7.1)	(0.9)	(1.5)	(8.6)	(8.6)	(8.1)	(7.2)
Cov(T,τ)	0.01	0.10	0.07	0.03	0.02	0.06	0.02	-0.01	-0.02	-0.18	-0.18	-0.18	-0.17
	(1.8)	(95.8)	(599.9)	(16.7)	(18.0)	(73.7)	(3.3)	(-0.5)	(-1.5)	(-2.0)	(-2.0)	(-2.2)	(-3.0)
Total $\times$100													
Var(c)	0.79	0.11	0.01	0.21	0.13	0.08	0.67	1.72	1.13	9.17	9.18	8.28	5.71
	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)

Notes: Forecast error variance decomposition calculated at a 4 quarter time horizon. Variance components presented in the table are multiplied by 100. Variance percent share in parentheses. Column percentiles correspond to the 0th, 50th, 90th, and 99th wealth percentiles.

6.2 Decomposition Results

I perform this decomposition on aggregates and decision rules for consumption and savings. Like in section 5.2, I decompose decision rules at the 10th, 50th, and 90th productivity percentiles and the 0th, 50th, 90th, and 99th wealth percentiles. Appendix G decomposes the IRFs for household behavior into each direct channel.

Table 6.1 presents the decomposition results for consumption. For low income households, changes in direct transfers and labor supply are extremely impactful on their consumption decisions, while for higher income households these factors are unimportant, especially transfers. Instead, interest rates are, compared to other factors, more important for higher income households than lower and middle income households. The variance decomposition for aggregate consumption is very similar to that of middle income, middle wealth households, suggesting that median households tend to act similarly to aggregate consumption.

There are large, negative covariances for many factors affecting the consumption of low income and, to a lesser extent, middle income households. This means that the macroeconomic effects of business cycle shocks push households in conflicting ways. In contrast, high income households have negligible negative covariances, meaning business cycle induced macroeconomic movements homogeneously push these households to either consume more or less.

The decomposition for household savings decisions is presented in Table 6.2. Consistent with the business cycle decomposition in Figure 5.2, low and middle income households at the 0th wealth percentile have no variance in their savings decisions. For all other households and in aggregate, the interest rate is by far the most important factor in determining household savings. Other factors, like the labor supply and taxes, are also important only to high income households. Unlike consumption, the variance components of aggregate savings are very different from that of any individual household, suggesting macroeconomic movements in aggregate savings tell us very little about any individual household.

The covariance terms between factors are very small for low and middle income households and very large for high income ones. This is opposite what was observed affecting household consumption decisions, and suggests that the factors affecting savings decisions after each shock for low and middle income households have unidirectional effects that either push households to only save more or save less. In contrast, shocks cause high income households to face diverging forces that, to some degree, cancel each other out.

7 Historical Decomposition

The variance shares of the model give a good general idea of which factors contribute to changes in macroeconomic aggregates and household decisions, however they do not give any specific view

Table 6.2: Direct Effects Decomposition: Savings

	Total	**Low Income**				**Middle Income**				**High Income**			
		0th	50th	90th	99th	0th	50th	90th	99th	0th	50th	90th	99th
Variance Components $\times 100$													
Var(L)	0.31	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.03	0.57	0.57	0.63	0.65
	(11.1)	(0.0)	(0.4)	(0.0)	(0.0)	(0.0)	(4.1)	(0.3)	(0.0)	(675.3)	(631.6)	(10.2)	(1.1)
Var(W)	0.14	0.00	0.00	0.01	0.04	0.00	0.01	0.06	0.10	0.19	0.20	0.26	0.32
	(4.9)	(0.0)	(0.3)	(0.2)	(0.1)	(0.0)	(1.5)	(0.7)	(0.2)	(231.1)	(218.1)	(4.3)	(0.5)
Var(R)	4.93	0.00	0.02	6.99	62.84	0.00	0.26	8.47	65.93	2.53	2.61	11.42	70.28
	(177.4)	(0.0)	(43.1)	(87.8)	(95.8)	(0.0)	(74.8)	(91.6)	(97.2)	(3,003.2)	(2,876.8)	(185.3)	(118.0)
Var(T)	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.02	0.02
	(0.1)	(0.0)	(5.3)	(0.1)	(0.0)	(0.0)	(1.6)	(0.1)	(0.0)	(16.4)	(15.6)	(0.3)	(0.0)
Var(τ)	0.12	0.00	0.00	0.06	0.08	0.00	0.01	0.05	0.06	0.88	0.88	0.96	1.04
	(4.5)	(0.0)	(4.4)	(0.7)	(0.1)	(0.0)	(2.7)	(0.5)	(0.1)	(1,039.2)	(970.0)	(15.6)	(1.8)
Covariance Components $\times 100$													
Cov(L,W)	-0.20	0.00	0.00	0.00	0.01	0.00	-0.01	-0.04	-0.05	-0.31	-0.32	-0.39	-0.43
	(-7.3)	(0.0)	(0.2)	(0.0)	(0.0)	(0.0)	(-1.5)	(-0.4)	(-0.1)	(-370.4)	(-348.2)	(-6.3)	(-0.7)
Cov(L,R)	-1.18	0.00	-0.00	0.06	0.36	0.00	-0.06	-0.25	-0.34	-1.20	-1.22	-1.91	-3.13
	(-42.3)	(0.0)	(-3.2)	(0.7)	(0.6)	(0.0)	(-17.1)	(-2.7)	(-0.5)	(-1,423.5)	(-1,345.6)	(-30.9)	(-5.2)
Cov(L,T)	0.02	0.00	-0.00	-0.00	-0.01	0.00	-0.01	0.01	0.01	0.05	0.05	0.08	0.09
	(0.7)	(0.0)	(-1.4)	(-0.0)	(-0.0)	(0.0)	(-2.0)	(0.1)	(0.0)	(61.5)	(58.7)	(1.3)	(0.2)
Cov(L,τ)	0.19	0.00	-0.00	0.00	0.02	0.00	-0.01	-0.04	-0.04	0.69	0.69	0.76	0.80
	(6.9)	(0.0)	(-1.1)	(0.0)	(0.0)	(0.0)	(-3.4)	(-0.4)	(-0.1)	(817.4)	(763.7)	(12.3)	(1.3)
Cov(W,R)	0.81	0.00	-0.00	0.23	0.85	0.00	0.03	0.57	1.60	0.67	0.69	1.50	3.16
	(29.3)	(0.0)	(-0.2)	(2.9)	(1.3)	(0.0)	(8.0)	(6.2)	(2.4)	(788.3)	(756.1)	(24.3)	(5.3)
Cov(W,T)	-0.02	0.00	-0.00	-0.01	-0.02	0.00	-0.00	-0.02	-0.04	-0.04	-0.04	-0.07	-0.08
	(-0.6)	(0.0)	(-0.7)	(-0.1)	(-0.0)	(0.0)	(-0.0)	(-0.2)	(-0.1)	(-51.0)	(-48.5)	(-1.1)	(-0.1)
Cov(W,τ)	-0.13	0.00	-0.00	0.03	0.05	0.00	0.00	0.05	0.07	-0.41	-0.41	-0.50	-0.57
	(-4.7)	(0.0)	(-0.2)	(0.3)	(0.1)	(0.0)	(1.1)	(0.5)	(0.1)	(-485.5)	(-455.8)	(-8.1)	(-1.0)
Cov(R,T)	-0.10	0.00	0.01	-0.18	-0.80	0.00	0.02	-0.26	-0.91	-0.11	-0.12	-0.44	-1.07
	(-3.8)	(0.0)	(12.2)	(-2.3)	(-1.2)	(0.0)	(7.0)	(-2.8)	(-1.3)	(-134.1)	(-133.4)	(-7.1)	(-1.8)
Cov(R,τ)	-0.77	0.00	0.01	0.32	0.88	0.00	0.05	0.31	0.55	-1.46	-1.49	-2.73	-5.28
	(-27.8)	(0.0)	(13.5)	(4.0)	(1.3)	(0.0)	(13.8)	(3.3)	(0.8)	(-1,733.0)	(-1,645.7)	(-44.3)	(-8.9)
Cov(T,τ)	0.02	0.00	0.00	-0.00	-0.02	0.00	0.01	-0.01	-0.02	0.08	0.08	0.12	0.14
	(0.6)	(0.0)	(4.3)	(-0.0)	(-0.0)	(0.0)	(1.7)	(-0.1)	(-0.0)	(97.6)	(92.6)	(1.9)	(0.2)
Total $\times 100$													
Var(a)	2.78	0.00	0.06	7.96	65.63	0.00	0.34	9.25	67.83	0.08	0.09	6.16	59.58
	(100.0)	(0.0)	(100.0)	(100.0)	(100.0)	(0.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)	(100.0)

Notes: Forecast error variance decomposition calculated at a 4 quarter time horizon. Variance components presented in the table are multiplied by 100. Variance percent share in parentheses. Column percentiles correspond to the 0th, 50th, 90th, and 99th wealth percentiles.

of which shocks and factors have been important over time. To analyze this, I perform a historical decomposition of the shocks to the model using the same macroeconomic series as the Bayesian estimation.

7.1 Decomposition Strategy

To perform the historical decomposition, I use the process in Auclert and Rognlie (2023). Using the deviation from trend in the observed data $d\mathbf{X}^{\text{data}}$ and the IRFs of the model $d\mathbf{X}$, I solve for a matrix of shocks $\boldsymbol{\epsilon}$ that create simulated paths for macroeconomic series $d\tilde{\mathbf{X}}$ to solve

$$\begin{aligned} \min_{\boldsymbol{\epsilon}} \quad & \sum_{t=0}^{T_{\text{obs}}} \left\| d\mathbf{X}_t^{\text{data}} - d\tilde{\mathbf{X}}_t \right\|^2 \\ \text{subject to} \quad & d\tilde{\mathbf{X}}_t = \sum_{s=0}^{T-1} d\mathbf{X}_s \boldsymbol{\epsilon}_{t-s}. \end{aligned}$$

Since I use seven data series to fit seven shocks that all have linearly independent IRFs, the sequences for shocks $\boldsymbol{\epsilon}$ when simulated $d\tilde{\mathbf{X}}_t$ perfectly match the data. Using the sequences for shocks in $\boldsymbol{\epsilon}$, the simulated $d\tilde{\mathbf{X}}_t$ can be decomposed as the sum of the effects from each individual shock. Figure H.1 shows the decompositions for each of the fitted data series.

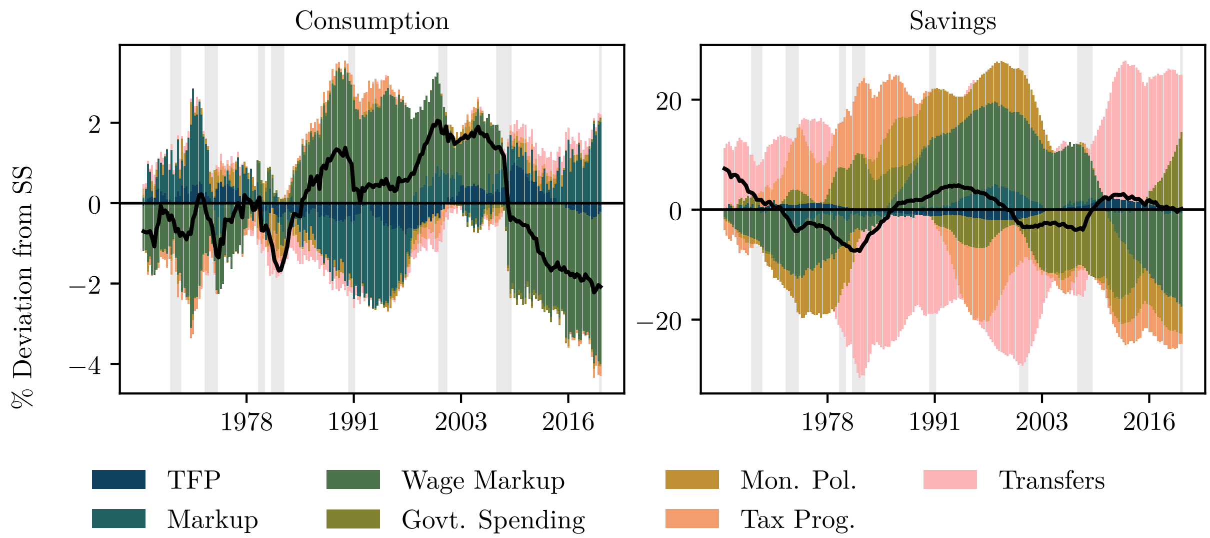
Then, I use the sequences of shocks to simulate the behavior of different households over time within the model. These series are pure simulation and not fit to any microdata, so they should not be taken as true paths for the consumption and savings decisions for actual households. Therefore, I interpret these sequences more weakly to get insight into the factors affecting household decisions. In addition, I apply a moving average to better get at general trends and reduce noise.

7.2 Historical Decompositions

The historical decompositions for aggregate consumption and savings are presented in Figure 7.1. Like in the variance decompositions, price and wage markup shocks have been the most important determinants of consumption. In contrast, many factors, including wage markups, monetary policy, and transfers, impact aggregate savings.

Looking at specific time periods, price markups increase consumption initially while wage markups decrease consumption. Then, in the 80s the two effects flip-flop and price markups start to decrease consumption while wage markups increase it. Finally, around the time of the Great Recession the two effects switch again until the end of the estimation window. Across almost all periods, the effects from wage markups are slightly stronger than those of price markups, consistent with the variance decomposition in Figure 5.1c. Instead of price markups, transfers and monetary policy have significant impacts on savings, but the direction of the effects again flips in the early 1980s and late 2000s.

Figure 7.1: Historical Decomposition: Household Aggregates

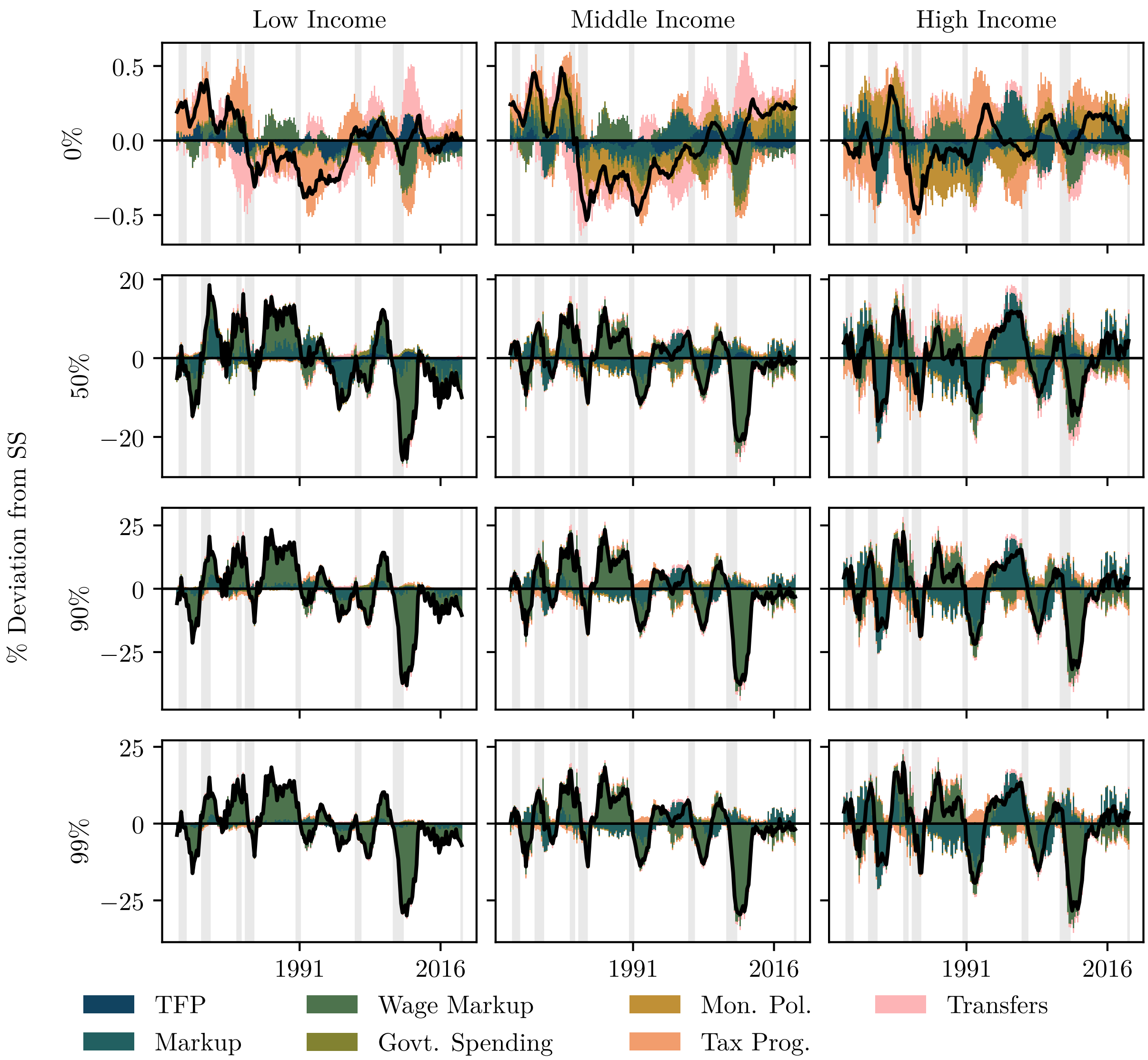


Notes: NBER-dated recessions highlighted in gray.

Figure 7.2 has historical decompositions for consumption decisions for households across the income and wealth distribution. Like in Section 5, I focus on low, middle, and high income households at the 0th, 50th, 90th, and 99th wealth percentiles. Simulated paths for consumption are very different for households at the 0th wealth percentile than other points along the wealth distribution, which all look very similar. Specifically, low wealth households are affected by a more diverse array of shocks, while the consumption patterns for higher wealth households are almost entirely explained by price and wage markups. Wage markup shocks impact low income households more than price markups, though for high income households price markup shocks are more important.

Tax progressivity shocks have opposite effects on low and high income households — when tax progressivity shocks cause low income households to consume more they cause high income households to consume less. Despite the decomposition only being fit on aggregate data, the effects of the Reagan-era tax cuts for higher income households are clear within the decomposition (Prasad 2012). Before the 80s when the top marginal tax rate in the US was highest, the level of tax progressivity makes higher income households consume less, and it makes lower and middle income households consume more. After the 80s, this flips and tax progressivity has positive effects on the consumption of high income households and negative effects on the consumption of low and

Figure 7.2: Historical Decomposition: Household Consumption

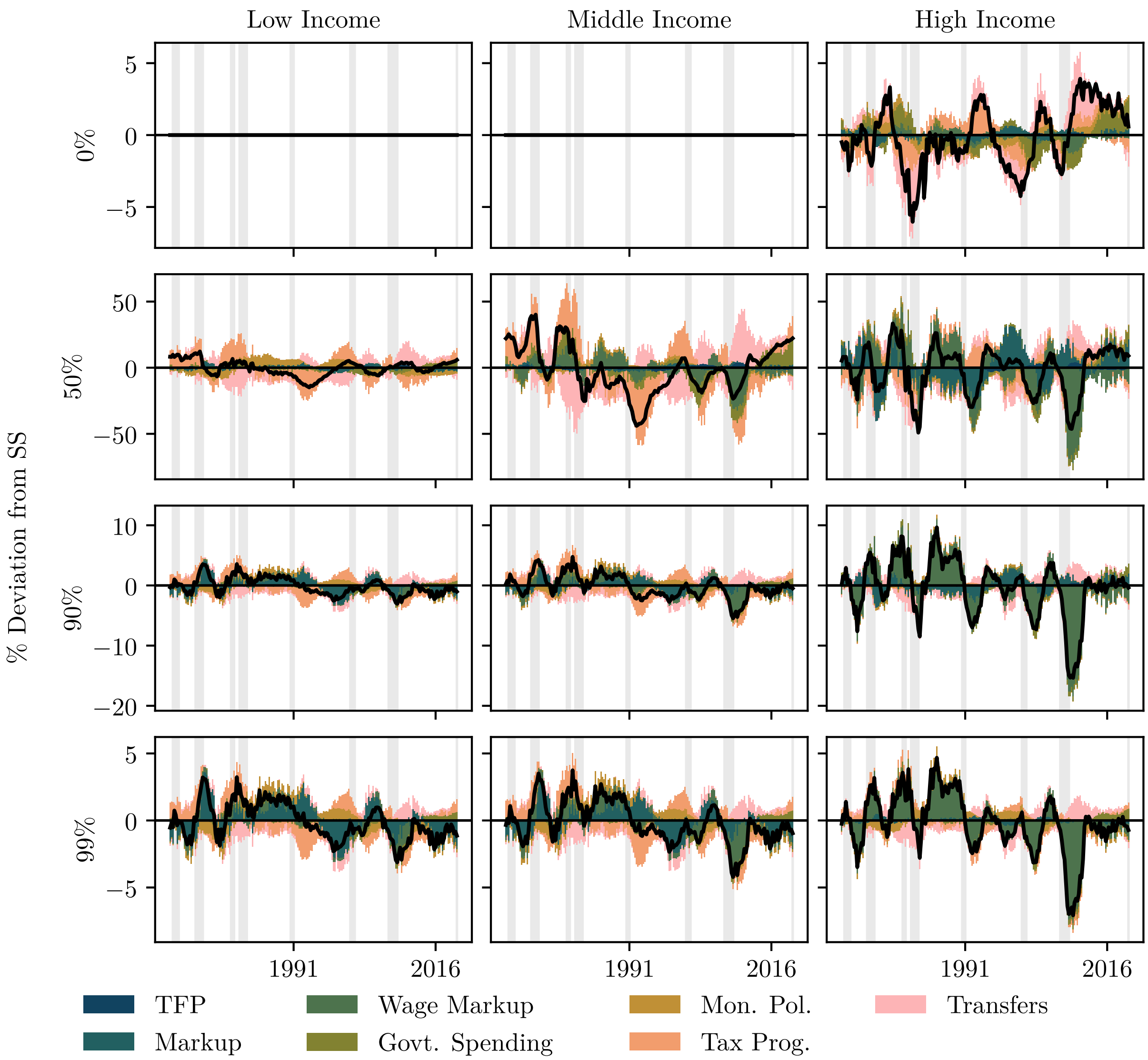


Notes: Row labeled by wealth percentile. 12 quarter moving average applied. NBER-dated recessions highlighted in gray.

middle income households. This lends credence to the use of shock paths fitted on aggregate data to gain understanding of individual-level phenomena within the model.

