Essays on Heterogeneous Agent Macroeconomics and Unemployment

by

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Abstract

This dissertation consists of three chapters that study how the microeconomic characteristics of unemployment shape business cycle dynamics and macroeconomic policy.

The first chapter investigates the macroeconomic consequences of a well documented microeconomic fact: Job loss results in a substantial decline in labor earnings that persists for over 20 years. This chapter argues that this 'scarring' effect of unemployment is a key determinant of the speed of a macroeconomic recovery following a recession. I incorporate human capital into a heterogeneous agent New Keynesian model with search and matching frictions. During unemployment, human capital depreciates, leading to lower wages for reemployed workers. Unemployment scarring, mediated by the fraction of temporary versus permanent layoffs, enables the model to capture both the sluggish recovery from the Great Recession and the swift rebound from the COVID Recession. In particular, the presence of scarring reveals the pivotal role that temporary layoffs fulfilled in preventing a sluggish post-pandemic recovery.

The second chapter examines how household beliefs about the probability of finding and losing a job evolve over the business cycle. We backcast expectations data on job finding and job loss from the Survey of Consumer Expectations and use real-time machine learning forecasts to construct proxies for their rational counterparts. Our analysis reveals that beliefs about job finding and job loss adjust sluggishly to real-time changes in labor market conditions and exhibit substantial heterogeneity across both observable and unobservable characteristics. We calibrate our empirical findings to a heterogeneous-agent consumption-saving model with persistent unemployment. While belief stickiness dampens the immediate precautionary

response in aggregate consumption during a recession, the resulting smaller precautionary buffers slow the recovery by limiting households' ability to draw down excess savings once conditions improve.

The third chapter evaluates and compares the effectiveness of commonly pursued fiscal stimulus policies during recessions. Using a heterogeneous agent model calibrated to match measured spending dynamics over four years following an income shock, we assess the effectiveness of three fiscal stimulus policies employed during recent recessions. Unemployment insurance (UI) extensions are the clear "bang for the buck" winner when effectiveness is measured in utility terms. Stimulus checks are second best and have two advantages (over UI): they arrive and are spent faster, and they are scalable to any desired size. A temporary (two-year) cut in the rate of wage taxation is considerably less effective than the other policies and has negligible effects in the version of our model without a multiplier.

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Chapter 1

The Macroeconomic Consequences of Unemployment Scarring[1]

1.1 Introduction

Since the seminal work of Jacobson et al. [1993], job loss from stable employment has been understood to cause large and persistent earnings losses.[2] On average, these earnings losses are 15% after 20 years [e.g. Davis and Wachter, 2011a, Huckfeldt, 2022], reflect a permanent loss in wages as opposed to hours [e.g. Moore and Scott-Clayton, 2019, Lachowska et al., 2020, Huckfeldt, 2022], worsen in recessions [Davis and Wachter, 2011a, Schmieder et al., 2023], and are concentrated among workers who switch into lower paying occupations [Huckfeldt, 2022].[3] While a growing *microeconomic* literature seeks to explain the origins of these 'scars', few *macroeconomic* papers explore whether these scars matter for business cycle dynamics, fiscal policy, and monetary policy.

In this paper, I argue that microeconomic unemployment scarring is a key determinant of the speed of macroeconomic recovery following a recession. In particular, I show that the extent to which micro-level scarring translates into a persistent loss in aggregate output is an important reason why the recovery from the COVID recession was markedly faster than the recovery from the Great Recession, even after accounting for the extraordinary fiscal stimulus

[2]In the microeconomic literature, these losses apply to workers who have been employed for 3 to 10 years.
[3]Huckfeldt [2022] and Fujita and Moscarini [2017] document that over 50% of the unemployed switch occupations.

during the pandemic. Furthermore, I quantify the impact of the unprecedented surge in temporary layoffs during the pandemic and demonstrate their crucial and complementary role to fiscal policy in preventing a sluggish recovery following the COVID Recession.