A similar decomposition for savings decisions is shown in Figure 7.3. Low and middle income households at the 0th wealth percentile never save, and therefore the decomposition is constant over time. Low and middle income households at other wealth levels do have some variability in their savings decisions, though substantially less than higher income households. This contrasts

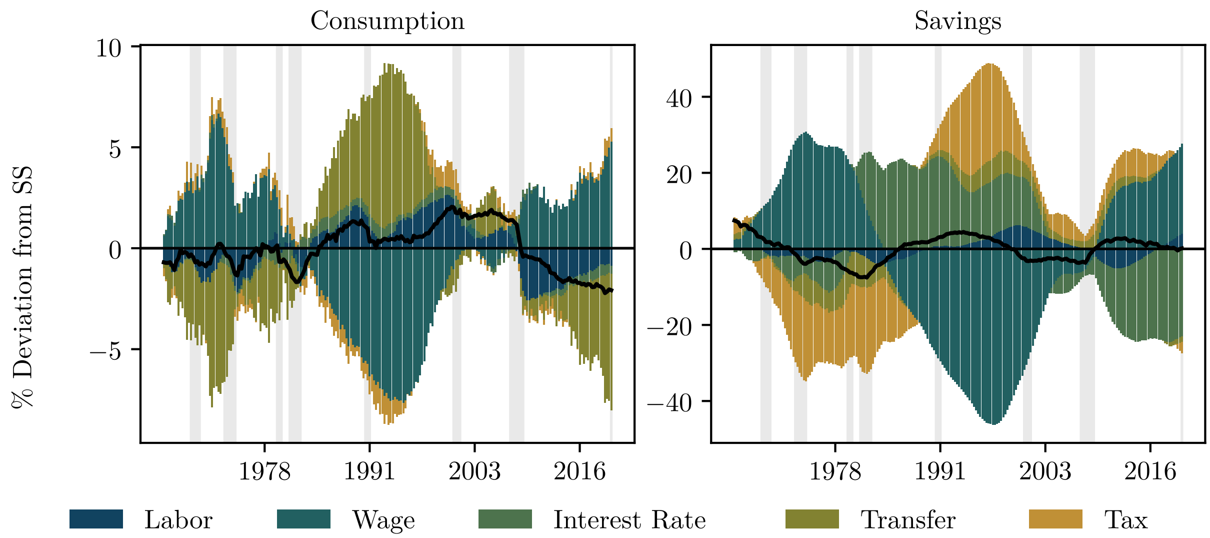
Figure 7.3: Historical Decomposition: Household Savings



Notes: Row labeled by wealth percentile. 12 quarter moving average applied. NBER-dated recessions highlighted in gray.

the consumption decomposition in Figure 7.2, where within a wealth band consumption has similar variability at all income levels. Price markups and tax progressivity are most important for low income households' savings decisions. Middle income household saving is similarly affected by price markups and tax progressivity though also face significant wage markup effects. Changes in savings decisions for high income households, especially at higher wealth levels, are almost entirely caused by wage markup shocks.

Figure 7.4: Historical Endogenous Decomposition: Household Aggregates



Notes: NBER-dated recessions highlighted in gray.

7.3 Historical Decomposition of Endogenous Effects

To get a more precise view of what specific macroeconomic factors households respond to, not just the overall macroeconomic shocks, I separate the decomposed paths into the direct factors that play into household decisions. Like outlined in Section 6, shocks affect households through labor supply, wages, interest rates, transfers, and taxes. Therefore, paths for aggregate and household consumption and saving can be explained as the sum of the effects from each of these sources.

Figure 7.4 shows the effect of each of these channels on aggregate consumption and saving. The specific paths for both series are identical to those in Figure 7.1. Wages and transfers, which move inverse to each other, are the most significant factors affecting consumption, though the labor supply decided by the union also plays an important role. In fact, the transfer and wage effects almost perfectly cancel each other out, so the overall series very nearly follows the path caused by changes in labor supply. Interest rates and taxes have minimal effects on aggregate consumption within the window.

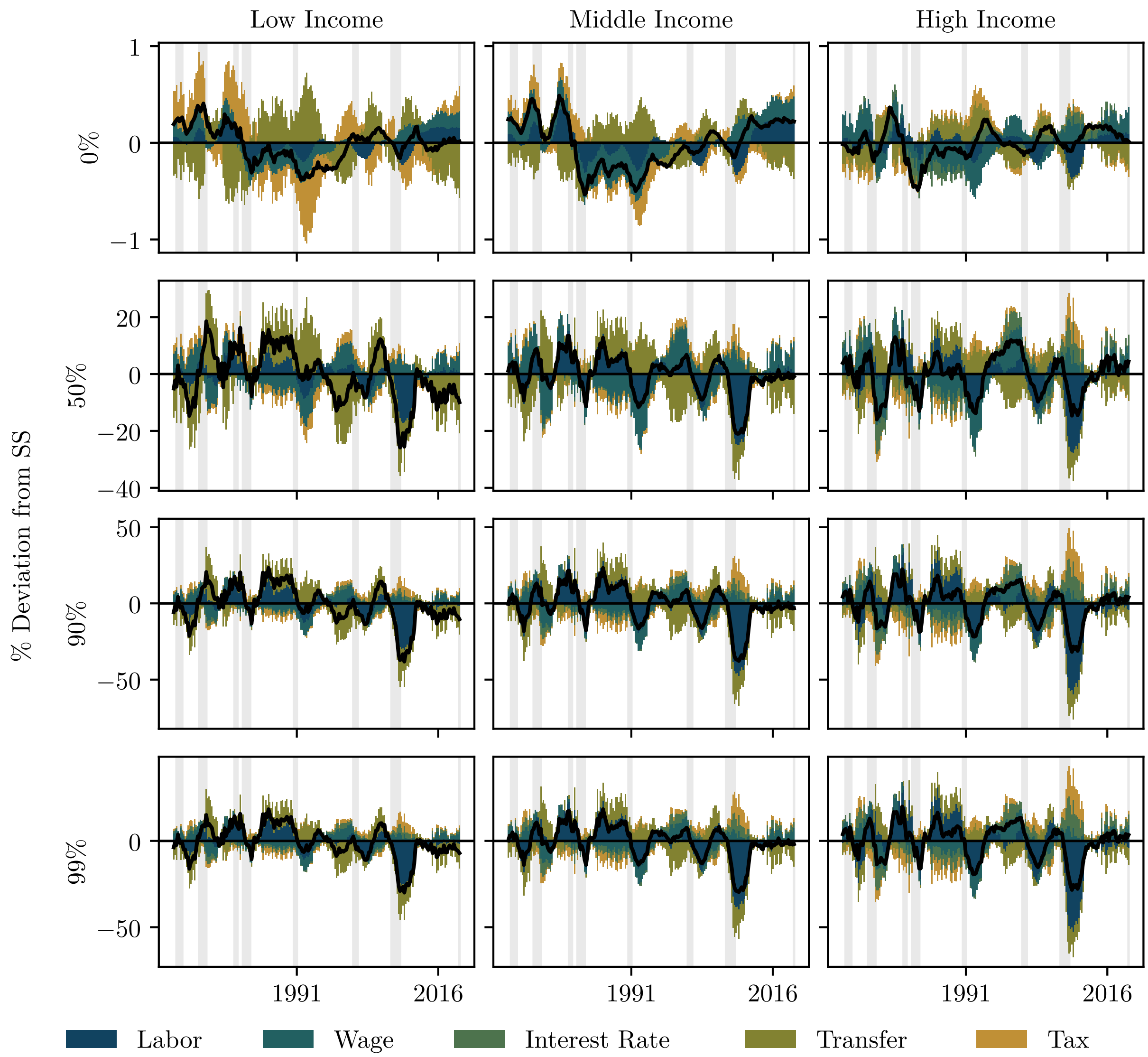
Wages, interest rates, and taxes are the most important determinants of aggregate savings. Likely due to the ρ_B parameter in the bond law of motion, the decomposed factors appear much smoother for savings than consumption, but the general shape of the savings decomposition is similar to that of the consumption decomposition, especially for the wage effects. Interest rates and taxes are far more important for savings than for consumption. The difference between the effects of taxes on consumption and savings suggests households in the model that were given tax breaks within the estimation window chose to save the extra money, not spend it. This could be because the largest tax breaks in the estimation window were given to higher wealth households, which have lower MPCs (Auclert, Bardóczy, and Rognlie 2023).

The decomposition separated by income and wealth level is presented in Figure 7.5. The labor supply choice is, in general, the most important factor affecting household consumption decisions, especially for higher income or higher wealth households. For lower income and lower wealth households, direct household transfers and taxes are also important. Wages and interest rates are moderately important to all households except low and middle income 0th percentile households that are never impacted by the interest rate.

Especially at higher wealth levels, the simulated paths for consumption are very similar within a wealth band. However, higher income households face larger, conflicting effects from individual shocks. Therefore, even when the observed decisions are the same, there can be substantial heterogeneity in the specific factors causing households to make those decisions emphasizing the importance of this type of decomposition for understanding the underlying mechanisms within the economy.

Figure 7.6 presents the same decomposition for household savings decisions. Again, low and middle income households at the 0th wealth percentile never choose to save. Interest rates are moderately important across all households, but most important to higher wealth households. In fact, interest rates determine almost all movement in savings decisions for 99th percentile low and middle income households. Households with either lower levels of wealth or higher income also face significant wage, labor, and tax effects. This suggests households choose to save more to consumption smooth after changes in income rather than to increase their future earnings when interest rates are higher, since shifts in the interest rate would have the largest impact on the incomes of the most affected groups while the potential changes in future income would impact all

Figure 7.5: Historical Endogenous Decomposition: Household Consumption

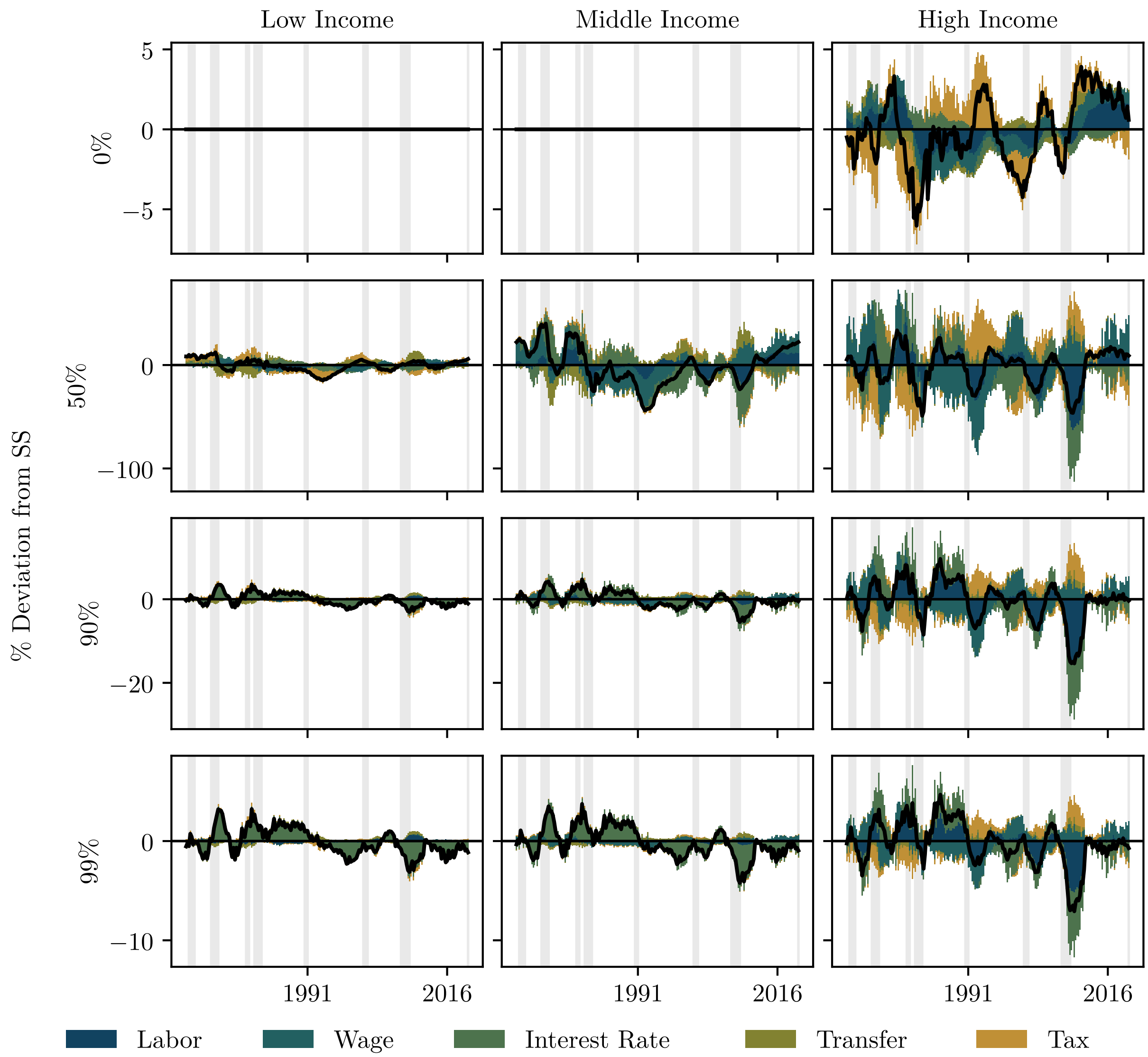


Notes: Row labeled by wealth percentile. 12 quarter moving average applied. NBER-dated recessions highlighted in gray.

households.

Since the simulated paths are the same, this decomposition shows more variability in the savings decisions for high income households than low or middle income households like in Figure 7.3. The important factors affecting the decisions of low and middle income households are very unidirectional. The different effects, for the most part, cause these households to either only save more or less. In contrast, higher income households face diverging effects that in part cancel each

Figure 7.6: Historical Endogenous Decomposition: Household Savings



Notes: Row labeled by wealth percentile. 12 quarter moving average applied. NBER-dated recessions highlighted in gray.

other out.

8 Conclusion

This paper explores how cross-sectional household heterogeneity is associated with different household behavior during business cycles. I find that the business cycle determinants differ substantially at different points along the distribution for wealth and earnings. In general, the factors driving consumption decisions vary substantially across the income distribution while household savings decisions vary most along the wealth distribution.

I also examine the effects of different transmission channels for these shocks during business cycles. Looking at the relative importance of each aggregate economic factor that directly affect households decisions, I find that interest rates are most important for high income households consumption and savings decisions. Low and median income households consumption decisions are most affected by changes in transfers and the labor supply and their savings decisions are most affected by changes in the interest rate. Factor comovement caused by macroeconomic shocks has clashing effects on low and middle income household consumption decisions and more consistent effects on high income household consumption decisions. In contrast, savings decisions have conflicting effects for high income households and more harmonious effects for low and middle income households.

Historical decompositions of the different shocks point to the 80s and Great Recession as key points where the effects on households from different shocks and factors flipped. In particular, before the 80s my historical decompositions suggest taxes increased consumption and saving for low income households and decreased consumption and saving for high income households. However, after the 80s the historical decompositions suggest taxes push low income households to consume and save less and high income households to consume and save more. This highlights the heterogeneity in how households are affected by macroeconomic shocks. More generally, since the historical decomposition was only fit to macro series and still replicates specific events, like the Reagan-era tax cuts, my estimates support the idea from Bayer, Born, and Luetticke (2024) and Iao and Selvakumar (2024) that macrodata can be sufficient to perform accurate estimations of HANK models.

This analysis focuses on changes to household decision rules at specific points on the steady-state wealth and income distribution. Also, I used no microdata in my estimates. The results, therefore, should be interpreted as generalizations of household behavior at different points on the wealth and income distributions, not a specific household's response to business cycle shocks. This is especially important for the household paths in the historical decomposition, which are merely a simulation and should not be treated as true paths for the decision rules.

My research suggests household responses to business cycles are very heterogeneous. Future work should explore these differences in behavior as a source of inequality. This is especially important given the important role business cycles play determining the levels of inequality (Bayer, Born, and Luetticke 2024).

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A Additional Model Details

A.1 Household Decision Rules

From the household budget and preferences in Section 3.1, households solve

$$\begin{aligned}
\max_{\{c_{i,t}, b_{i,t}\}_{t=0}^{\infty}} \quad & \mathbb{E} \sum_{t=0}^{\infty} \beta^t \left[\frac{c_{i,t}^{1-\gamma}}{1-\gamma} - \phi \frac{\ell_{i,t}^{1+\chi}}{1+\chi} \right] \\
\text{subject to} \quad & b_{i,t} + c_{i,t} = R_t b_{i,t-1} + W_t z_{i,t} \ell_{i,t} + D_t + \eta_t - \tau_t^L z_{i,t}^{\tau_t^P} \\
& b_{i,t} \geq \underline{b}.
\end{aligned}$$

This gets the Lagrangian

$$\begin{aligned}
\mathcal{L} = \mathbb{E} \sum_{t=0}^{\infty} \beta^t \Bigg[& \frac{c_{i,t}^{1-\gamma}}{1-\gamma} - \phi \frac{\ell_{i,t}^{1+\chi}}{1+\chi} \\
& + \lambda_{i,t} \left(R_t b_{i,t-1} + W_t z_{i,t} \ell_{i,t} + D_t + \eta_t - \tau_t^L z_{i,t}^{\tau_t^P} - b_{i,t} - c_{i,t} \right) \\
& + \mu_{i,t} \left(b_{i,t} - \underline{b} \right) \Bigg]
\end{aligned}$$

which has the FOCs

$$\lambda_{i,t} = c_{i,t}^{-\gamma} \qquad (c_{i,t})$$

$$\lambda_{i,t} = \mathbb{E} \beta R_{t+1} \lambda_{i,t+1} + \mu_{i,t} \qquad (b_{i,t})$$

for consumption and bonds respectively. Combining the FOCs for consumption and bonds gets

$$c_{i,t}^{-\gamma} = \beta R_{t+1} c_{i,t+1}^{-\gamma} + \mu_{i,t}.$$

Since $\mu_{i,t} \geq 0$, this becomes the Euler Equation

$$c_{i,t}^{-\gamma} \geq \beta R_{t+1} c_{i,t+1}^{-\gamma}$$

which holds with equality whenever the borrowing constraint is not binding and $b_{i,t} > \underline{b}$.

A.2 Labor Packer Demand Function

Since the labor packer earns revenue $W_t N_t$ and has costs given by $\int_0^1 w_{k,t} n_{k,t} dk$, the profit maximization condition is

$$\max_{\{n_{k,t}\}_{k\in[0,1]}} \quad W_t N_t - \int_0^1 w_{k,t} n_{k,t} dk.$$

Plugging in the aggregator, this becomes

$$\max_{\{n_{k,t}\}_{k\in[0,1]}} \quad W_t \left(\int_0^1 n_{k,t}^{\frac{1}{\psi_t^W}} dk \right)^{\psi_t^W} - \int_0^1 w_{k,t} n_{k,t} dk.$$

This has the FOC

$$w_{k,t} = W_t \left(\int_0^1 n_{k,t}^{\frac{1}{\psi_t^W}} dk \right)^{\psi_t^W - 1} n_{k,t}^{\frac{1-\psi_t^W}{\psi_t^W}}$$

which, rearranged, becomes the demand function

$$n_{k,t} = \left(\frac{w_{k,t}}{W_t} \right)^{\frac{\psi_t^W}{1-\psi_t^W}} \left(\int_0^1 n_{k,t}^{\frac{1}{\psi_t^W}} dk \right)^{\psi_t^W} = N_t \left(\frac{w_{k,t}}{W_t} \right)^{\frac{\psi_t^W}{1-\psi_t^W}}.$$

A.3 Wage Philips Curve

At time t, unions decide ℓ_k by solving

$$\begin{aligned}
\max_{\{w_{k,s},\ell_{k,s}\}_{s=t}^{\infty}} \quad & \mathbb{E} \sum_{s=t}^{\infty} \beta^{s-t} \left[\int \frac{c_s(b,z)^{1-\gamma}}{1-\gamma} d\Gamma_s(b,z) - \phi \int_0^1 \frac{\ell_{k,s}^{1+\chi}}{1+\chi} dk - m_{k,s}^W \right] \\
\text{subject to} \quad & c_s(b,z) + b_s(b,z) = R_s b + z \int_0^1 w_{k,s} \ell_{k,s} dk + D_s + \eta_s - \tau_s^L z^{\tau_s^P}, \quad (b,z) \in \Gamma_t(b,z) \\
& m_{k,s}^W = \frac{\psi_s^W}{\psi_s^W - 1} \frac{1}{2\kappa^W} \log \left(\frac{w_{k,s}}{\overline{\pi}^W w_{k,s-1}} \right)^2 \\
& n_{k,s} = \ell_{k,s} \int z d\Gamma_t^z(z) \\
& n_{k,s} = N_s \left(\frac{w_{k,s}}{W_s} \right)^{\frac{\psi_s^W}{1-\psi_s^W}}.
\end{aligned}$$

Letting

$$h_s(b,z) = R_s b + D_s + \eta_s - \tau_s^L z^{\tau_s^P} - b_s(b,z)$$

this becomes

$$\max_{\{w_{k,s},\ell_{k,s}\}_{s=t}^{\infty}} \quad \mathbb{E}\sum_{s=t}^{\infty}\beta^{s-t}\Bigg[\int \frac{\left(h_s(b,z)+z\int_0^1 w_{k,s}\ell_{k,s}dk\right)^{1-\gamma}}{1-\gamma}d\Gamma_s(b,z)-\phi\int_0^1 \frac{\ell_{k,s}^{1+\chi}}{1+\chi}dk$$
$$-\frac{\psi_s^W}{\psi_s^W-1}\frac{1}{2\kappa^W}\log\left(\frac{w_{k,s}}{\overline{\pi}^W w_{k,s-1}}\right)^2\Bigg]$$
$$\text{subject to} \quad N_s\left(\frac{w_{k,s}}{W_s}\right)^{\frac{\psi_s^W}{1-\psi_s^W}} = \ell_{k,s}\int z d\Gamma_t^z(z).$$

Therefore, we have the Lagrangian

$$\mathcal{L}=\mathbb{E}\sum_{s=t}^{\infty}\beta^{s-t}\Bigg[\int \frac{\left(h_s(b,z)+z\int_0^1 w_{k,s}\ell_{k,s}dk\right)^{1-\gamma}}{1-\gamma}d\Gamma_s(b,z)-\phi\int_0^1 \frac{\ell_{k,s}^{1+\chi}}{1+\chi}dk$$
$$-\frac{\psi_s^W}{\psi_s^W-1}\frac{1}{2\kappa^W}\log\left(\frac{w_{k,s}}{\overline{\pi}^W w_{k,s-1}}\right)^2$$
$$+\lambda_{k,s}\left(N_s\left(\frac{w_{k,s}}{W_s}\right)^{\frac{\psi_s^W}{1-\psi_s^W}}-\ell_{k,s}\int z d\Gamma_t^z(z)\right)\Bigg].$$

This has the FOCs

$$z w_{k,s} c_s(z,b)^{-\gamma} = \phi\ell_{k,s}^{\chi}+\lambda_{k,s}z \qquad (\ell_{k,s})$$
$$\frac{\psi_s^W}{\psi_s^W-1}\frac{1}{w_{k,s}\kappa^W}\log\left(\frac{w_{k,s}}{\overline{\pi}^W w_{k,s-1}}\right)=\ell_{k,s}\int z c_s(b,z)^{-\gamma}d\Gamma_s(b,z) \qquad (w_{k,s})$$
$$-\frac{\psi_s^W}{\psi_s^W-1}\lambda_{k,s}N_s\left(\frac{w_{k,s}}{W_s}\right)^{\frac{\psi_s^W}{1-\psi_s^W}}w_{k,s}^{-1}$$
$$+\frac{\psi_s^W}{\psi_s^W-1}\frac{1}{w_{k,s}\kappa^W}\log\left(\frac{w_{k,s+1}}{\overline{\pi}^W w_{k,s}}\right).$$

Since the conditions for unions are all identical, we can plug in $w_{k,s}=W_s$, $\ell_{k,s}=L_s$, and $\lambda_{k,s}=\Lambda_s$. Integrating and rearranging the FOC for $\ell_{k,s}$ gets

$$\Lambda_s=\frac{W_sL_s\int z c_s(b,z)^{-\gamma}d\Gamma_s(b,z)-\phi L_s^{1+\chi}}{L_s\int z d\Gamma_s^z(z)}=\frac{W_sL_s\int z c_s(b,z)^{-\gamma}d\Gamma_s(b,z)-\phi L_s^{1+\chi}}{N_s}.$$

Plugging this into the FOC for $w_{k,s}$ and multiplying by $\kappa^W W_s \frac{\psi_s^W - 1}{\psi_s^W}$ gets the Philips curve

$$\log\left(\frac{\pi_s^W}{\overline{\pi}^W}\right) = \kappa^W \left(\phi L_s^{1+\chi} - \frac{1}{\psi_s^W} W_s L_s \int z c_s(b,z) d\Gamma_s(b,z)\right) + \beta \log\left(\frac{\pi_{s+1}^W}{\overline{\pi}^W}\right).$$

A.4 Final Goods Firm Conditions

Final goods firms earn revenue $P_t Y_t$ and have costs $\int_0^1 y_{j,t} p_{j,t} dj$. Therefore, the profit maximization condition for firms is

$$\max_{\{y_{j,t}\}_{j\in[0,1]}} \quad P_t Y_t - \int_0^1 p_{j,t} y_{j,t} dj.$$

Plugging in the aggregator, this becomes

$$\max_{\{y_{j,t}\}_{j\in[0,1]}} \quad P_t \left(\int_0^1 y_{j,t}^{\frac{1}{\psi_t}} dj\right)^{\psi_t} - \int_0^1 p_{j,t} y_{j,t} dj$$

which has the FOC

$$p_{j,t} = P_t \left(\int_0^1 y_{j,t}^{\frac{1}{\psi_t}} dj\right)^{\psi_t - 1} y_{j,t}^{\frac{1-\psi_t}{\psi_t}}.$$

Rearranging this gets

$$y_{j,t} = \left(\frac{p_{j,t}}{P_t}\right)^{\frac{\psi_t}{1-\psi_t}} \left(\int_0^1 y_{j,t}^{\frac{1}{\psi_t}} dj\right)^{\psi_t} = Y_t \left(\frac{p_{j,t}}{P_t}\right)^{\frac{\psi_t}{1-\psi_t}}$$

which is the demand for intermediate good j. Plugging this back into the aggregator means

$$\begin{aligned} Y_t &= \left(\int_0^1 \left(Y_t \left(\frac{p_{j,t}}{P_t}\right)^{\frac{\psi_t}{1-\psi_t}}\right)^{\frac{1}{\psi_t}} dj\right)^{\psi_t} \\ &= Y_t \frac{1}{P_t^{\frac{\psi_t}{1-\psi_t}}} \left(\int_0^1 p_{j,t}^{\frac{1}{1-\psi_t}} dj\right)^{\psi_t}. \end{aligned}$$

Rearranging this gets the price aggregator

$$P_t = \left(\int_0^1 p_{j,t}^{\frac{1}{1-\psi_t}} dj\right)^{1-\psi_t}.$$

A.5 Philips Curve

Intermediate goods firms pick prices to maximize expected discounted real profits solving

$$\begin{aligned}
\max_{\{p_{j,s}\}_{s=t}^{\infty}} \quad & \mathbb{E}\sum_{s=t}^{\infty} R_{t,s}^{-1}\left[\frac{p_{j,s}}{P_s}y_{j,s} - W_s n_{j,s} - m_{j,s}\right] \\
\text{subject to} \quad & m_{j,s} = \frac{\psi_s}{\psi_s - 1}\frac{1}{2\kappa}\log\left(\frac{p_{j,s}}{\overline{\pi}p_{j,s-1}}\right)^2 Y_s \\
& y_{j,s} = A_s n_{j,s} \\
& y_{j,s} = Y_s\left(\frac{p_{j,s}}{P_s}\right)^{\frac{\psi_s}{1-\psi_s}}
\end{aligned}$$

where $R_{t,s} = \prod_{q=t+1}^{s} R_q$ represents the real gross return of bonds from period t to s. Plugging in the demand function, production function, and adjustment costs gets

$$\max_{\{p_{j,s}\}_{s=t}^{\infty}} \quad \mathbb{E}\sum_{s=t}^{\infty} R_{t,s}^{-1}Y_s\left[\left(\frac{p_{j,s}}{P_s}\right)^{\frac{1}{1-\psi_s}} - \frac{W_s}{A_s}\left(\frac{p_{j,s}}{P_s}\right)^{\frac{\psi_s}{1-\psi_s}} - \frac{\psi_s}{\psi_s - 1}\frac{1}{2\kappa}\left(\frac{p_{j,s}}{\overline{\pi}p_{j,s-1}} - 1\right)^2\right]$$

This has the FOC of

$$\begin{aligned}
\frac{\psi_s}{\psi_s - 1}\frac{1}{\kappa}Y_s\log\left(\frac{p_{j,s}}{\overline{\pi}p_{j,s-1}}\right)p_{j,s}^{-1} =& \frac{\psi_s}{\psi_s - 1}Y_s\frac{W_s}{A_s}\left(\frac{p_{j,s}}{P_s}\right)^{\frac{\psi_s}{1-\psi_s}}p_{j,s}^{-1} - \frac{1}{\psi_s - 1}Y_s\left(\frac{p_{j,s}}{P_s}\right)^{\frac{1}{1-\psi_s}}p_{j,s}^{-1} \\
&+ \frac{\psi_s}{\psi_s - 1}\frac{1}{\kappa}R_{s+1}^{-1}Y_{s+1}\log\left(\frac{p_{j,s+1}}{\overline{\pi}p_{j,s}}\right)p_{j,s}^{-1}.
\end{aligned}$$

Since firm conditions are identical, we can assume price symmetry across firms so $p_{j,s} = p_{j',s}$ for $j \neq j'$. Using the price aggregator, this gets

$$P_s = \left(\int_0^1 p_{j,s}^{1-\psi_s}dj\right)^{\frac{1}{1-\psi_s}} = \left(p_{j,s}^{1-\psi_s}\right)^{\frac{1}{1-\psi_s}} = p_j.$$

Plugging this in and rearranging the system yields the Philips Curve

$$\log\left(\frac{\pi_t}{\overline{\pi}}\right) = \kappa\left(\frac{W_t}{A_t} - \frac{1}{\psi_t}\right) + R_{t+1}\frac{Y_{t+1}}{Y_t}\log\left(\frac{\pi_{t+1}}{\overline{\pi}}\right).$$

A.6 Aggregation

In the model, firm conditions are perfectly symmetrical. Therefore, for $j \neq j'$ we can assume

$$
\begin{aligned}
y_{j,t} &= y_{j',t} \\
n_{j,t} &= n_{j',t} \\
d_{j,t} &= d_{j',t} \\
m_{j,t} &= m_{j',t}
\end{aligned}
$$

Using the aggregators for each variable this gets

$$
\begin{aligned}
Y_t &= \left(\int_0^1 y_{j,t}^{\frac{\psi_t - 1}{\psi_t}} dj \right)^{\frac{\psi_t}{\psi_t - 1}} = \left(y_{j,t}^{\frac{\psi_t - 1}{\psi_t}} \right)^{\frac{\psi_t}{\psi_t - 1}} = y_{j,t} \\
N_t &= \int_0^1 n_{j,t} dj = n_{j,t} \\
D_t &= \int_0^1 d_{j,t} dj = d_{j,t} \\
M_t &= \int_0^1 m_{j,t} dj = m_{j,t}.
\end{aligned}
$$

Then, integrating across the production function gets

$$
Y_t = \int_0^1 y_{j,t} dj = \int_0^1 A_t n_{j,t} dj = A_t N_t,
$$

integrating across the dividend expression gets

$$
D_t = \int_0^1 d_{j,t} dj = \int_0^1 \left(\frac{p_{j,t}}{P_t} y_{j,t} - W_t n_{j,t} - m_{j,t} \right) dj = Y_t - W_t N_t - M_t,
$$

and integrating across the adjustment cost expression gets

$$
M_t = \int_0^1 m_{j,t} dj = \int_0^1 \frac{\psi_t}{\psi_t - 1} \frac{1}{2\kappa} \left(\frac{p_{j,t}}{\overline{\pi} p_{j,t-1}} - 1 \right)^2 Y_t dj = \frac{\psi_t}{\psi_t - 1} \frac{1}{2\kappa} \left(\frac{\pi_t}{\overline{\pi}} - 1 \right)^2 Y_t.
$$

A.7 Characterization

The model is characterized by the household decision rules

$$
\begin{gathered}
b_t(b_{i,t-1}, z_{i,t}) + c_t(b_{i,t-1}, z_{i,t}) = R_t b_{i,t-1} + W_t z_{i,t} L_t + D_t + \eta_t - \tau_t^L z_{i,t}^{\tau_t^P} \\
c_t(b_{i,t-1}, z_{i,t})^{-\gamma} = \beta \mathbb{E} R_{t+1} c_{t+1}(b_{i,t-1}, z_{i,t}),
\end{gathered}
$$

distributional movement condition

$$
\Gamma_{t+1}(b', z') = \int_{\{(b,z): b_t(b,z)=b'\}} \Pr(z'|z) d\Gamma_t(b, z),
$$

aggregate equations

$$
\begin{aligned}
\pi_t^W &= \frac{W_t}{W_{t-1}} \\
L_t &= \frac{N_t}{\int z d\Gamma_t^z(z)} \\
\log\left(\frac{\pi_t^W}{\overline{\pi}^W}\right) &= \kappa^W \left(\phi L_t^{1+\chi} - \frac{1}{\psi_t^W} W_t L_t \int z c_t(b, z) d\Gamma_s(b, z)\right) + \beta \log\left(\frac{\pi_{t+1}^W}{\overline{\pi}^W}\right) \\
Y_t &= A_t N_t \\
M_t &= \frac{\psi_t}{\psi_t - 1} \frac{1}{2\kappa} \left(\frac{\pi_t}{\overline{\pi}} - 1\right)^2 Y_t \\
\log\left(\frac{\pi_t}{\overline{\pi}}\right) &= \kappa \left(\frac{W_t}{A_t} - \frac{1}{\psi_t}\right) + R_{t+1} \frac{Y_{t+1}}{Y_t} \log\left(\frac{\pi_{t+1}}{\overline{\pi}}\right) \\
D_t &= Y_t - W_t N_t - M_t \\
G_t &= g_t Y_t \\
B_t &= \overline{B} + \rho_B \left(R_t B_{t-1} - \overline{RB} + G_t - \overline{G} + \eta_t - \overline{\eta}\right) \\
R_t B_{t-1} + G_t + \eta_t &= \tau_t^L \int z d\Gamma_t^Z(z) + B_t \\
I_t &= \overline{I} \left(\frac{\pi_t}{\overline{\pi}}\right)^{\omega_\pi} \left(\frac{Y_t}{\overline{Y}}\right)^{\omega_Y} \xi_t \\
R_t &= \frac{I_{t-1}}{\pi_t},
\end{aligned}
$$

and market clearing condition

$$B_t = \int b_t(b, z) d\Gamma_t(b, z)$$

where the goods market clears by Walras's Law.

B Data

B.1 Calibration Data

I calibrate parameters in the model to match historical US averages relative to GDP. To match the estimation window, all data is quarterly from 1966 to 2019. Since the calibration target for $\overline{N}$ implies $\overline{Y} = 1$, I calibrate both levels ($\overline{B}$ and $\overline{\eta}$) and rates ($\overline{g}$) to their average fraction of GDP. The data is all from FRED (FRED codes in parentheses).

Debt Target. I target the steady state level of debt to match the mean US debt to GDP ratio. To calculate this ratio, I divide the historical nominal debt level (GFDEBTN) by the historical nominal GDP level (GDP). To account for differences in units, I divide this ratio by 1,000. Taking the mean gets $\overline{B} = 0.577$.

Government Spending. I target the steady state rate of government spending to match the mean fraction of GDP spent by the government To calculate this, I divide nominal government spending (GCE) by nominal GDP (GDP). Taking the mean gets $\overline{g} = 0.202$.

Transfers. I target the steady state government transfers to households to match the ratio of government transfers to households to GDP. I divide nominal social benefits transfers to households (B087RC1Q027SBEA) by nominal GDP (GDP). Taking the mean gets $\overline{\eta} = 0.081$.

B.2 Estimation Data

I estimate Y_t, π_t, I_t, N_t, C_t, B_t, and W_t against US aggregate data for GDP, inflation, the Federal Funds Rate, hours worked, consumption, government debt, and wages. I get the data from FRED (FRED codes in parentheses) at a quarterly frequency from 1966 to 2019. Since the model works in levels instead of percent deviation, the series are all multiplied by the steady state variable in the model before estimation.

GDP. To represent Y_t in the model, I use nominal GDP (GDP). I divide by the GDP deflator (GDPDEF) to get real GDP and by population (POPTHM) to make it per-capita. Then, I use the difference from the log-linear trend to estimate off of. Finally, I divide by 4 to make it quarterly and multiply by 100 to make it a percent.

Inflation. To represent π_t in the model, I use the log quarter to quarter difference in the GDP deflator (GDPDEF). I then subtract out the mean to make it into the difference from trend and multiply by 100 to make it a percent.

Federal Funds Rate. To represent I_t in the model, I use the Federal Funds Rate (FEDFUNDS). I subtract out the mean to make it into the difference from trend and divide by 4 to make it quarterly.

Hours Worked. To represent N_t in the model, I use total hours worked (HOANBS). I divide by population (POPTHM) to make it per capita. Then, I take the difference from log-linear trend to estimate off of. Finally, I divide by 4 to make it quarterly and multiply by 100 to make it a percent.

Consumption. To represent C_t in the model, I use personal consumption expenditure (PCE). I divide by the GDP deflator (GDPDEF) to get real consumption and by population (POPTHM) to make it per capita. Then, I take the difference from the log-linear trend, divide by 4 to make it quarterly, and multiply by 100 to make it a percent.

Government Debt. To represent B_t in the model, I use the level of government debt (GFDEBTN). I divide by the GDP deflator (GDPDEF) to get real debt and by population (POPTHM) to make it per capita. Then, I take the difference from the log-linear trend. Finally, I divide by 4 to make it quarterly and multiply by 100 to make it a percent.

Wages. To represent W_t in the model, I use the average hourly earnings of production and nonsupervisory employees (AHETPI). I divide by the GDP deflator (GDPDEF) to get real wages. Then, I take the difference from the log-linear trend, divide by 4 to make it quarterly, and multiply by 100 to make it a percent.

C Computational Error

Figures C.1 through C.7 look at the effect of the truncation horizon on the IRFs in the model. I compare the first 216 periods (the total estimation window) of the IRFs to the IRFs with a truncation horizon of 1,500 for the series I estimate on at the posterior mean parameters in Table 4.2.