To quantify the macroeconomic role of microeconomic unemployment scarring, I extend a heterogeneous agent New Keynesian (HANK) model with search and matching (SAM) frictions to include human capital dynamics. In the model, households make a consumption/saving decision in the face of unemployment risk and search frictions in the labor market. To account for the empirical fact that only workers who are permanently laid off suffer from scarring [Fujita, 2016], [4] the model differentiates between permanent layoffs, temporary layoffs, and other types of unemployment. Temporary layoffs can transition to permanent layoffs and, motivated by recent evidence using U.S. that suggests these scars reflect a loss in productivity [5], only households who find reemployment after a permanent layoff spell *may* experience human capital depreciation.[6] The model does not capture the sources that lead firms to engage in temporary layoffs. Instead, using the estimates from Gertler et al. [2022], the unemployment process across different layoff states is calibrated to match *how* each state evolves during recessions.

I begin by showing that when the model accounts for the microeconomic estimates of unemployment scarring from Davis and Wachter [2011a], the resulting decline in macroeconomic activity is sufficiently persistent to validate unemployment scarring as a new microfoundation for hysteresis and endogenous growth. In particular, with scarring, recessions induce a near-permanent decline in output, consumption, and aggregate labor productivity. Furthermore, since these scars arise from a loss of human capital that reduces both labor income and

[4] A permanent layoff refers to a worker who has been permanently separated from their previous employer.

[5] The current literature suggests that,in the U.S., the these scars are largely due to losses in firm specific human capital. To begin, Lachowska et al. [2020] find that the decline in wages is largely explained by losses in match specific productivity. Poletaev and Robinson [2008] find that reemployed workers who suffer large wage losses employ substantially different skills in their new job. Huckfeldt [2022] documents that scarring is concentrated among workers who switch into lower paying occupations.

[6] Unsurprisingly, it has been documented that workers who have experienced a temporary layoff do not suffer long term earnings losses [Fujita, 2016].

productivity, the persistent decline in macroeconomic activity occurs without a sustained rise in the unemployment rate. In addition, unemployment scarring induces a permanent increase in wage dispersion that results in a lasting increase in income inequality, a result supported by the data but unaccounted for in standard models of hysteresis or endogenous growth. Finally, the near-permanent decline in wages caused by scarring reduces future tax revenues, increasing the pressure that recessions place on the fiscal deficit since losses in tax revenues necessitate a larger increase in debt to sustain government expenditures.

Having shown that scarring induces large and persistent declines in macroeconomic activity, I then demonstrate that unemployment scarring, when disciplined by the microeconomic evidence, explains a substantial portion of the sluggish recovery from the Great Recession, a challenging feat that can only be accomplished by a model that can generate a decline in income that is more persistent than the increase in the unemployment rate. To do so, I simulate the model to replicate the path of unemployment from 2008 to 2019 and then compare the untargeted paths of consumption and output against the data. The goal of this exercise is to ask, does the model's predicted path of consumption and output, conditional on the unemployment rate, match the data? Without unemployment scarring, the model only accounts for the first year of the sluggish recovery of consumption and output from The Great Recession. With unemployment scarring, the model's untargeted paths of consumption and output replicate the data from 2008 to 2015, highlighting the substantial role of scarring during the Great Recession. In addition, unemployment scarring also allows the model to replicate the untargeted path of hourly labor compensation for the whole simulation period, providing further validation that the role of scarring during and after the Great Recession is being captured. Finally, unemployment scarring enables the model successfully captures the permanent rise in income inequality following the Great Recession —a result that standard HANK models with search and matching frictions cannot replicate. In those models, income inequality is largely shaped by the path of unemployment, which, during the Great Recession, increased persistently but not permanently. Overall, the model suggests that scarring played a key role in driving the sluggish recovery from the Great Recession, explaining most of the recovery from 2008 to 2015. This result, however, does not rule out other explanations for the slow recovery from the Great Recession. The aim is to emphasize that unemployment scarring was one of the primary channels that drove the sluggish recovery from the Great Recession.