Figure C.1: TFP (A) Shock Computational Error

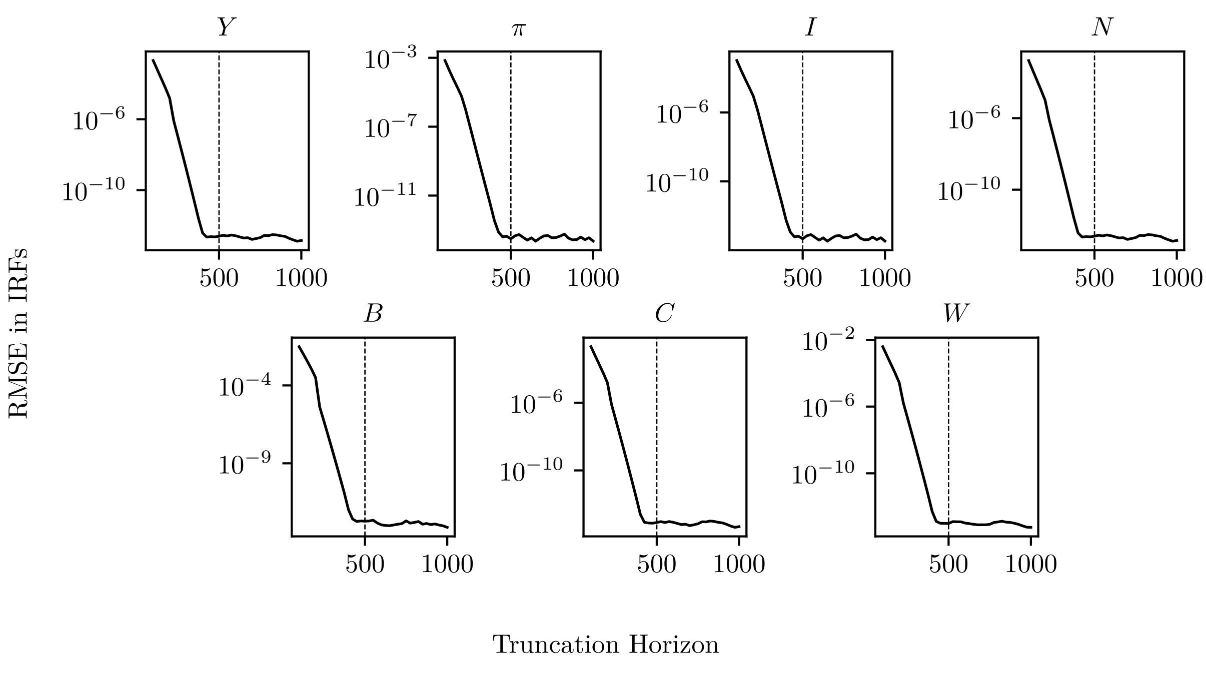


Figure C.2: Markup (ψ) Shock Computational Error

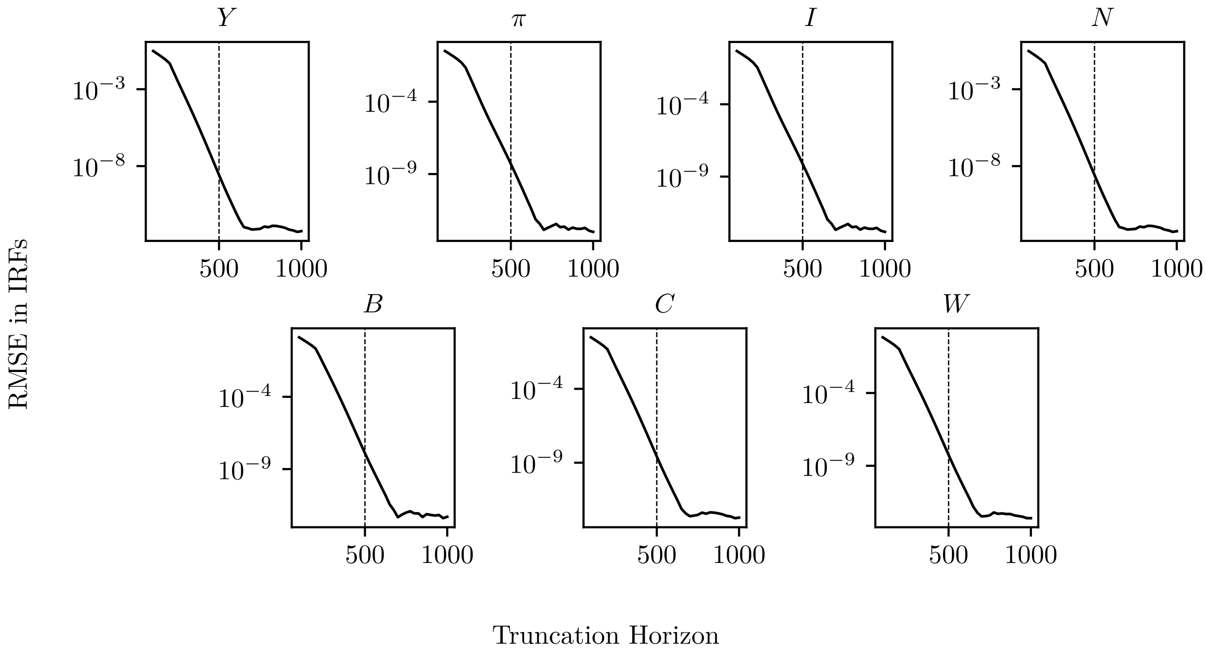


Figure C.3: Wage Markup (ψ^W) Shock Computational Error

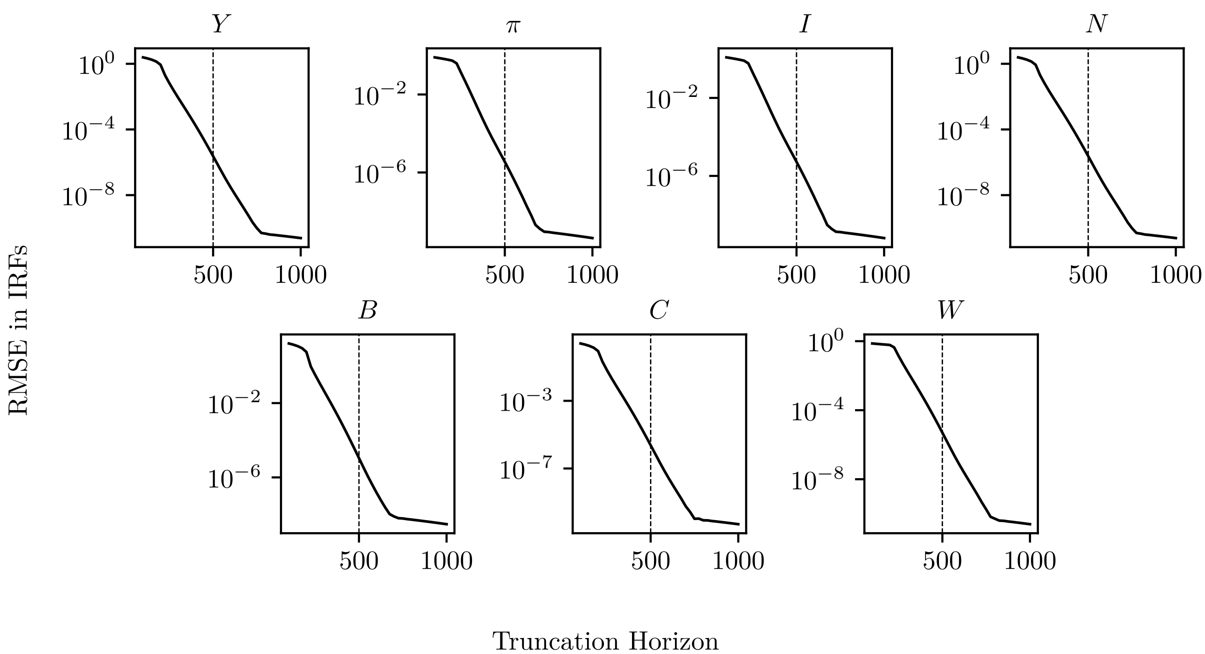


Figure C.4: Govt. Spending (g) Shock Computational Error

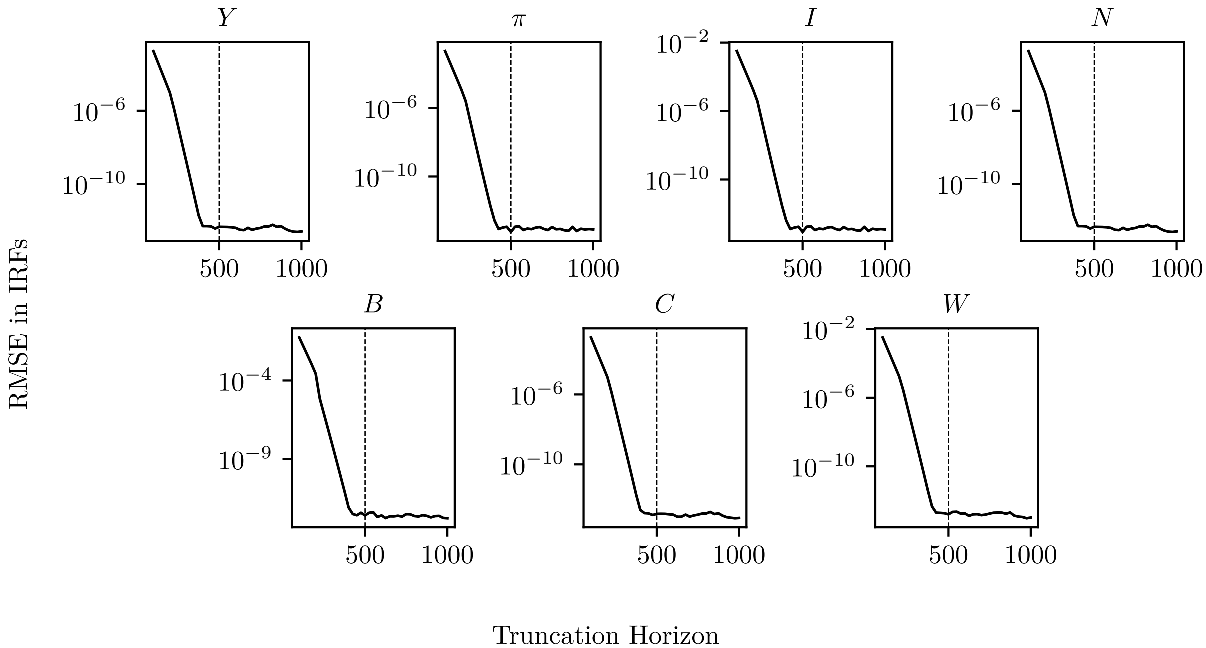


Figure C.5: Monetary Policy (ξ) Shock Computational Error

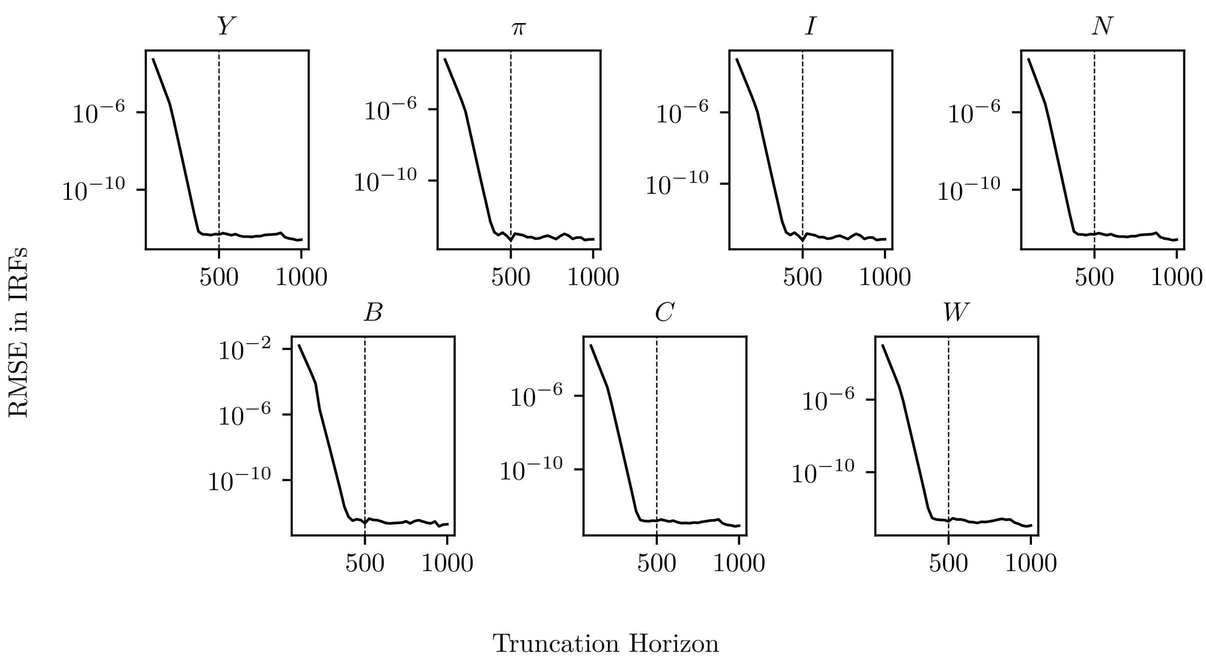


Figure C.6: Tax Progressivity (τ^P) Shock Computational Error

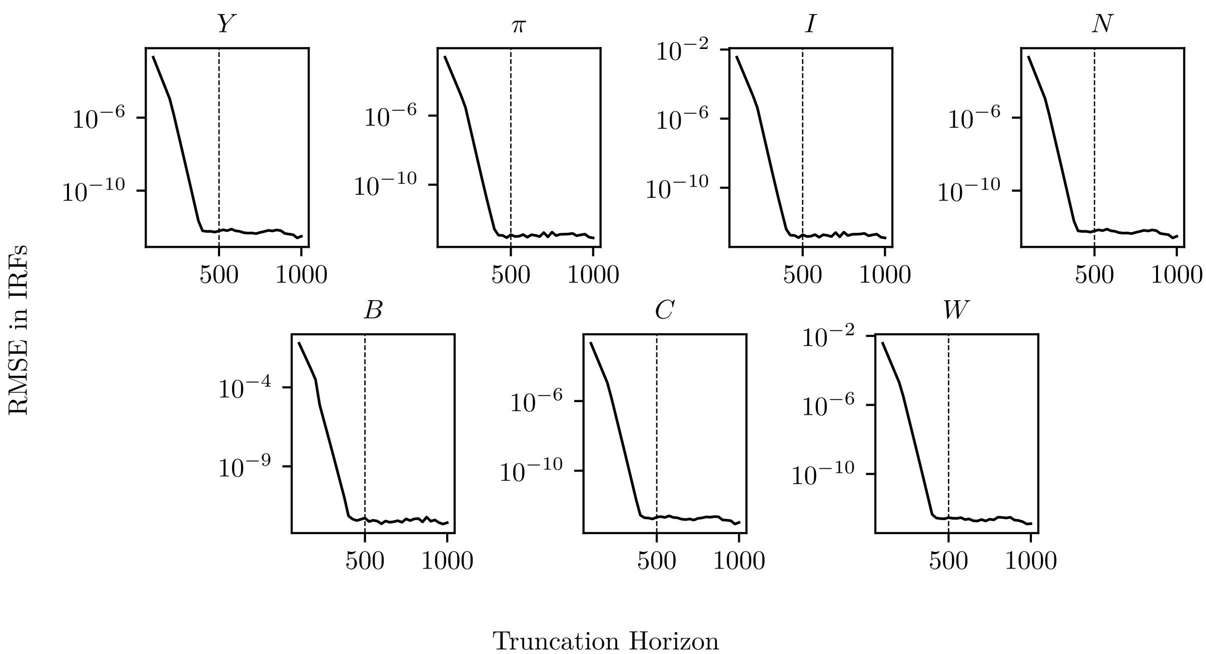
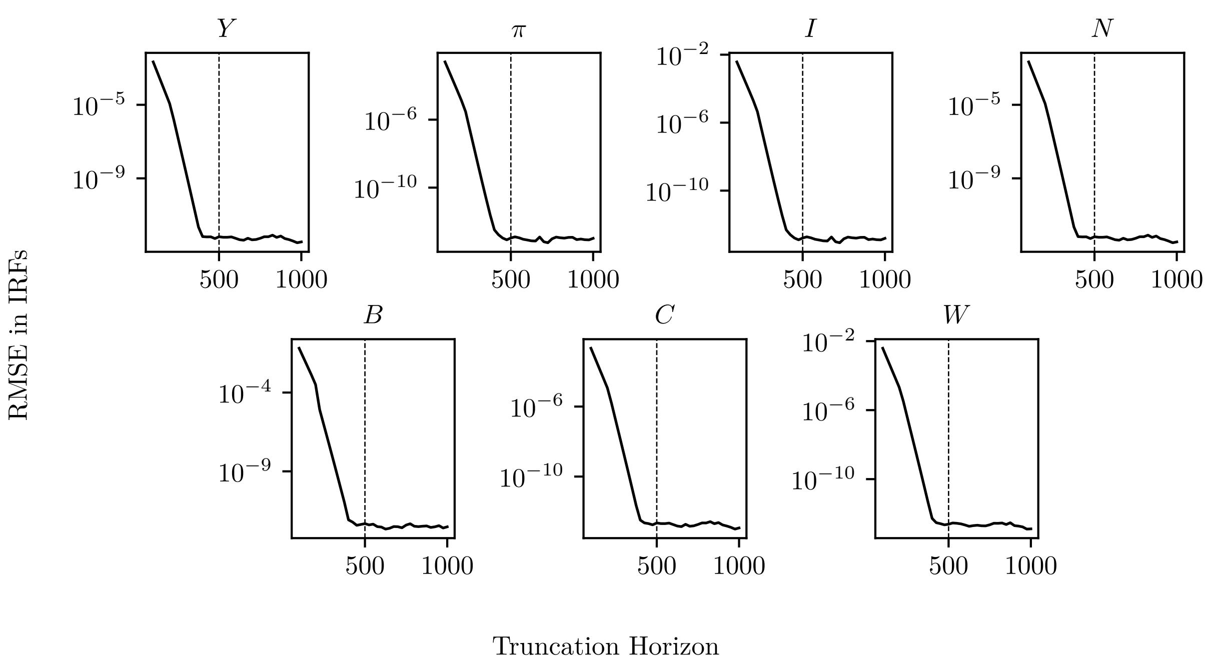


Figure C.7: Household Transfer (η) Shock Computational Error



D Estimation Results

Figure D.1: Recursive Means

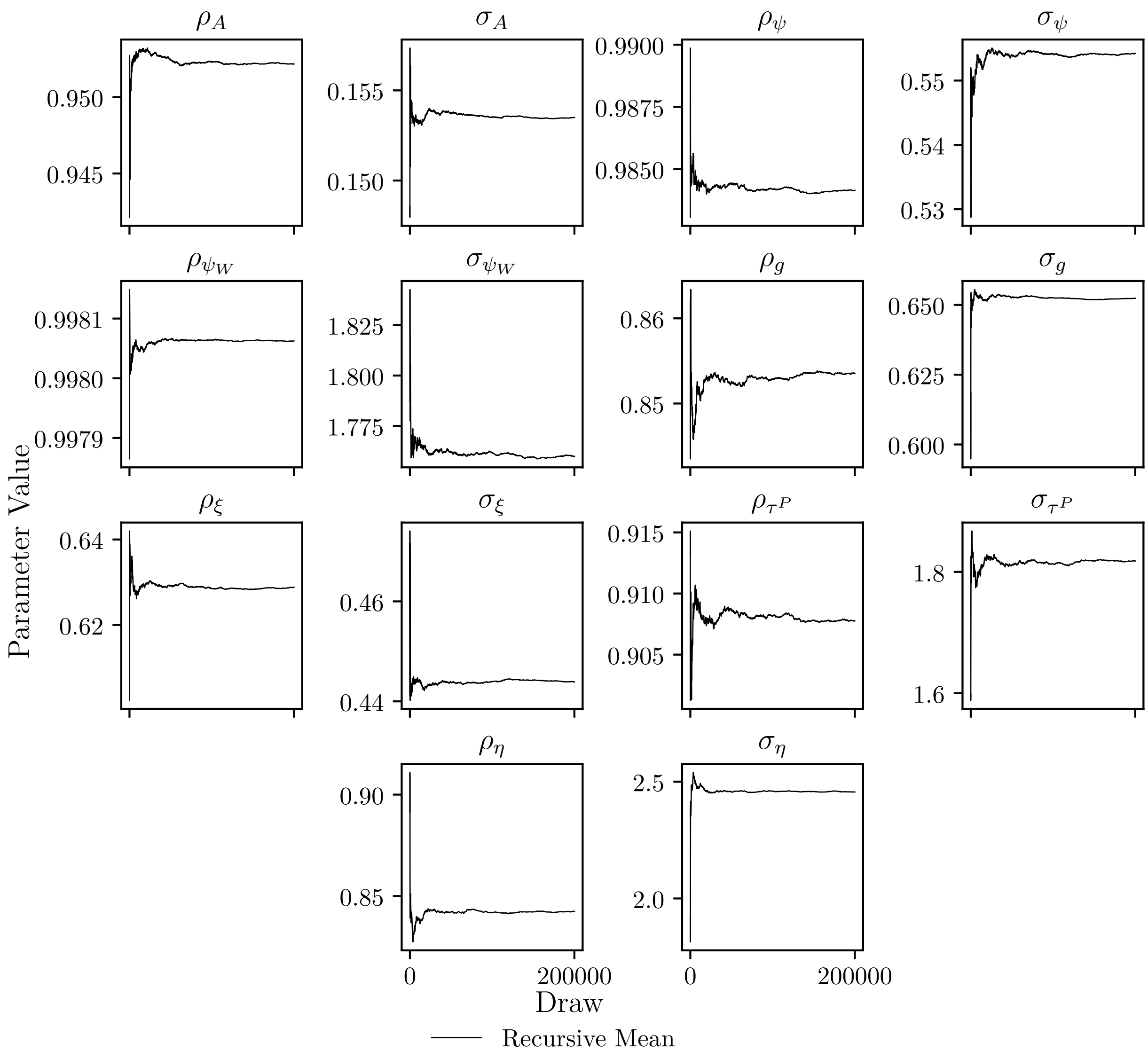


Figure D.2: Posterior Distributions

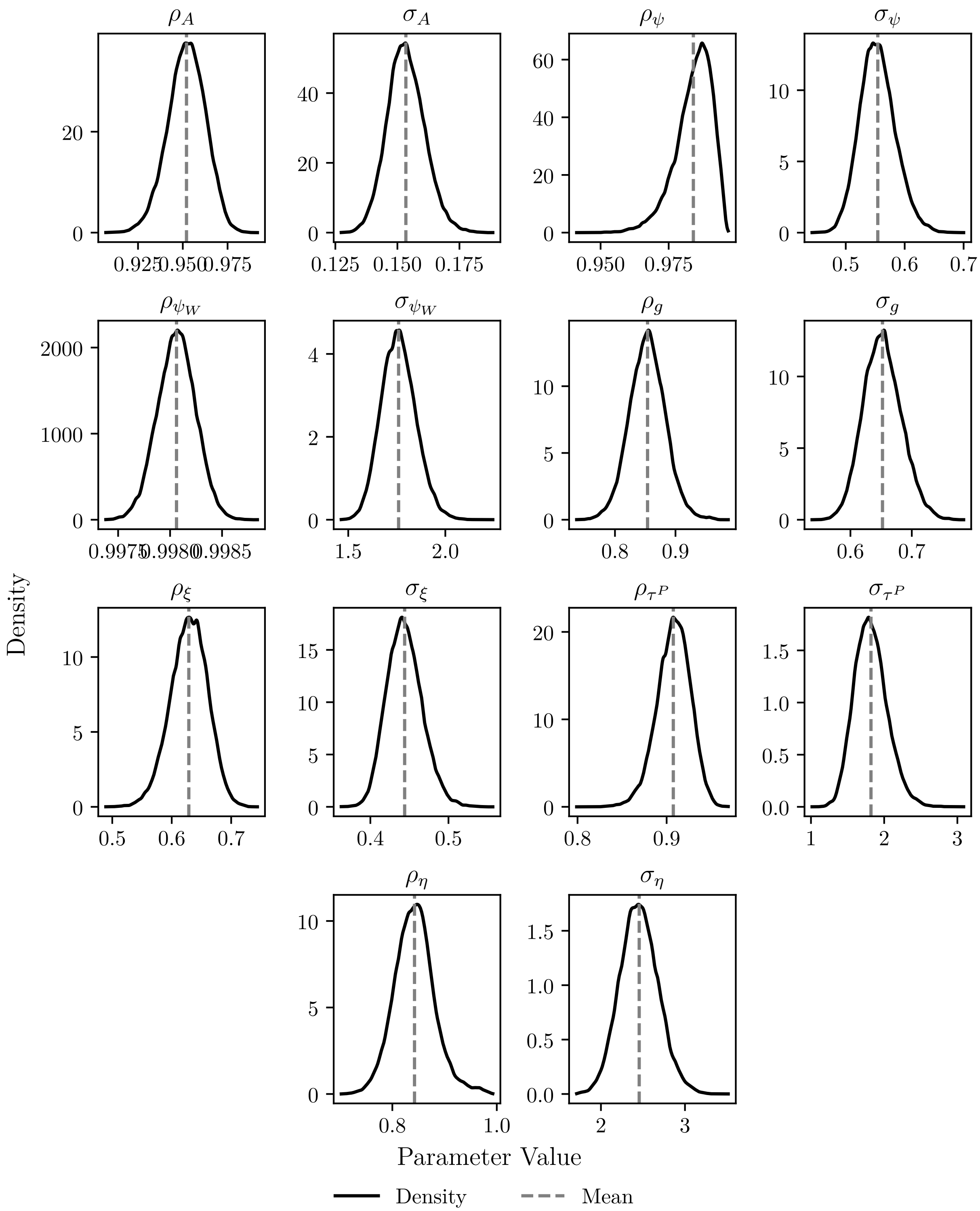
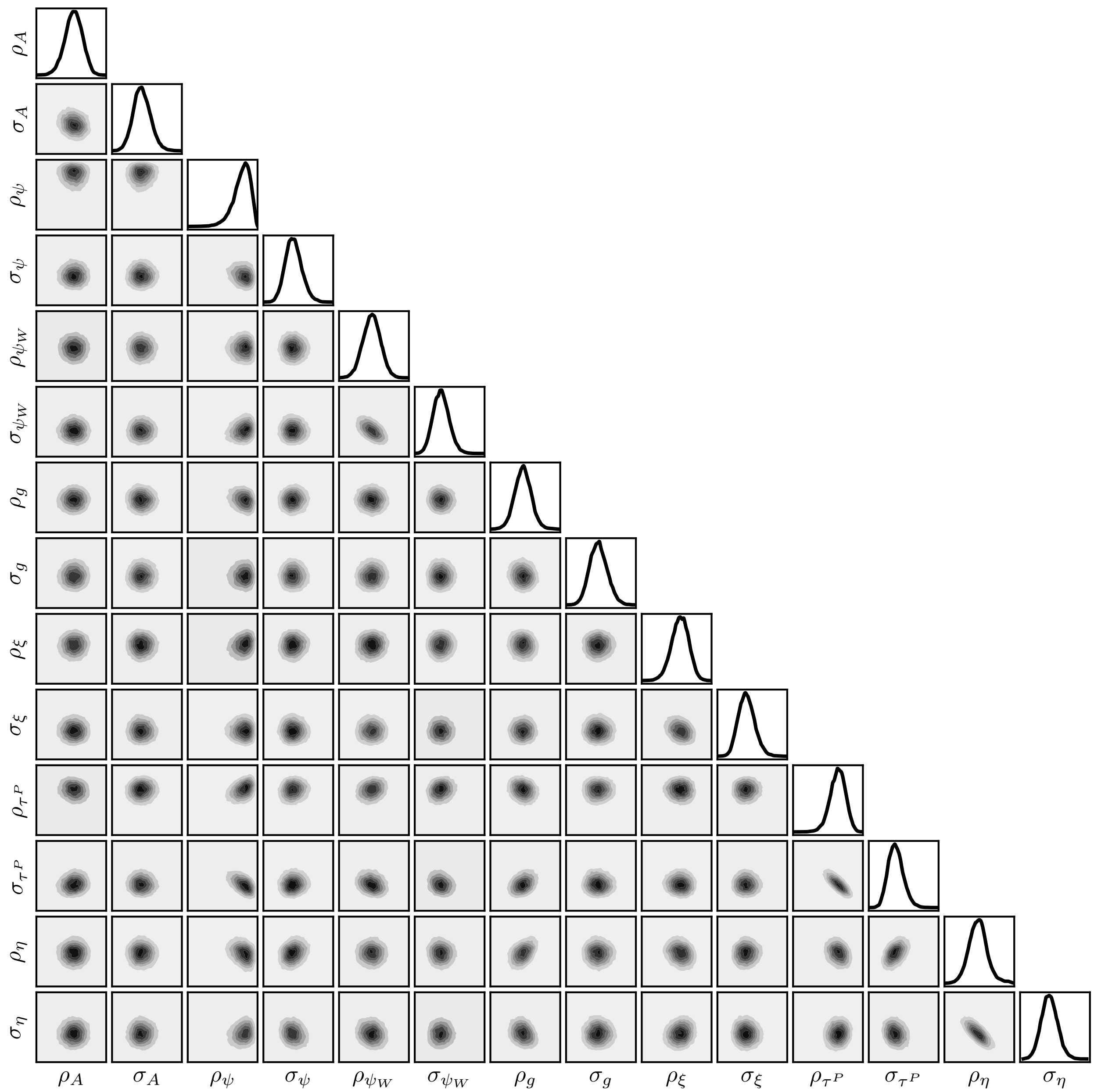


Figure D.3: Posterior Covariences



E Aggregate IRFs

Figure E.1: TFP (A) Shock Impulse Response Functions

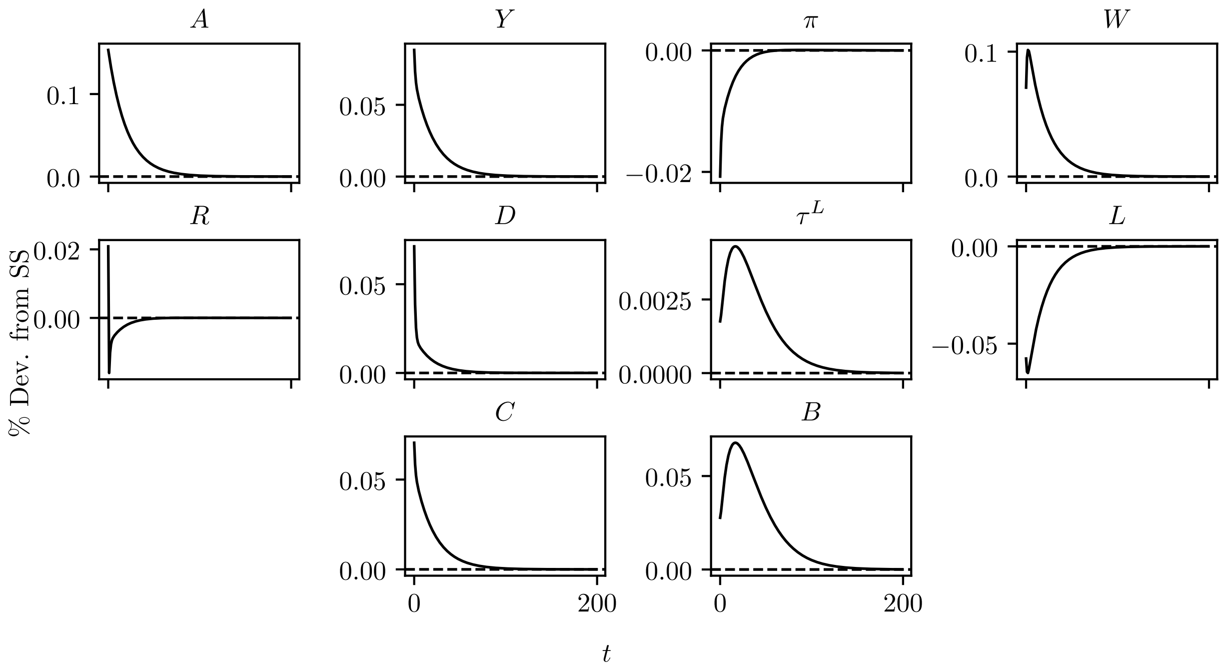


Figure E.2: Price Markup (ψ) Shock Impulse Response Functions

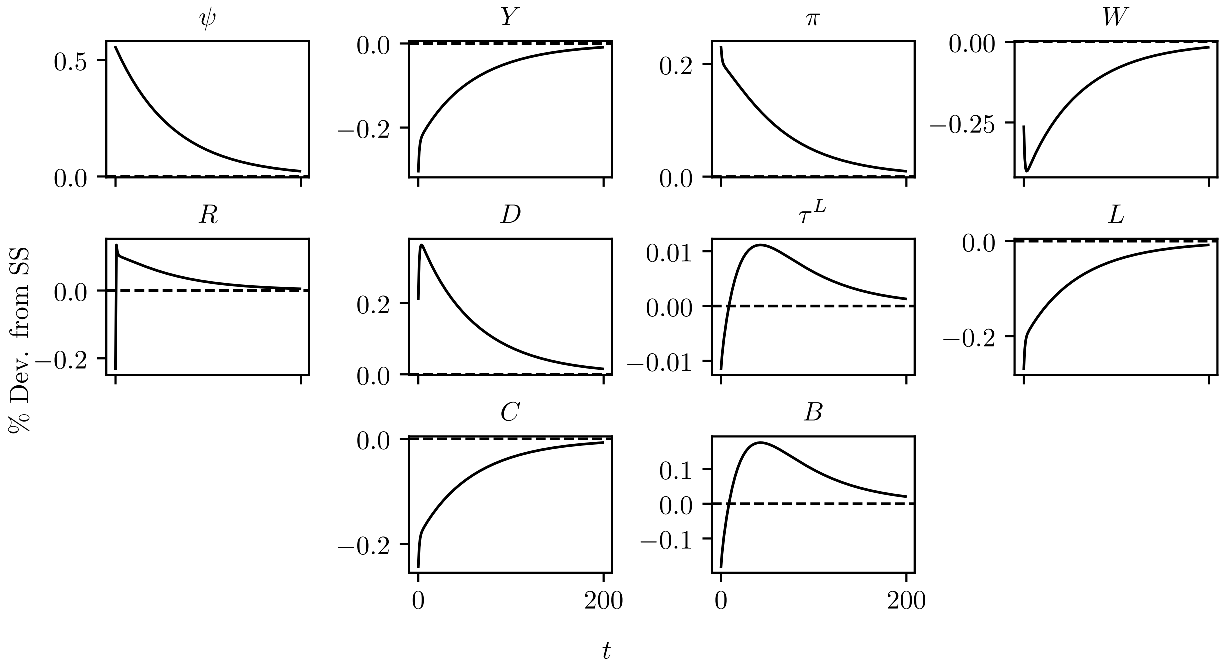


Figure E.3: Wage Markup (ψ_W) Shock Impulse Response Functions

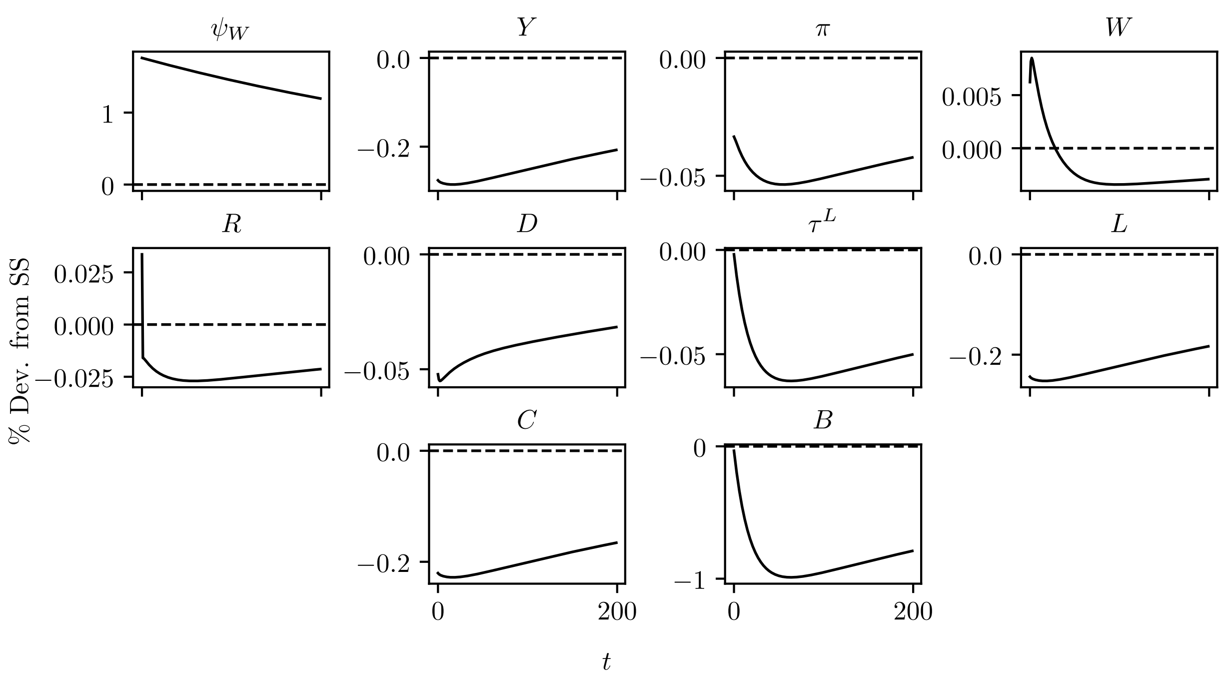


Figure E.4: Govt. Spending (g) Shock Impulse Response Functions

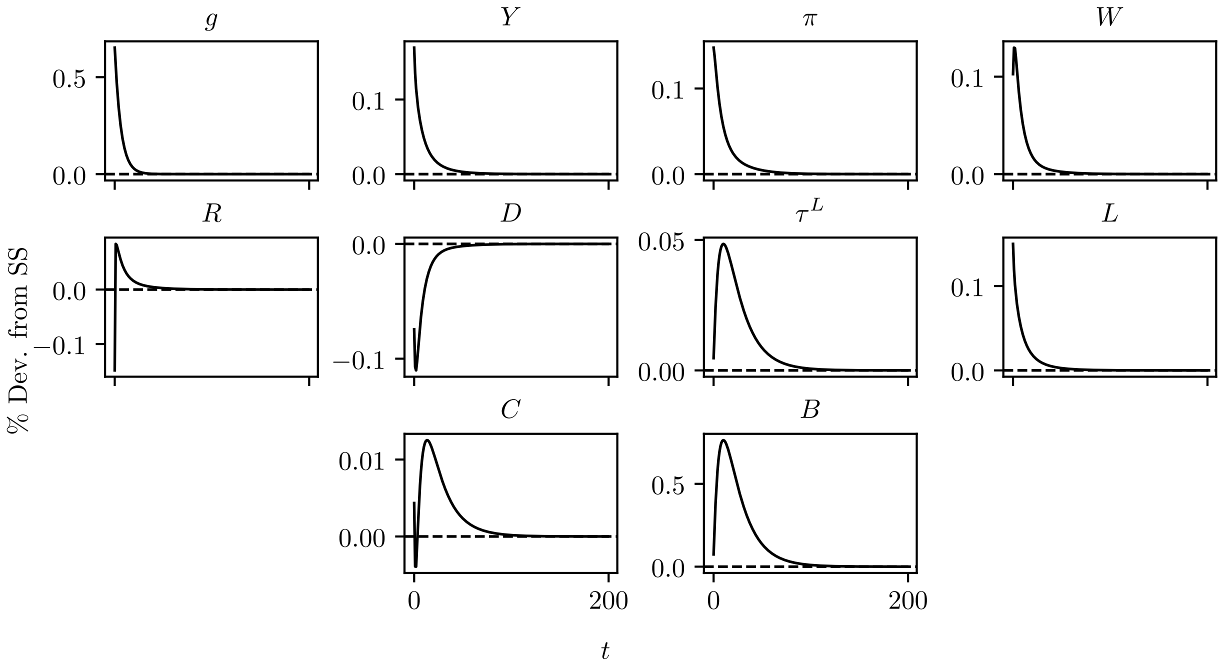


Figure E.5: Monetary Policy (ξ) Shock Impulse Response Functions

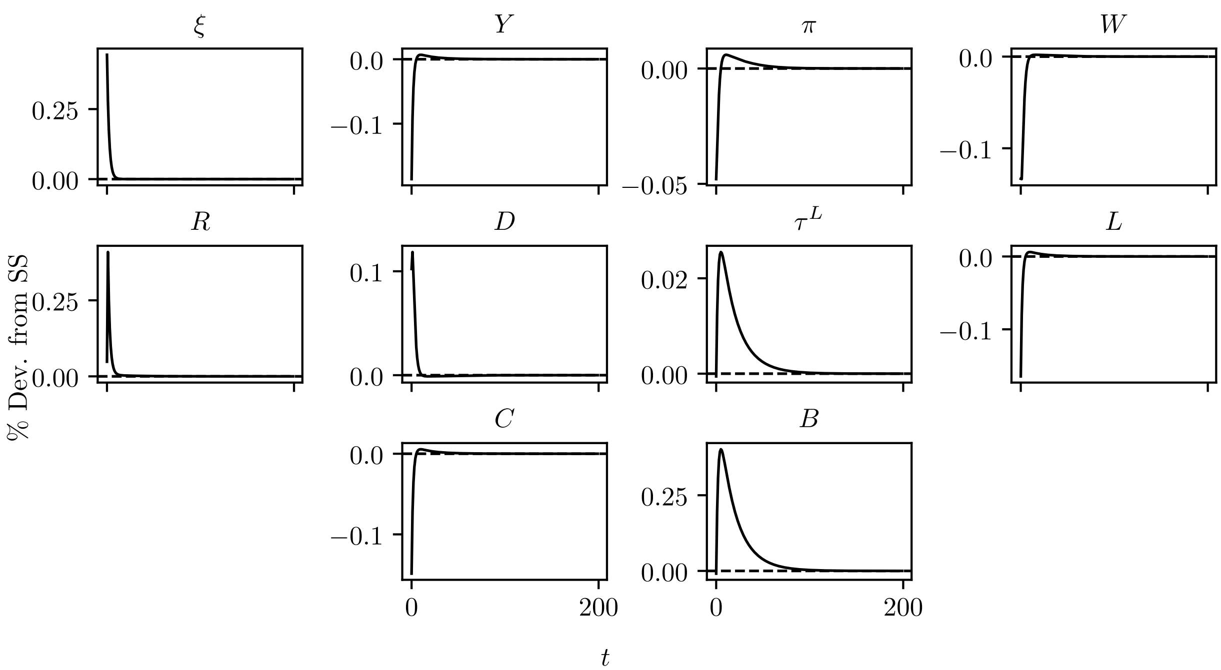


Figure E.6: Tax Progressivity (τ^P) Shock Impulse Response Functions

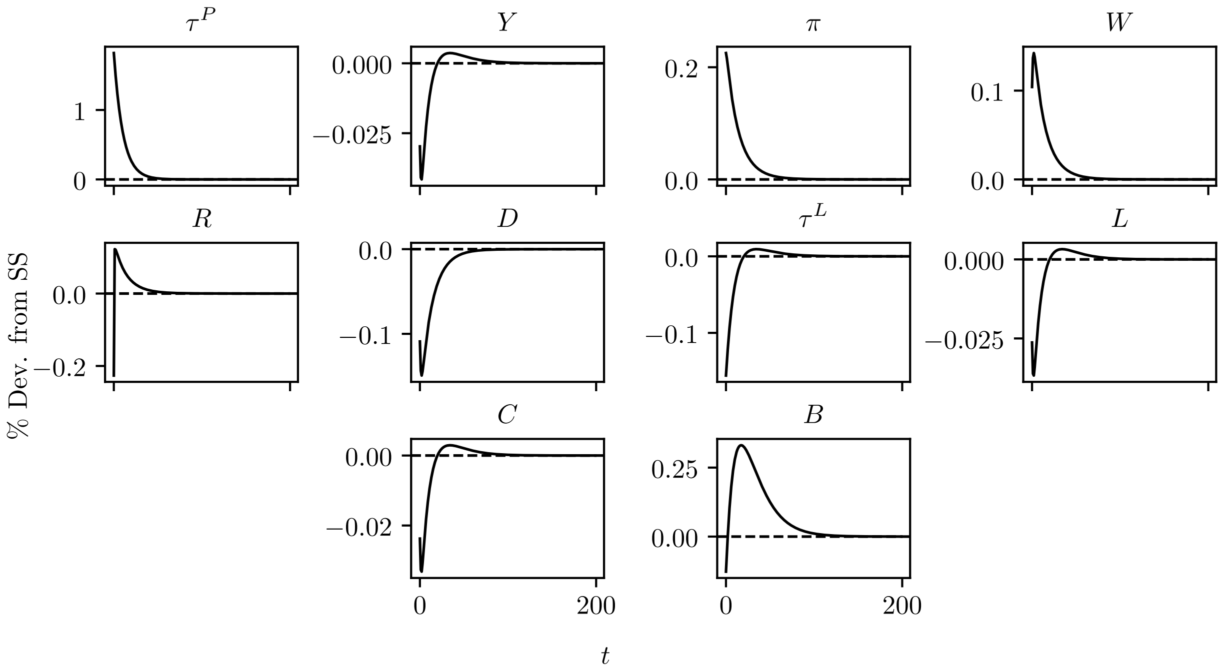
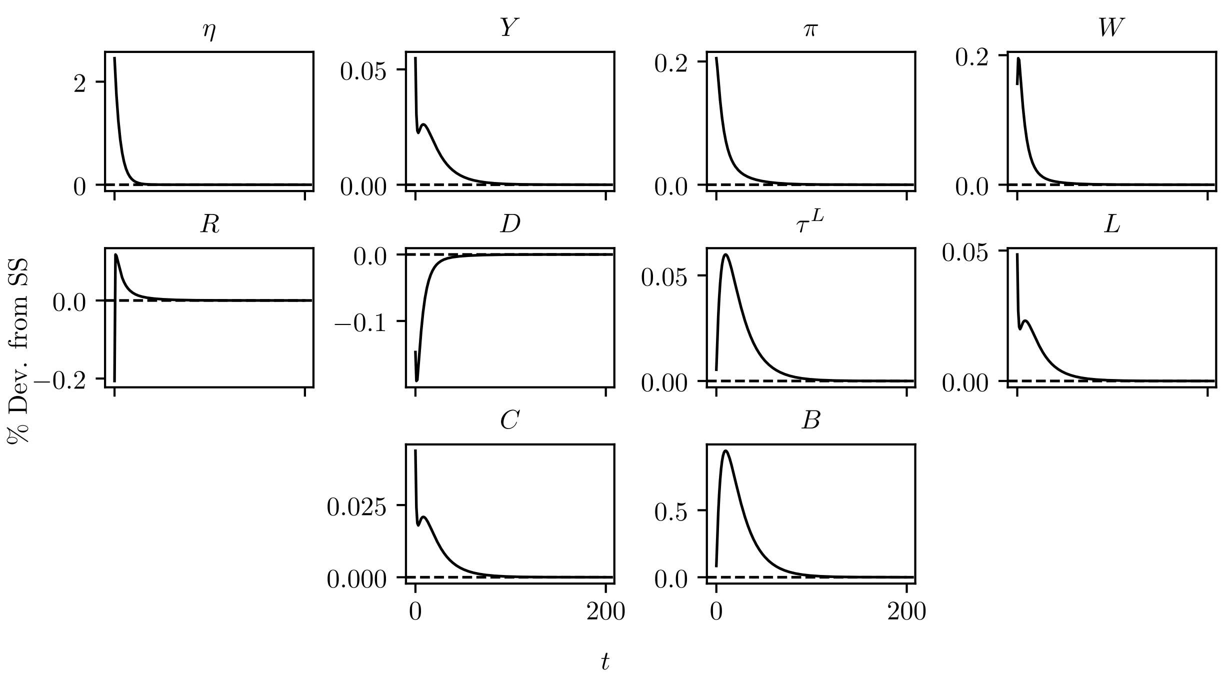