Although unemployment scarring explains a substantial fraction of the recovery from the Great Recession, it is the model's ability to predict *both* the swift rebound from the COVID Recession and the slow recovery from the Great Recession that validates unemployment scarring as a key determinant of the speed of macroeconomic recovery from recessions. To illustrate this, I repeat the estimation exercise of matching the path of unemployment during and after the COVID recession and then comparing the untargeted paths of consumption, output, and the Gini index for income. I recalibrate the model such that 98.8% of an increase in unemployment is attributed to temporary layoffs, the proportion of the rise in the unemployment rate accounted by temporary layoffs estimated in Gertler et al. [2022]. Naturally, with an enormous proportion of temporary layoffs, micro unemployment scarring does not translate to macro scarring. As a result, the model is able to replicate the swift rebound in consumption and output observed in the data, along with the transitory increase in the income Gini.[7]

The model's success in capturing the COVID recession reveals the crucial role that temporary layoffs fulfilled in supporting the swift post-pandemic recovery and in preventing a lasting rise in inequality. Specifically, I show that had the increase in unemployment during the COVID recession been driven primarily by permanent layoffs, GDP would have failed to return to its pre-recession trend and the income Gini index would have exhibited a persistent rise. To illustrate this, I replicate the COVID recession simulation and recalibrate the model to minimize the share of temporary layoffs contributing to the surge in unemployment.

[7]The simulation exercise implicitly incorporates the macroeconomic impact of the fiscal policy response because the model is made to match the *observed* unemployment rate in the data during and after the pandemic.

In this counterfactual scenario where temporary layoffs account for only 5% of the rise in unemployment, GDP would have settled on a new trend that is a 2% deviation below the pre-2020 trend and the income Gini index would have permanently increased by 0.2 percentage points. The emphasis on temporary layoffs does not diminish the role of fiscal policy in accelerating the recovery after the Pandemic. In contrast, temporary layoffs likely complemented fiscal policy, supporting the rapid return to the pre-recession trend. In fact, Gertler et al. [2022] find that the *Paycheck Protection Program* increased employment by increasing the likelihood of being recalled during a temporary layoff. Given this paper's insight that temporary layoffs can prevent unemployment scarring from translating into macroeconomic scarring, the *Paycheck Protection Program* likely played a crucial role in supporting a swift recovery through mitigating the effects of unemployment scarring.

The transmission of fiscal policy changes considerably in the presence of unemployment scarring. Contractionary fiscal multipliers are 0.4 to 1.0 larger and rise, instead of fall, with the horizon due to persistent losses in output. Unemployment scarring also shapes the dynamics of debt in response to contractionary fiscal policy. In particular, when the government cuts spending, losses in future tax revenues increase pressure to issue government debt. This increase in debt combined with larger fiscal multipliers can significantly reduce the effectiveness of fiscal policies aimed at sustaining debt. Furthermore, because unemployment scarring induces a near permanent rise in income inequality, this naturally implies that contractionary fiscal policy also leads to a persistent increase in income inequality.

To quantify the effectiveness of fiscal consolidation, I consider a counterfactual where the U.S. engages in a reduction of government transfers during the Great Recession, a policy pursued by a number of European countries during this period. I demonstrate that unemployment scarring leads fiscal consolidation to cause a significant and prolonged contraction in GDP, with only a minimal reduction in debt-to-GDP. In particular, without scars to unemployment, a 2% of GDP reduction in government transfers lowers debt-to-GDP by 2.4 percentage points. With scarring, the decline in debt-to-GDP is only 1 percentage point. In addition, the fall in GDP from this consolidation lasts 3 to 4 years longer because of losses to human capital that stem from unemployment scarring.

Fiscal consolidation, however, is not always ineffective at stabilizing debt-to-GDP. The zero lower bound plays a crucial role in the ineffectiveness of a U.S. fiscal consolidation during the Great Recession. Without the zero lower bound, debt to GDP would fall by 5 percentage points instead of 1.2 percentage points. The larger decline in debt-to-GDP stems from the monetary authority's ability to lower the cost of debt that the government faces. On the other hand, the effects of a lower interest rate do little to mitigate the scarring effects of unemployment on output unless the nominal interest rate is kept lower for considerably longer.

Literature Review This paper's contributions lie at the intersection of several strands of literature.

The first strand is the nascent literature on the role of unemployment scarring in shaping business cycle dynamics and macroeconomic policy. To date, this literature comprises only of Alves and Violante [2023] and Alves and Violante [2024], both of which examine how scarring affects the transmission of monetary policy. This paper makes three contributions to this literature. First, it demonstrates that the degree to which unemployment scarring translates to macroeconomic hysteresis is a key factor that explains why the recovery from the Great Recession was much more sluggish than the recovery from the COVID Recession. Second, it shows that temporary layoffs played a pivotal role during the pandemic by preventing a sluggish and incomplete recovery. This second contribution highlights that the unusually large share of temporary layoffs during the pandemic was a key reason the post-COVID recovery was significantly faster than the recovery from the Great Recession, even after accounting for the unprecedented fiscal stimulus during COVID. Third, this paper quantifies the importance of scarring in the transmission of fiscal policy.

The second is the theoretical literature on endogenous growth and hysteresis that largely emphasizes the role of endogenous innovation and R&D as a micro foundation that explains the sluggish recovery of productivity from past recessions [Comin and Gertler, 2006, Moran and Queralto, 2018, Bianchi et al., 2019]. Although unemployment scarring has long been considered as a potential mechanism for the sluggish recoveries from past recessions [Cerra et al., 2023], there is surprisingly little work that captures unemployment scarring in a macroeconomic model of the business cycle. This paper addresses this gap by quantifying the importance of these unemployment scars across past recessions. More interestingly, I show that unemployment scarring is a mechanism for hysteresis that can also explain the swift recovery from the COVID Recession when accounting for the large fraction of temporary layoffs during the pandemic. Finally, papers in the literature have also documented that contractionary monetary policy can have persistent effects on the economy [Moran and Queralto, 2018, Jorda et al., 2023]. I show that unemployment scarring is an alternative theoretical mechanism that can explain their results (see appendix B.1).

This paper also relates to the literature that documents that fiscal consolidation during the Great Recession induced large and persistent contractions in output [Jorda and Taylor, 2016, Fatás and Summers, 2018, House et al., 2020]. Most closely related is the work of Fatás and Summers [2018], who estimate the impact of fiscal consolidation on output in Europe during the Great Recession. They find that, on average, the austerity measures pursued by European countries were 'self-defeating'. had persistent and contractionary effects on GDP that lasted for at least 10 years. Further, the authors consider unemployment scarring as a possible explanation for their empirical findings. Overall, the authors conclude that fiscal consolidation was 'self-defeating'. This paper complements their work by assessing their conjecture with a macroeconomic model that accounts for the microeconomic evidence on unemployment scarring. I show that fiscal consolidation is ineffective at stabilizing debt-to-GDP and has both contractionary and persistent effects on GDP.

With regards to the distributional consequences of fiscal consolidation, using a sample of 17 OECD countries over the period 1978-2009, Ball et al. [2013] show that fiscal consolidation raises income inequality. This paper provides a quantitative basis that confirms their empirical results by demonstrating that in the presence of scarring, fiscal contractions lead to a substantial and permanent increase in the Gini index for income.

Finally, this paper also contributes to the literature on heterogeneous agent New Keynesian (HANK) models, in particular those with search and matching (SAM) frictions. This HANK and SAM literatures emphasizes the interaction between nominal rigidities, search and matching frictions, and incomplete markets to generate counter-cyclical unemployment risk that amplify business cycle fluctuations [McKay and Reis, 2016a, Ravn and Sterk, 2017b, Den Haan et al., 2018]. The first contribution of this paper to this literature is the construction of a HANK and SAM model that can capture the scarring effect of unemployment with the inclusion of human capital. The second contribution, found in appendix A.2, is that the role of unemployment risk as an amplifier of business cycles is considerable larger in the presence of scarring.

Outline The rest of the paper is as follows. Section 2 presents the model. Section 3 describes the parameterization of the model. Section 4 shows that the model is consistent with the microeconomic estimates of earnings loss following job displacement, Section 5 through 10 presents the results. Section 11 concludes.

1.2 Model

I present a heterogenous agents model with human capital dynamics, search and matching frictions, and nominal rigidities.