Figure E.7: Household Transfer (η) Shock Impulse Response Functions



F Forecast Error Variance Decomposition Calculation

To calculate the forecast error variance decomposition (FEVD) in the sequence space, I start with the moving average process from Auclert et al. (2021)

$$d\tilde{\mathbf{X}}_t = \sum_{s=0}^{\infty} d\mathbf{X}_s \epsilon_{t-s}$$

where $d\tilde{\mathbf{X}}_t$ is a vector of outcome differences from trend $d\tilde{x}_{j,t}$, $d\mathbf{X}_s$ is a matrix of impulse responses where the i-jth element represents the change in outcome j s periods after a shock to ϵ_i, $\frac{dx_{j,s}}{d\epsilon_{j,s}}$, and ϵ_t is a vector of iid shocks $\epsilon_{i,t}$ with diagonal variance-covariance matrix Σ. Assuming no effects from shocks at time t, we know

$$d\tilde{\mathbf{X}}_{t+h} - d\tilde{\mathbf{X}}_t = \sum_{s=0}^{h-1} d\mathbf{X}_s \epsilon_{t+h-s}.$$

This gets Mean Squared Error for output j of

$$\begin{aligned}
\text{MSE}\left(d\tilde{x}_{j,t+h}\right) &= \mathbb{E}\left[\left(\sum_{s=0}^{h-1} dx_{j,s}\epsilon_{t+h-s}\right)^2\right] \\
&= \mathbb{E}\left[\sum_{s=0}^{h-1}\sum_{r=0}^{h-1} dx_{j,s}\epsilon_{t+h-s}\epsilon_{t+r-s}^{\top} dx_{j,r}^{\top}\right] \\
&= \sum_{s=0}^{h-1} dx_{j,s}\Sigma dx_{j,s}^{\top} \\
&= \text{Var}\left(d\tilde{x}_{j,t+h}\right)
\end{aligned}$$

where the part of the variance coming from by shock i is

$$\sum_{s=0}^{h-1} dx_{ij,s}\sigma_i^2 dx_{ij,s}^{\top}.$$

Therefore, the FEVD is

$$\text{FEVD}_{ij} = \frac{\sum_{s=0}^{h-1} dx_{ij,s}\sigma_i^2 dx_{ij,s}^{\top}}{\sum_{s=0}^{h-1} dx_{j,s}\Sigma dx_{j,s}^{\top}}.$$