1.2.1 Households

There is a continuum of households of mass 1 indexed by i who face both idiosyncratic permanent and transitory income shocks, stochastic transitions between employment and unemployment, and is subject to human capital accumulation or erosion. A household's employment state is indexed by n_{it}. Employed households ($n_{it} = 1$) receive a wage w_t that is taxed at rate τ_t, accumulate human capital h_{it} with probability π_L, and separate from employment with probability ω. If an employed household is separated, he finds a job in the same period with probability $\eta_{r,t}$ or else he transitions to unemployment ($n_{it} = 0$). When a household becomes unemployed, he randomly enters one of three unemployment states X_{it}. A household is either a permanent layoff (P), a temporary layoff (T), or a quitter/other (O). The probability of entering each state is $\lambda(X)$ where $X \in \{P, T, O\}$. As in Gertler et al. [2022], households who are in temporary layoff can transition to a permanent layoff with probability p_{TLPL}. During a permanent or temporary layoff spell, households receive unemployment benefits that expire after $\bar{d}$ periods. Quitters/other types of unemployment do not receive unemployment benefits. During unemployment, a household in unemployed state X_{it} finds employment with probability $\eta_t(X_{it})$. Only households who reenter employment from a permanent layoff have a probability of experiencing human capital erosion that is realized during the new employment spell. In addition, households are subject to a constant probability of death (perpetual youth) and are ex-ante heterogeneous in their discount factors. After all shocks and transitions are realized, households choose to consume and save into government bonds.

The timing of the household problem is illustrated in figure 1-1

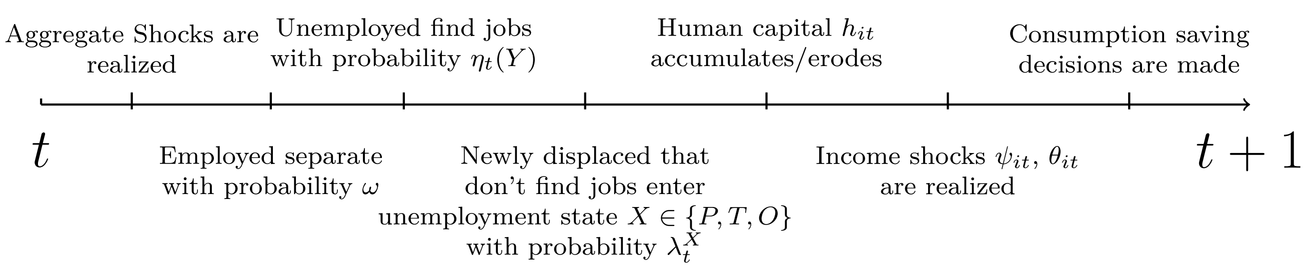


Figure 1-1. Timing of model

The Bellman problem is:

$$v_t\left(m_{it}, p_{it}, h_{it}, n_{it}, X_{it}\right) = \max_{\{c_{it}, a_{it}\}} \{U\left(c_{it}\right)) + \beta_i(1-D)\mathrm{E_t}\left[v_{t+1}\left(m_{t+1}, p_{it+1}, h_{it+1}, n_{it+1}, X_{it+1}\right)\right]\}$$

subject to the budget constraint

$$a_{it} = m_{it} - c_{it}$$

$$a_{it} + c_{it} = z_{it} + (1 + r_t^a)a_{it-1}$$

$$a_{it} \geq 0$$

where m_{it} denotes market resources to be expended on consumption or saved into government bonds. c_{it} is the level of consumption and a_{it} is the value of government bonds where the return is r_{t+1}^a. m_{it} is determined by labor income, z_{it}, and the gross return on assets from the last period, $(1 + r_t^a)a_{it-1}$. D is the probability of death and β_i is the discount factor. When households die, their market resources are distributed to those alive in proportion to how much market resources is owned with respect to the aggregate level of wealth. Newborns are born with no wealth in order to raise the marginal propensity to consume (MPC).

1.2.1.1 Labor Income and Human Capital

Labor income is composed of permanent income p_{it}, transitory income θ_{it}, human capital h_{it}, and (un)employment income ζ_{it}.

$$z_{it} = p_{it}\theta_{it}\zeta_{it}h_{it}$$

Permanent income is subject to shocks ψ_{it+1}.

$$p_{it+1} = p_{it}\psi_{it+1}$$

Both θ_{it} and p_{it} are iid mean one lognormal with standard deviation σ_θ and σ_ψ, respectively.