G Household Decision Rules

Figure G.1: Household Decision Rules

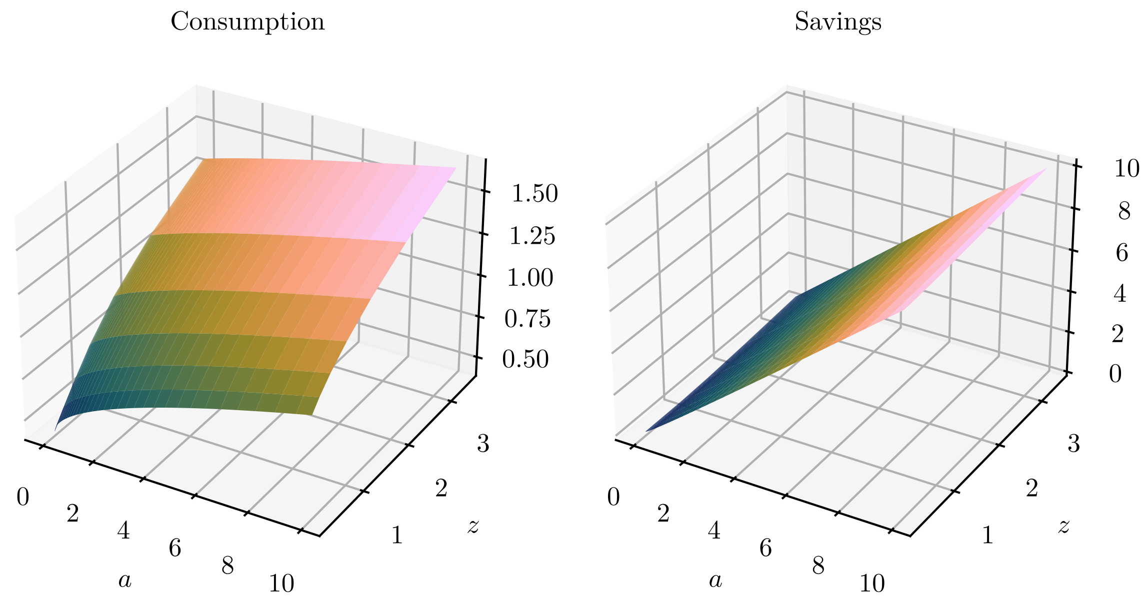


Figure G.2: Household Income Shares

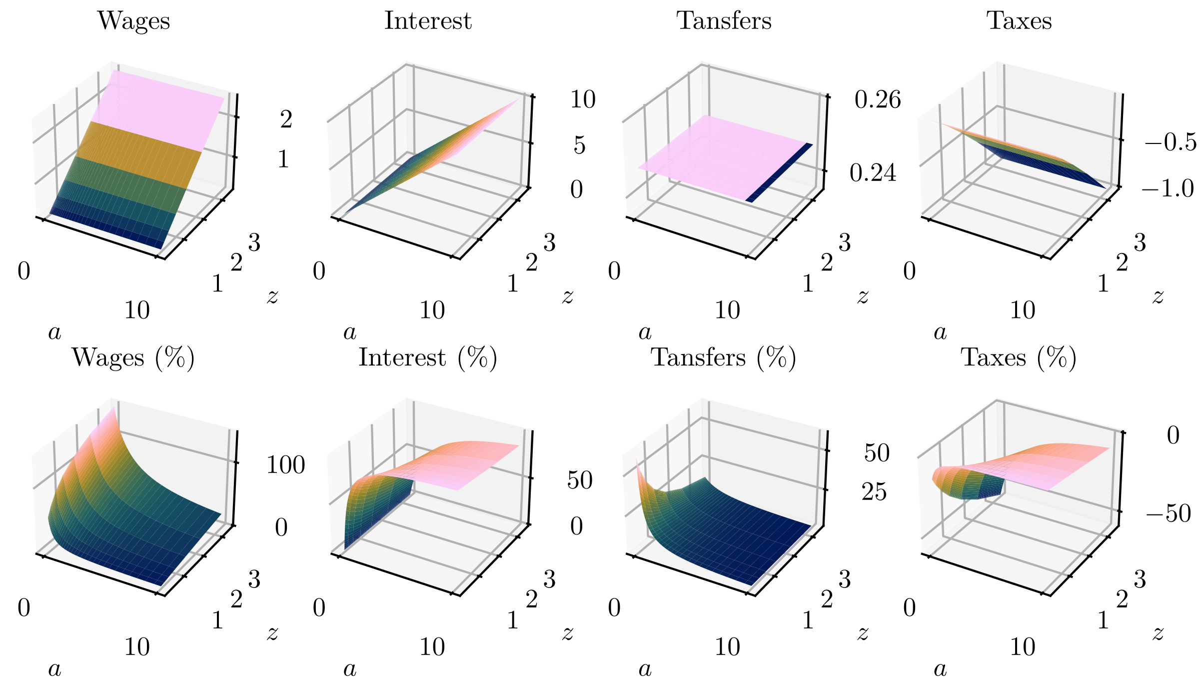


Figure G.3: Consumption Response to a TFP Shock

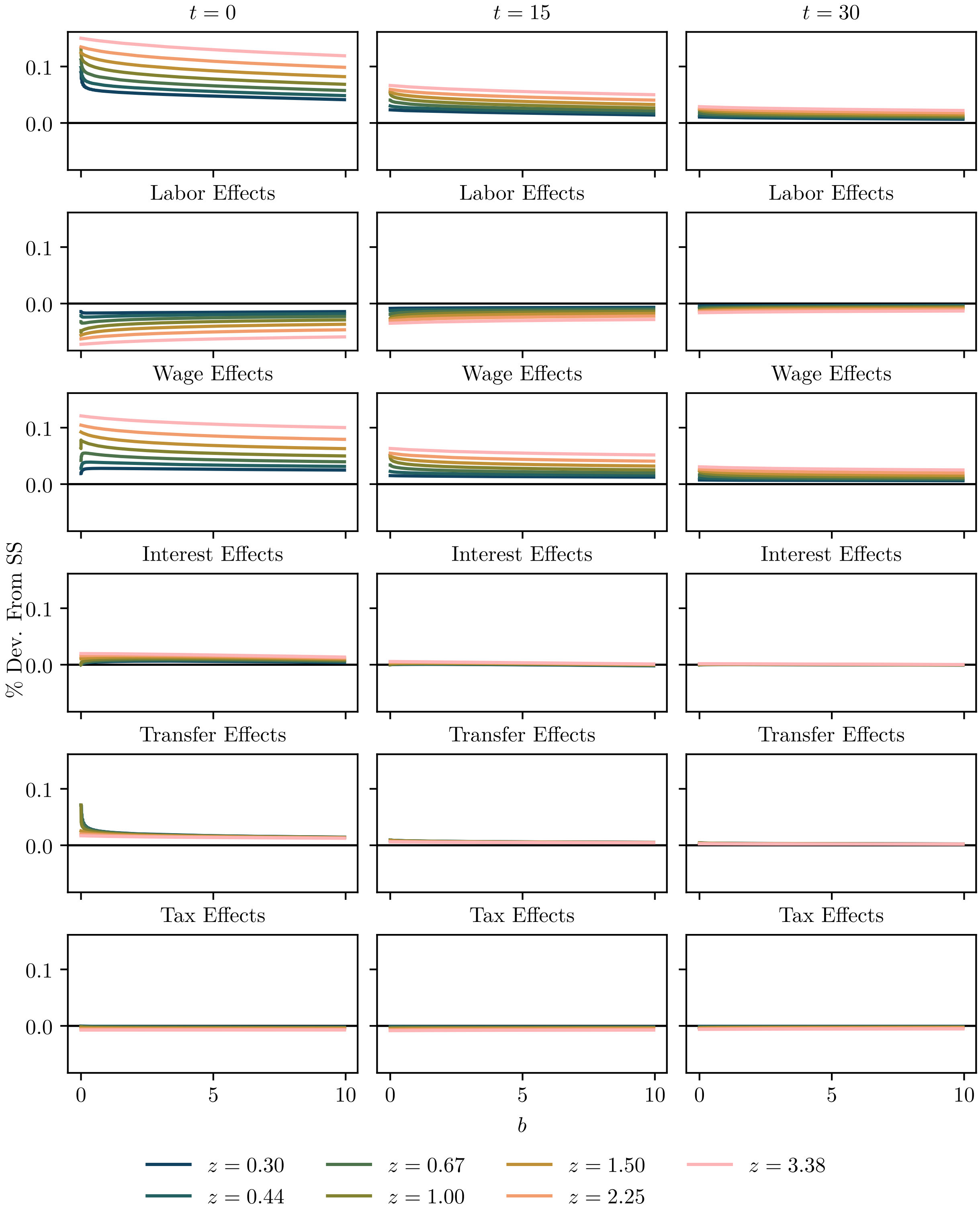


Figure G.4: Savings Response to a TFP Shock

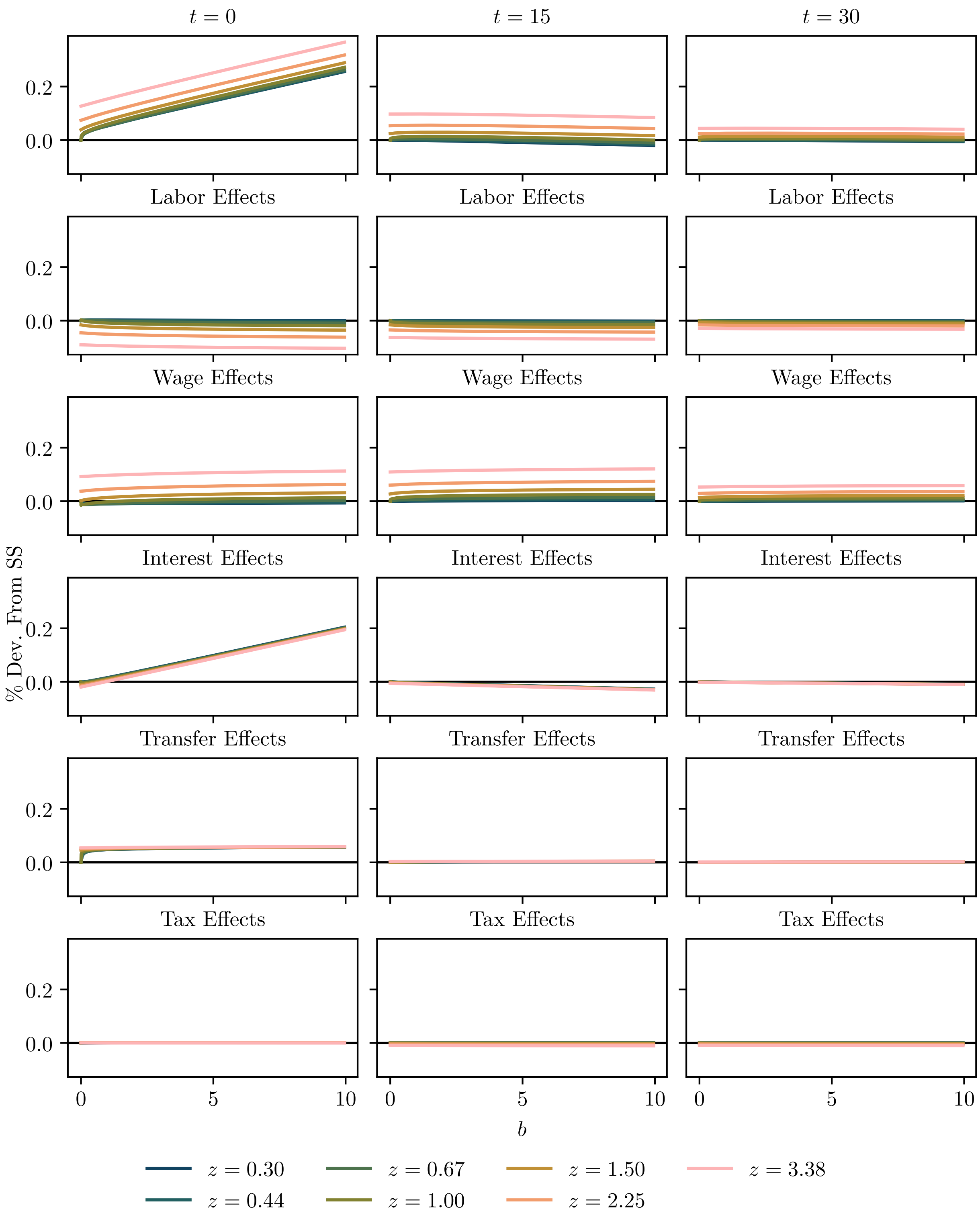


Figure G.5: Consumption Response to a Markup Shock

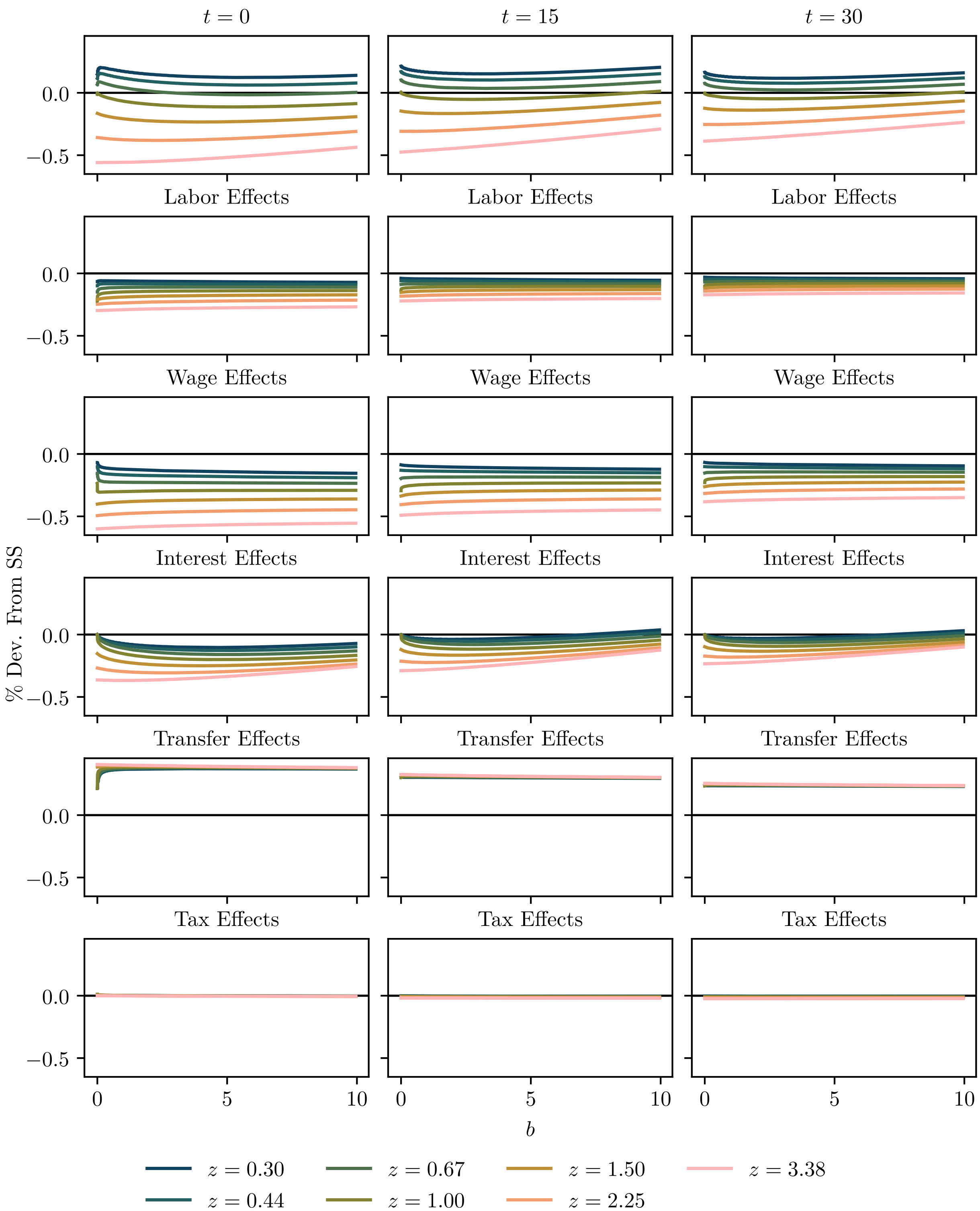


Figure G.6: Savings Response to a Markup Shock

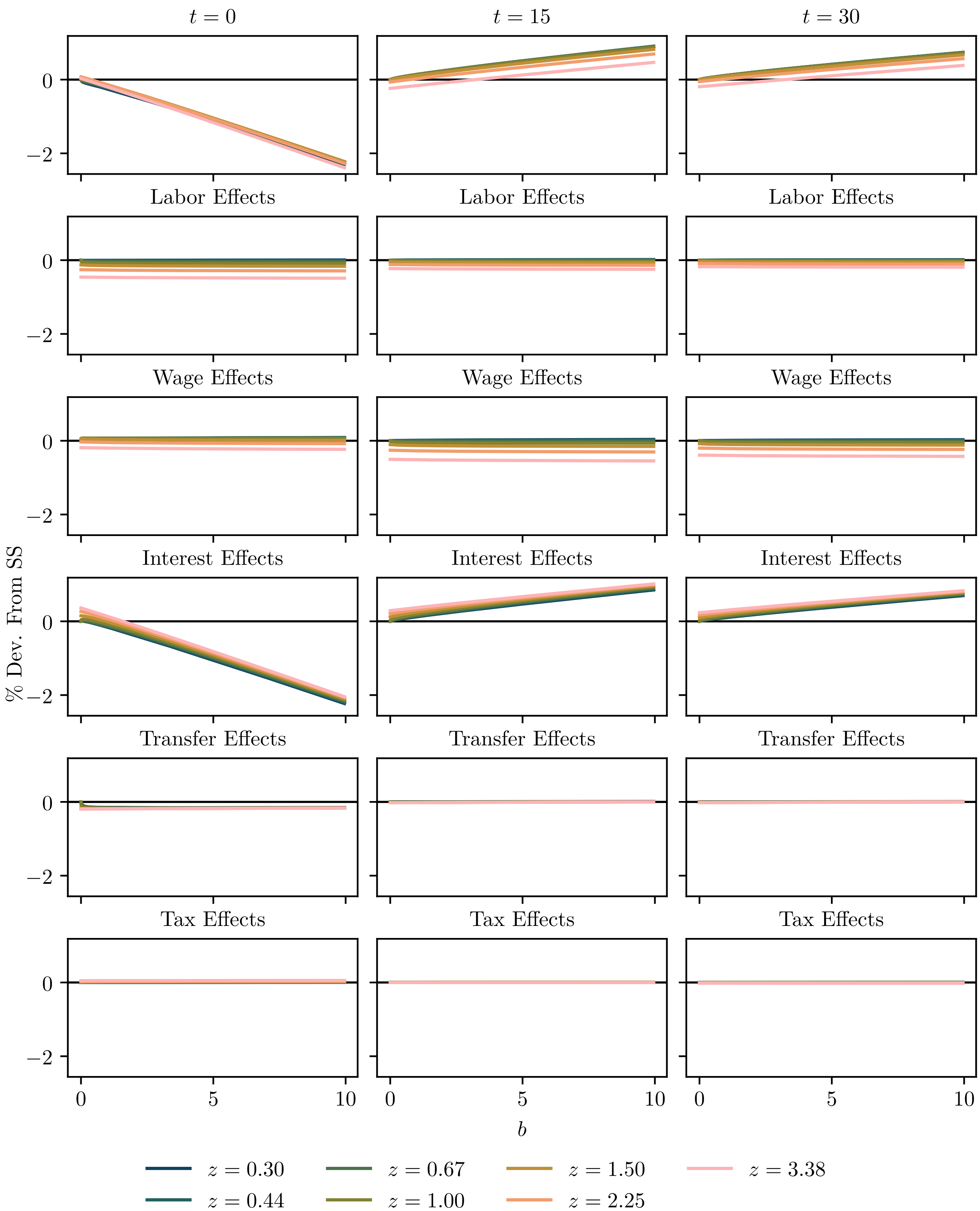


Figure G.7: Consumption Response to a Wage Markup Shock

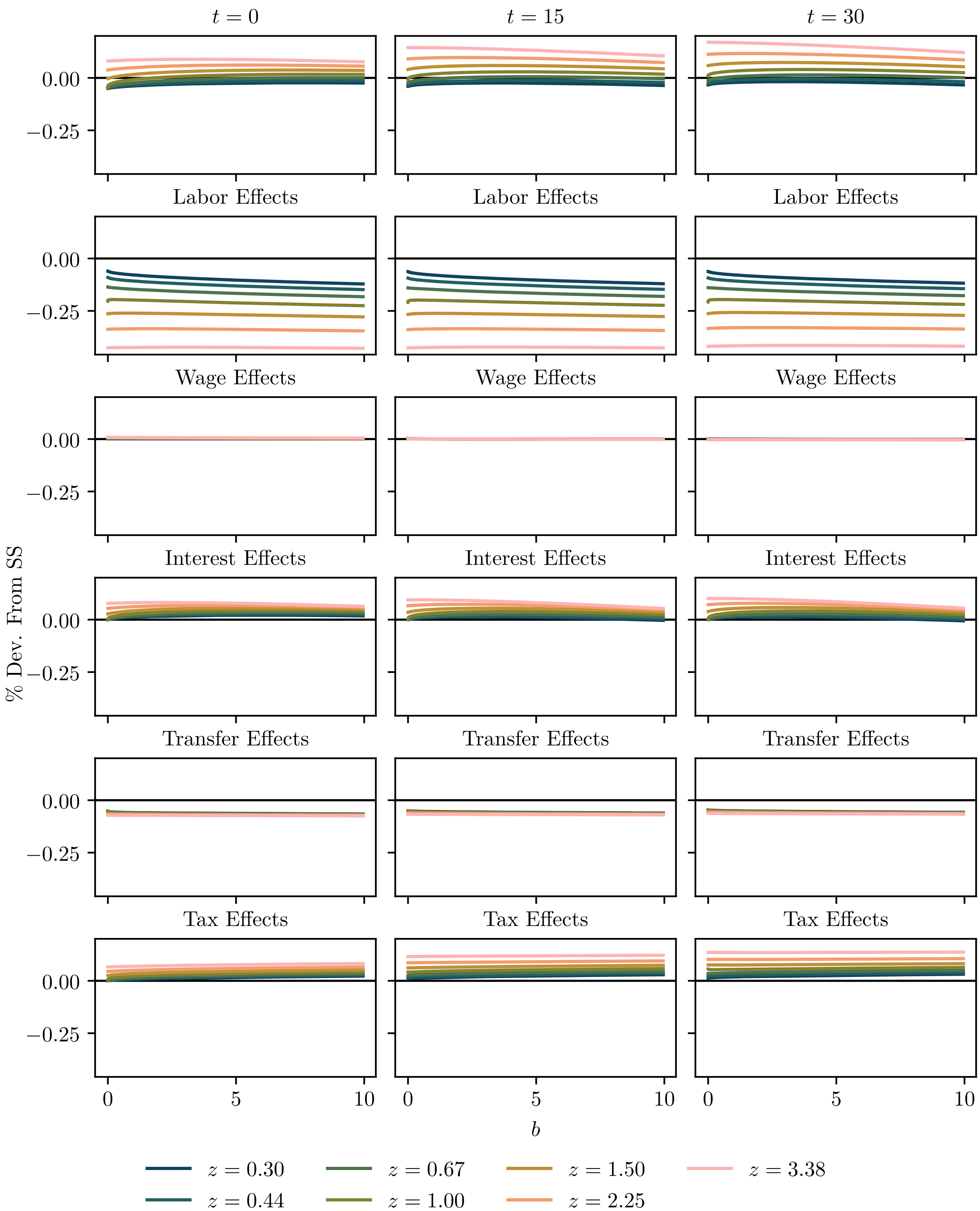


Figure G.8: Savings Response to a Wage Markup Shock

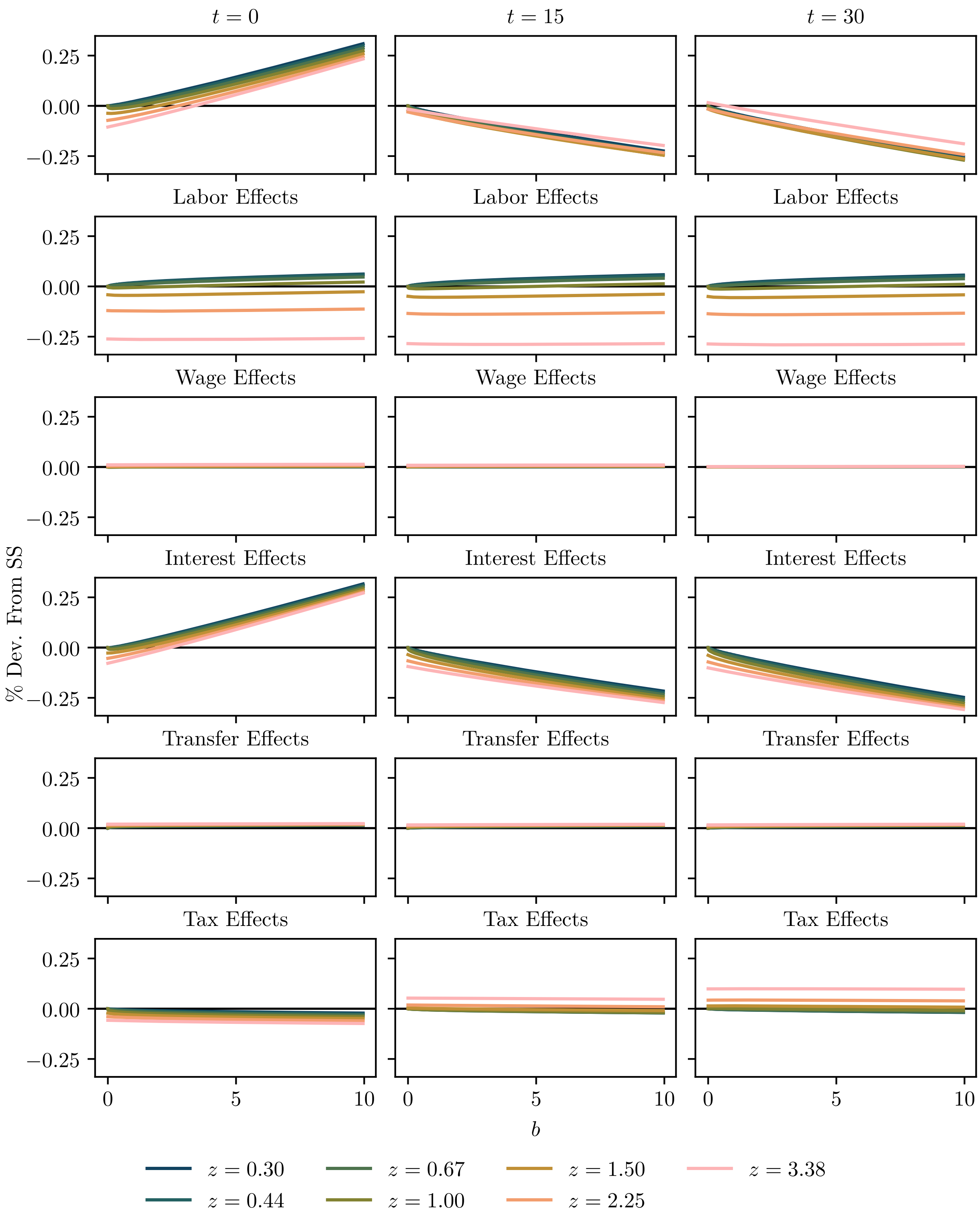


Figure G.9: Consumption Response to a Government Spending Shock

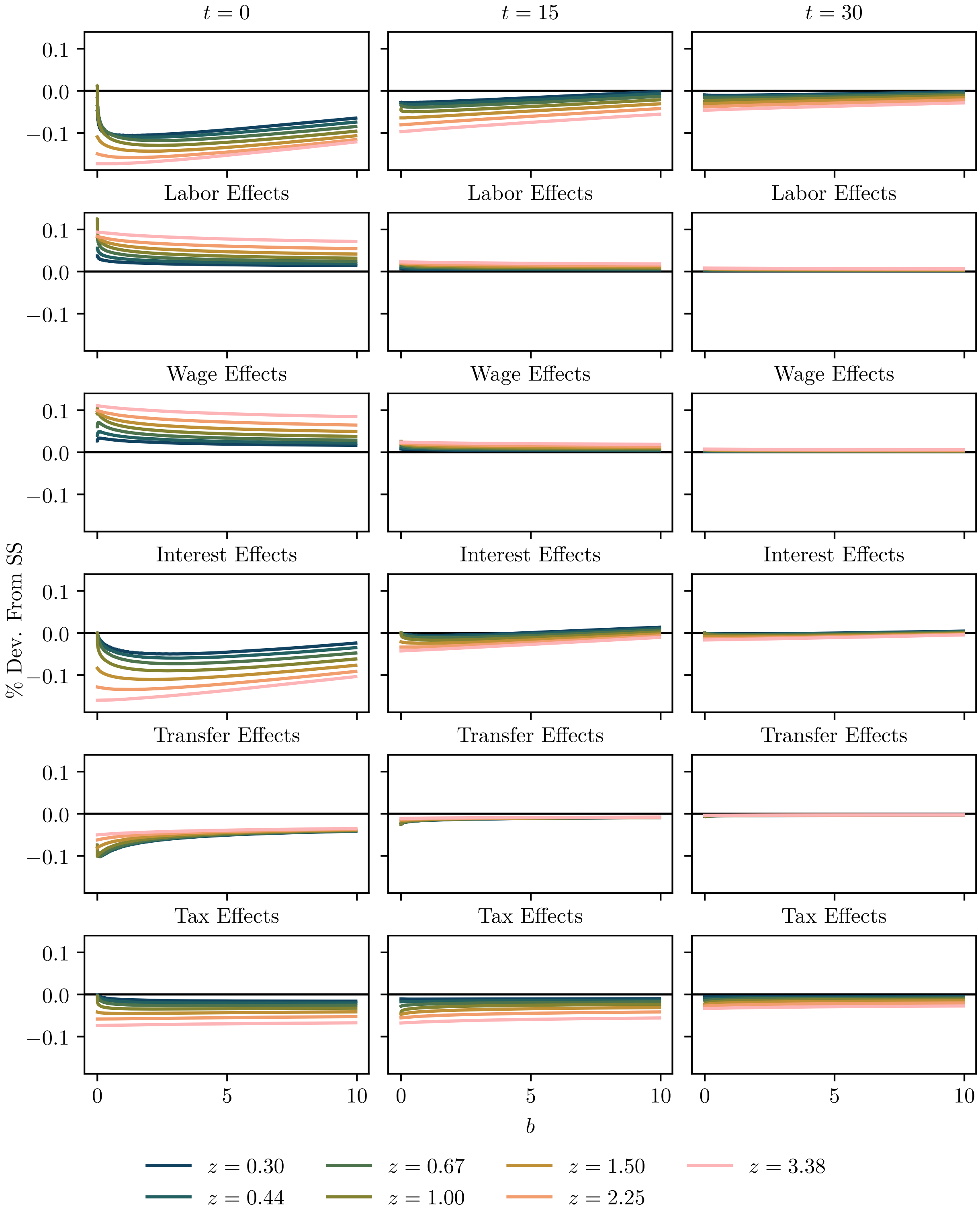