Following Birinci [2019], human capital lies on an equally spaced grid with a minimum value of $\underline{h}$ and a maximum value of $\bar{h}$. I define $\mathbf{h}_{it}$ as "shadow" human capital. The purpose of this variable is to capture the erosion of human capital during unemployment without allowing unemployment income to fall during a household's unemployment spell. This ensures that losses to human capital are only realized upon reemployment and is meant to capture the microeconomic fact that displaced households receive a lower wage after finding a new job. The dynamics of h_{it} and $\mathbf{h}_{it}$ are elaborated below.

To simplify the discussion on the dynamics of human capital, define:

- E: Employment

- U: Unemployment (Any type)

- U_P: Permanent layoff unemployment

- U_T: Temporary layoff unemployment

- U_O: Quit or other types of unemployment

If a household transitions from $E \rightarrow E$, then human capital accumulates with probability π_L.

$$h_{it+1} = \begin{cases} h_{it} & \text{with probability } 1 - \pi_L \\ h_{it} + \Delta_E & \text{with probability } \pi_L \end{cases}$$

And shadow human capital does not change.

$$\mathbf{h}_{it+1} = h_{it}$$

If a household transitions from $E \rightarrow U$ or $U \rightarrow U$, human capital is unaffected while shadow human capital erodes with probability π_U.

$$h_{it+1} = h_{it}$$

$$\mathbf{h}_{it+1} = \begin{cases} \mathbf{h}_{it} & \text{with probability } 1-\pi_U \\ \mathbf{h}_{it} - \Delta_U & \text{with probability } \pi_U \end{cases}$$

Only when a household transitions from $U_P \rightarrow E$ does the erosion to their shadow human capital becomes realized as their new human capital.

$$h_{it+1} = \mathbf{h}_{it}$$

Otherwise, for a household transitioning from $U_T \rightarrow E$ or $U_O \rightarrow E$, their human capital does not change.

$$h_{it+1} = h_{it}$$

$$\mathbf{h}_{it+1} = h_{it}$$

As documented in Kekre [2023a], non UI income makes up a large proportion of the income of the unemployed. This income is likely supplemented from a spouse as an "added worker effect", or other social insurance programs such as SNAPS. In order to capture these non UI income sources, I follow Kekre [2023a] and assume (Un)Employment income follows

$$\zeta_{it} = \begin{cases} (1-\tau_t)w_t, \text{ if employed} \\ \\ UI_t + \omega_1 w_{ss}, \text{ if unemployed and receiving UI} \\ \\ T^s + \omega_2 w_{ss}, \text{ if unemployed and not receiving UI} \\ \end{cases}$$

where $UI_t = bw_{ss}(1-\tau_{ss})$, b is the unemployment insurance replacement rate, T^s is a parameter that captures other social programs, w_{ss} and τ_{ss} are the real wage and tax rate in steady state. The parameters ω_1 and ω_2 allow me to calibrate the amount of non UI income to be empirically consistent with administrative data.

1.2.2 Goods Market

There is a continuum of monopolistically competitive intermediate good producers indexed by $j \in [0,1]$ who produce intermediate goods Y_{jt} to be sold to a final good producer at price P_{jt}. I assume intermediate good producers consume all profits each period. Using intermediate goods Y_{jt} for $j \in [0,1]$, the final good producer produces a final good Y_t to be sold to households at price P_t.

1.2.2.1 Final Good Producer

A perfectly competitive final good producer purchases intermediate goods Y_{jt} from intermediate good producers at price P_{jt} and produces a final good Y_t according to a CES production function.

$$Y_t = \left(\int_0^1 Y_{jt}^{\frac{\epsilon_p - 1}{\epsilon_p}} \, dj \right)^{\frac{\epsilon_p}{\epsilon_p - 1}}$$

where ϵ_p is the elasticity of substitution.