Figure G.10: Savings Response to a Government Spending Shock

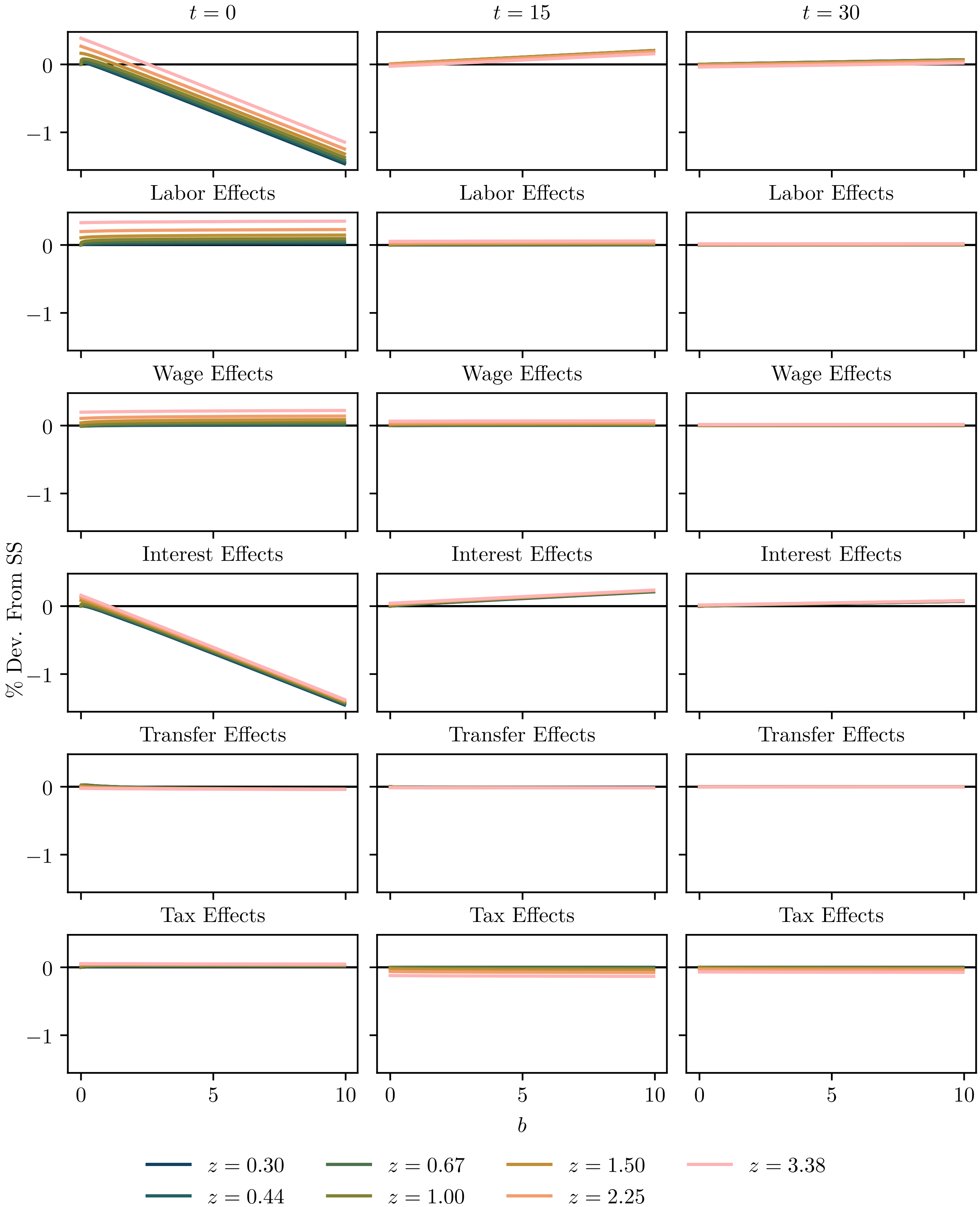


Figure G.11: Consumption Response to a Monetary Policy Shock

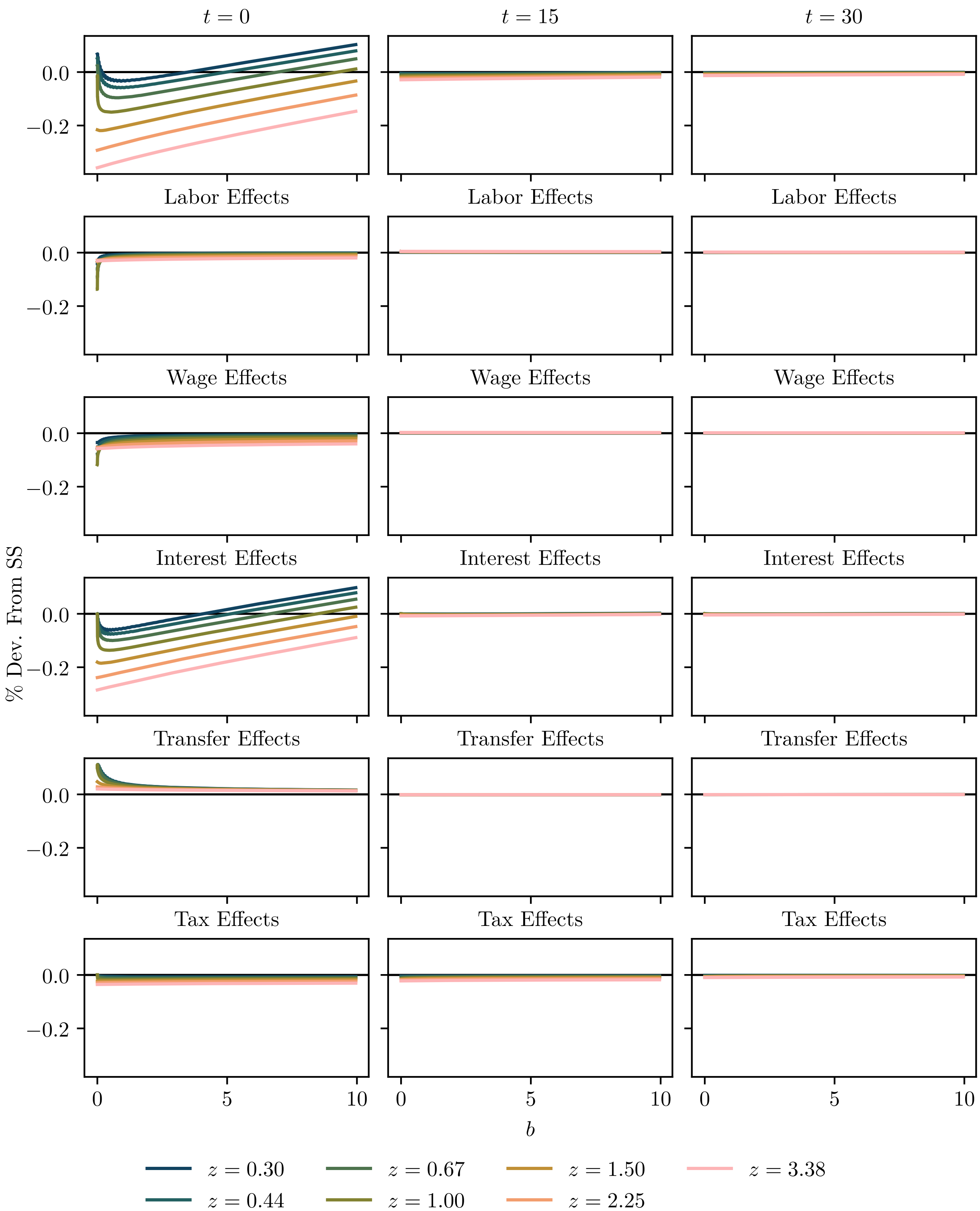


Figure G.12: Savings Response to a Monetary Policy Shock

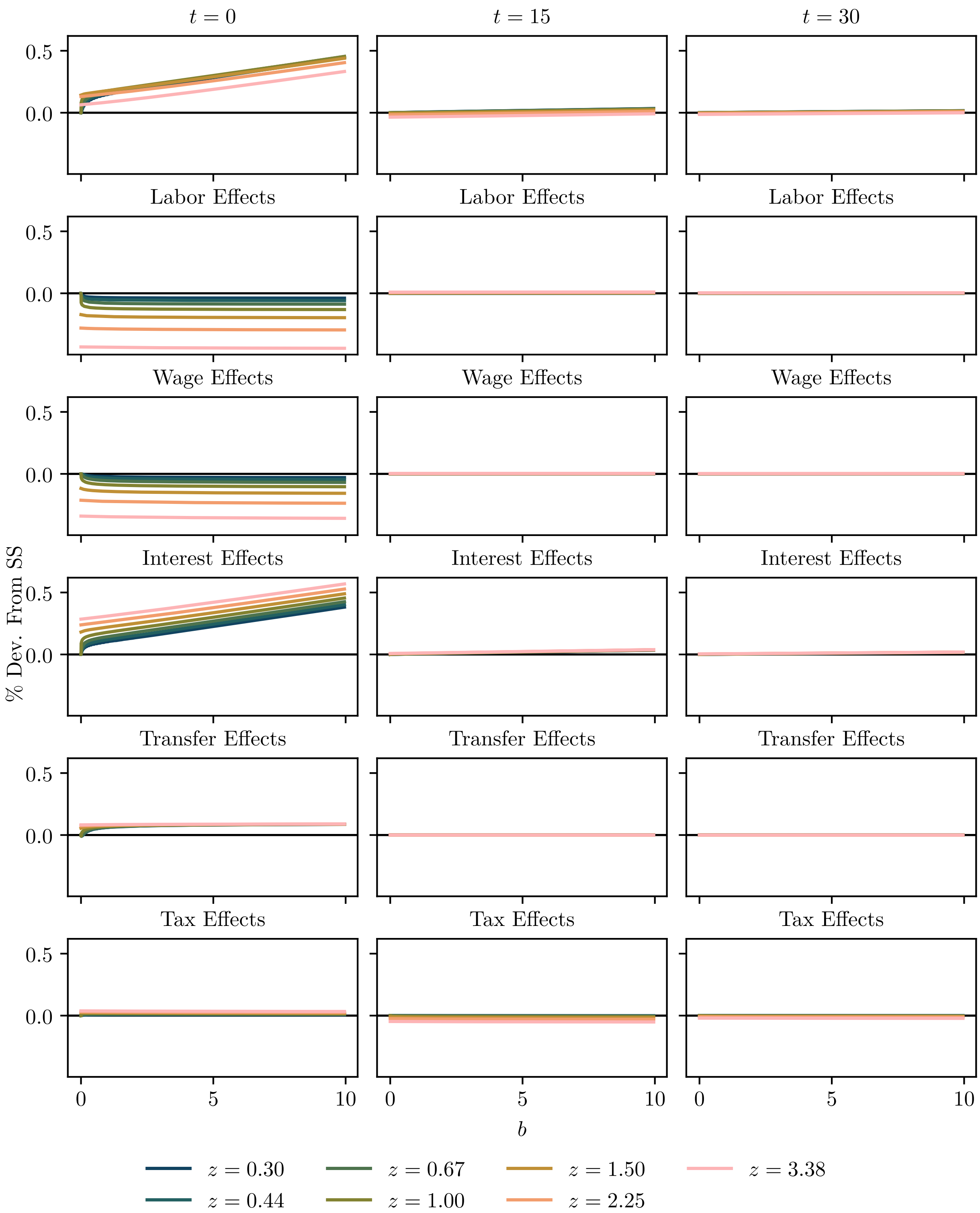


Figure G.13: Consumption Response to a Government Transfer Shock

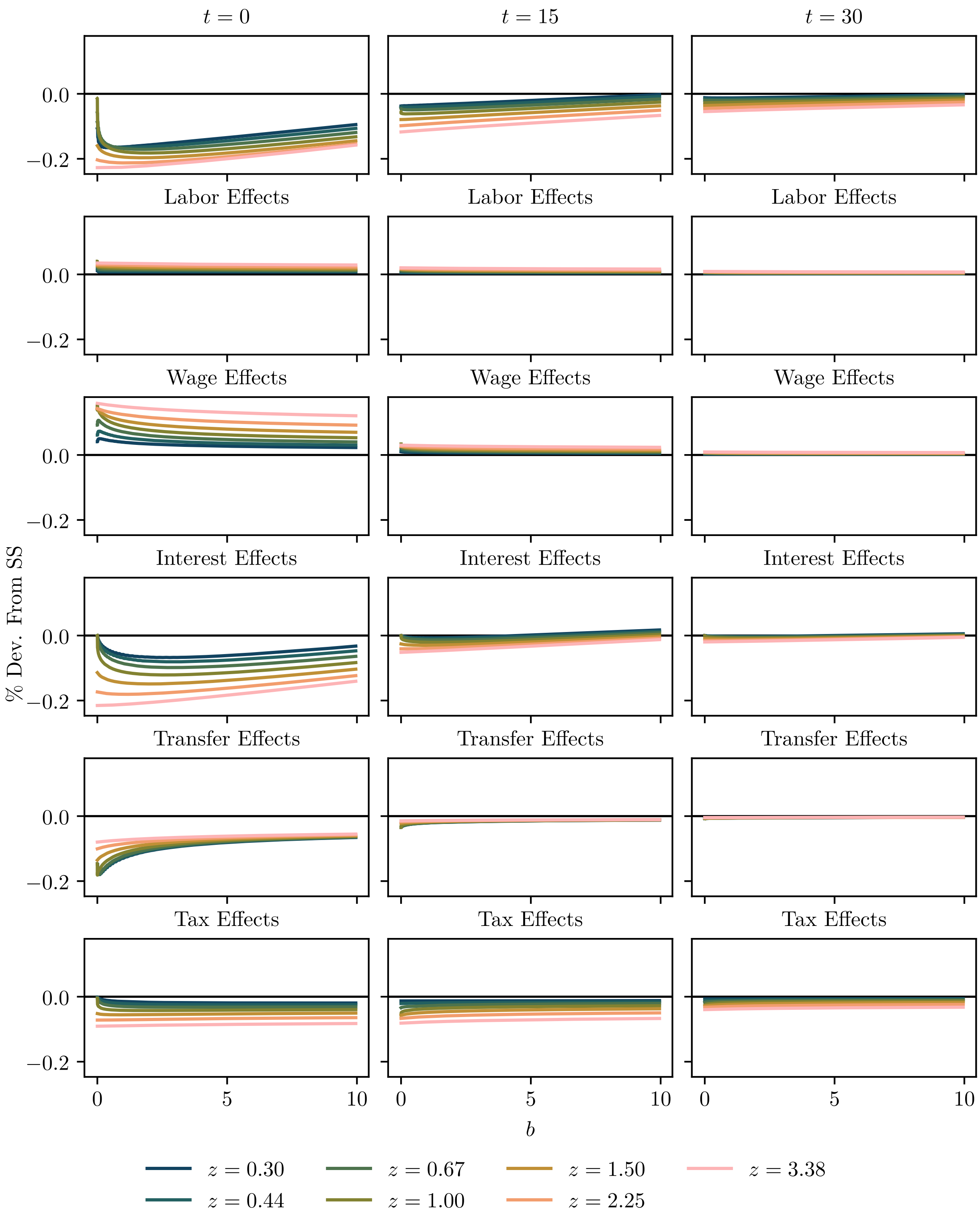


Figure G.14: Savings Response to a Government Transfer Shock

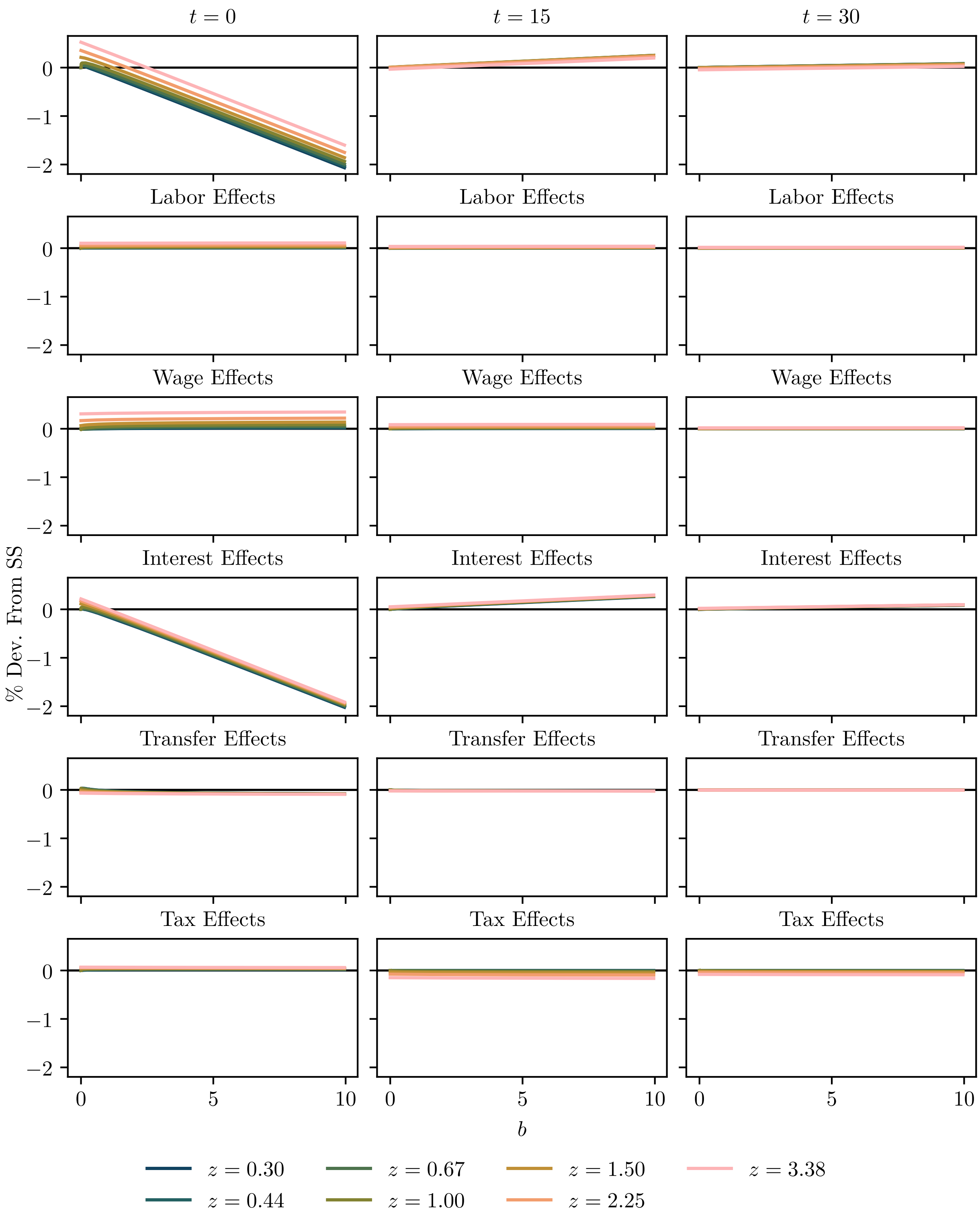


Figure G.15: Consumption Response to a Tax Progressivity Shock

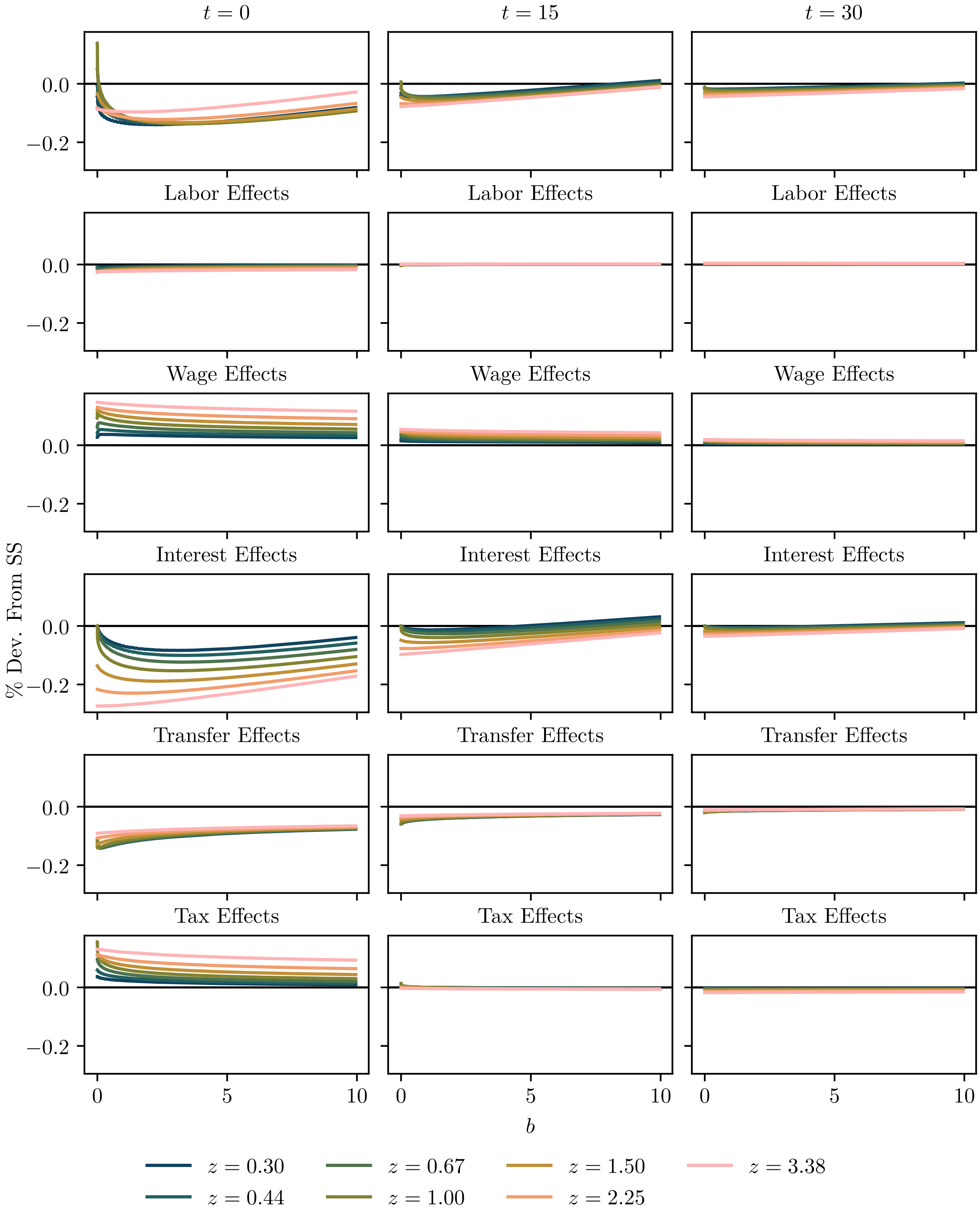
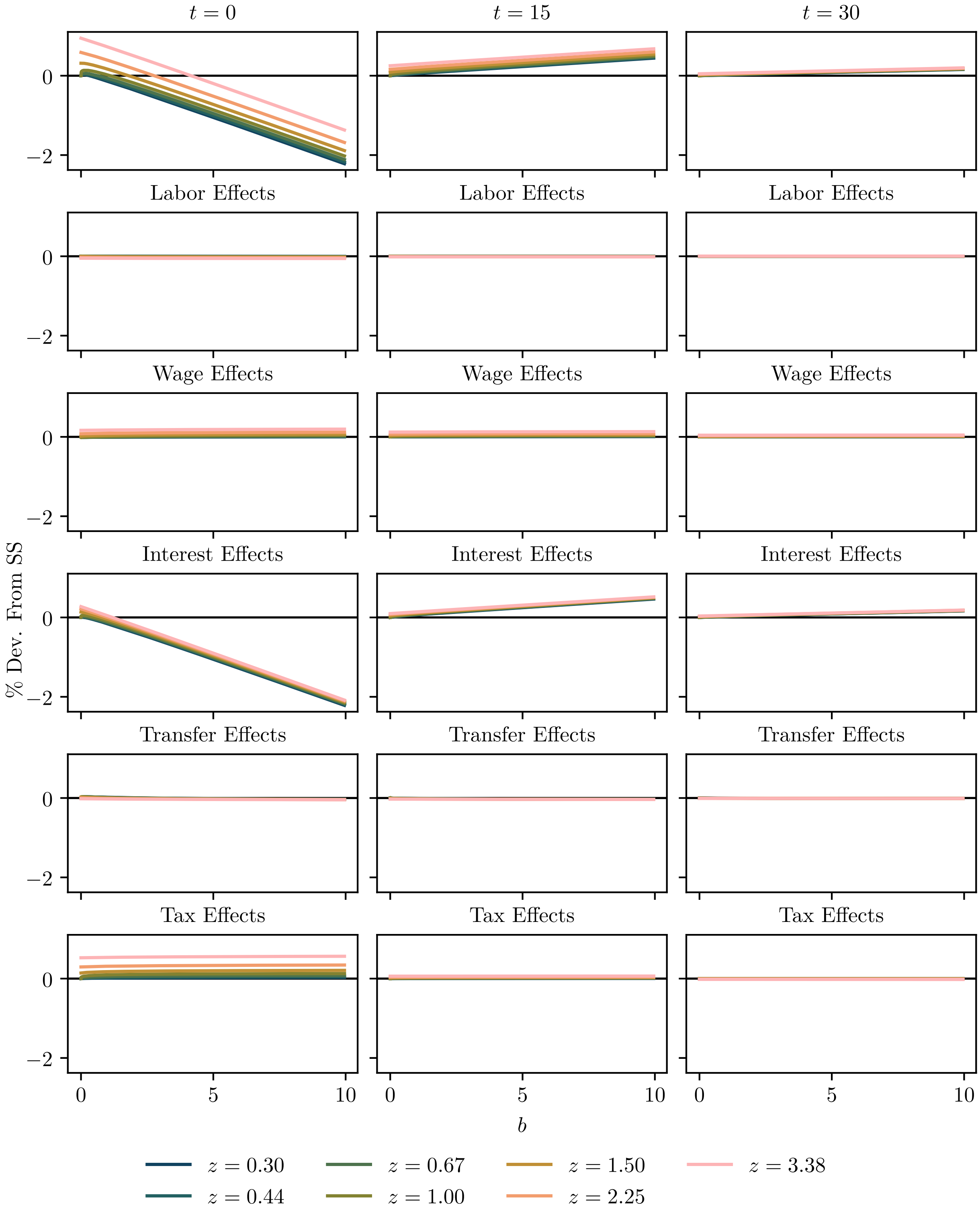
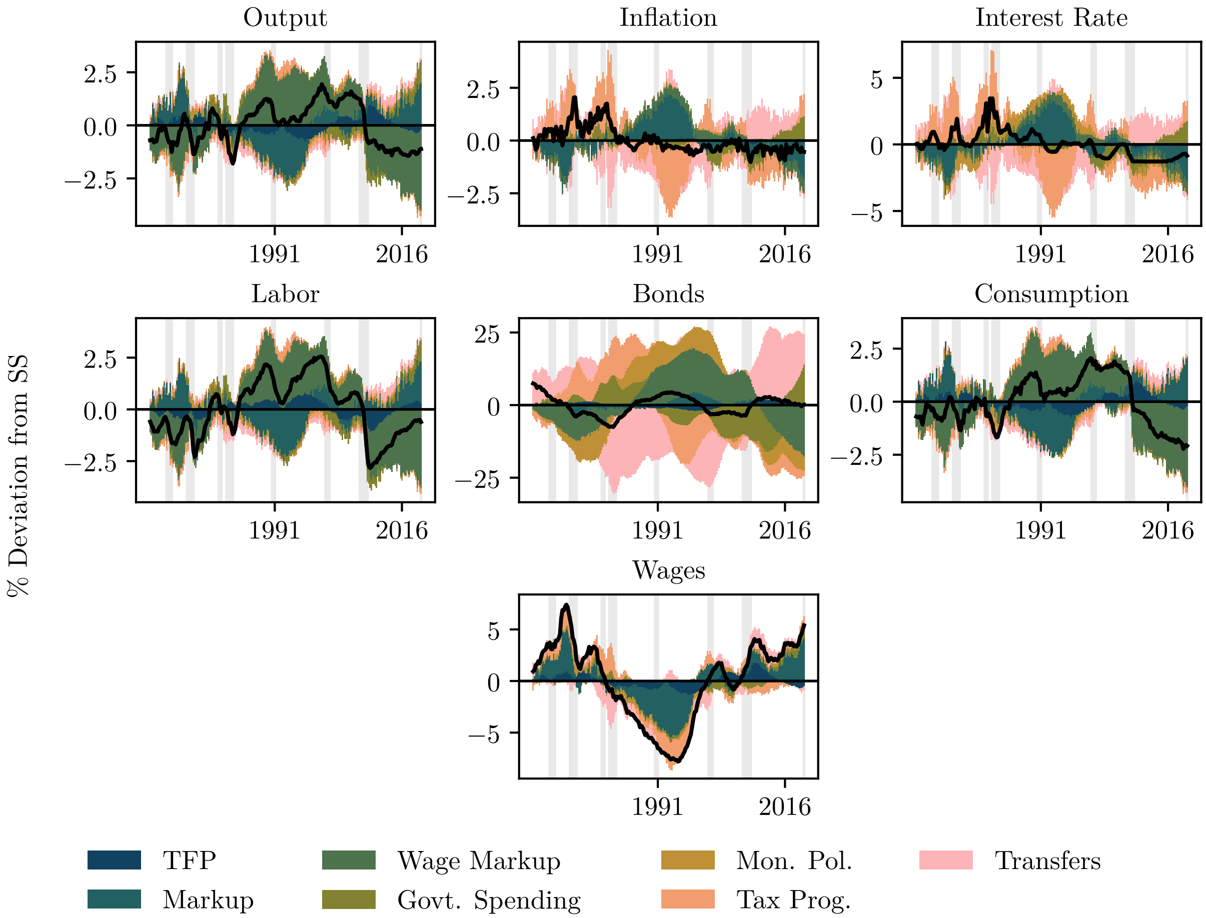


Figure G.16: Savings Response to a Tax Progressivity Shock



H Additional Historical Decompositions

Figure H.1: Fitted Historical Decompositions



Notes: NBER-dated recessions highlighted in gray.