Given P_{jt} , the price of intermediate good j , the final good producer maximizes his profit by solving:

$$\max_{Y_{jt}} P_t \left(\int_0^1 Y_{jt}^{\frac{\epsilon_p - 1}{\epsilon_p}} \, dj \right)^{\frac{\epsilon_p}{\epsilon_p - 1}} - \int_0^1 P_{jt} Y_{jt}, \, dj$$

The first order condition leads to demand for good j

$$Y_{jt} = \left(\frac{P_{jt}}{P_t} \right)^{-\epsilon_p} Y_t$$

and the price index

$$P_t = \left(\int_0^1 P_{jt}^{1-\epsilon_p} \, dj \right)^{\frac{1}{1-\epsilon_p}}$$

1.2.2.2 Intermediate Good Producer

Intermediate goods producers produce according to a production function linear in labor L_t.

$$Y_{jt} = Z_t L_{jt}$$

where $log(Z_t) = \rho_Z log(Z_{t-1}) + \epsilon_Z$

Each Intermediate goods producer hires labor L_t from a labor agency at cost κ_t^h. Given the cost of labor, each Intermediate goods producer chooses P_{jt} to maximize its profit facing price stickiness a la Rotemberg [1982b]. I assume intermediate good producers hold all profits as HANK models with sticky prices produce countercyclical profits which combined with households with high MPCs can lead to countercyclical consumption responses out of dividends. I therefore abstract from consumption behavior in response to firm profits. Intermediate goods producers maximize profit by solving:

$$J_t\left(P_{jt}\right) = \max_{\{P_{jt}\}} \left\{ \frac{P_{jt} Y_{jt}}{P_t} - c_t L_{jt} - \frac{\varphi}{2} \left(\frac{P_{jt} - P_{jt-1}}{P_{jt-1}} \right)^2 Y_t + J_{t+1}\left(P_{jt+1}\right) \right\}$$

The problem can be rewritten as the standard New Keynesian maximization problem:

$$\max_{\{P_{jt}\}} \mathrm{E}_t \left[\sum_{s=0}^{\infty} M_{t,t+s} \left(\left(\frac{P_{jt+s}}{P_{t+s}} - MC_{t+s} \right) Y_{jt+s} - \frac{\varphi}{2} \left(\frac{P_{jt+s}}{P_{jt+s-1}} - 1 \right)^2 Y_{t+s} \right) \right]$$

where $MC_t = \frac{\kappa_t^h}{Z_t}$

Given all firms face the same adjustment costs, there exists a symmetric equilibrium where all firms choose the same price with $P_{jt} = P_t$ and $Y_{jt} = Y_t$.

The resulting Phillips Curve is

$$\epsilon_p MC_t = \epsilon_p - 1 + \varphi(\Pi_t - 1)\Pi_t - M_{t,t+1}\varphi(\Pi_{t+1} - 1)\Pi_{t+1}\frac{Y_{t+1}}{Y_t}$$

where $\Pi_t = \frac{P_t}{P_{t+1}}$.

1.2.3 Labor market

1.2.3.1 Labor agency

A risk neutral labor agency sells effective labor $L_t = \int_0^1 h_{it}n_{it}di$ to intermediate good producers at cost c_t by hiring households. To hire households, the labor agency posts vacancies v_t that are filled with probability ϕ_t. Households search is random. Following Bardóczy [2020], I assume the labor agency cannot observe the labor productivity of individual households. Instead, the labor agency can only observe the average productivity of all employed workers $H_t^E =: \int_0^1 h_{it}\mathbb{1}(n_{it} = 1)\, di$. Since $\int_0^1 h_{it}n_{it}\, di = H_t^E N_t$, this assumption is sufficient for the labor agency to choose the optimal level of households to hire.

$$J_t(N_{t-1}) = \max_{N_t, v_t}\{(\kappa_t^h - w_t)\left(\int_0^1 h_{it}n_{it}\, di\right) - \kappa v_t + \mathrm{E_t}\left[\frac{J_{t+1}(N_t)}{1 + r_t^a}\right]\}$$

s.t.

$$N_t = (1 - \omega)N_{t-1} + \phi_t v_t$$

The resulting job creation curve is:

$$\frac{\kappa}{\phi_t} = (c_t - w_t)H_t^E + (1 - \omega)\mathrm{E_t}\left[\frac{\kappa}{(1 + r_t^a)\phi_{t+1}}\right]$$

1.2.3.2 Matching

Household and labor agency matching follows a Cobb Douglas matching function:

$$m_t = \chi e_t^\alpha v_t^{1-\alpha}$$

where m_t is the mass of matches, e_t is the mass of job searchers, and χ a matching efficiency parameter.

The vacancy filling probability ϕ_t, job finding probabilities $\eta_t(X_{it})$ of a household in state $X_{it} \in$ {P, T, O} and the job finding probability $\eta_{r,t}$ of a recently separated (but not unemployed) household evolve according to:

$$\eta_{r,t} = \chi \Theta_{it}^{1-\alpha}$$

$$\eta_t(X) = \chi q(X) \Theta_{it}^{1-\alpha}$$

$$\phi_t = \chi \Theta_t^{-\alpha}$$

where $\Theta_t = \frac{v_t}{e_t}$ is labor market tightness and $q(X)$ captures the search efficiency of state X.

1.2.3.3 Employment to Unemployment transition dynamics

An employed individual who separates from their job in period t and does not find a job within the same period transitions to unemployment in $t+1$. In particular, probability of transitioning from employment to unemployment (EU) is:

$$EU_t = \omega(1 - \eta_t)$$

where ω is the job separation probability.

Upon job loss, a household is either in permanent layoff unemployment (P), temporary layoff unemployment (T), or quits/other unemployment (O). In order to capture the empirical fact that increases in the unemployment rate is largely explained by increases in permanent layoffs and that EU transition probabilities to quits/others is acyclic, I assume the probability of entering each unemployment state follows:

$$\lambda_t^X = \lambda_{ss}^X + \zeta^X (EU_t - EU_{ss})$$

ζ^X for $X \in \{P, T, O\}$ provide freedom to match the proportion of the increase in the unemployment rate that is attributed to permanent layoffs without explicitly modeling firm decisions of whether to permanently or temporarily layoff households.

1.2.4 Wage Determination

Similar to Gornemann et al. [2021] and Blanchard and Gali [2010] , I assume the real wage follows the rule :

$$log\left(\frac{w_t}{w_{ss}}\right) = \phi_w log\left(\frac{w_{t-1}}{w_{ss}}\right) + (1-\phi_w) log\left(\frac{N_t}{N_{ss}}\right)$$

where ϕ_w dictates the extent real wages are rigid.

1.2.5 Fiscal Policy

The government issues long term bonds B_t at price q_t^b in period t that pays δ^s in period $t+s+1$ for $s = 0, 1, 2, ..$

The bond price satisfies the no arbitrage condition:

$$q_t^b = \frac{1 + \delta \mathrm{E}_t[q_{t+1}^b]}{1 + r_t^a}$$

The government finances its expenditures with debt and taxes.

$$(1 + \delta q_t^b) B_{t-1} + G_t + S_t = \tau_t w_t \int_0^1 h_{it} n_{it} \, di + q_t^b B_t$$

where S_t are payments for unemployment insurance and other transfers.

Following Auclert et al. [2019], the tax rate adjusts to stabilize the debt to GDP ratio:

$$\tau_t - \tau_{ss} = \phi_B q_{ss}^b \frac{B_{t-1} - B_{ss}}{Y_{ss}}$$

where ϕ_B governs the speed of adjustment.

1.2.6 Monetary Policy

The central bank follows the Taylor rule:

$$i_t = r^* + \phi_\pi \pi_t + \phi_Y (Y_t - Y_{ss}) + \epsilon_t^m$$

where ϕ_π and ϕ_Y are the Taylor rule coefficient for inflation and output, respectively. r^* is the steady state interest rate, Y_{ss} is the steady state level of output, $\epsilon_t^m = \rho_v \epsilon_{t-1}^m + \varepsilon_t$ are innovations to the Taylor rule.

1.2.7 Equilibrium

An equilibrium in this economy is a sequence of:

- Policy Functions $(c_{it}(m))_{t=0}^{\infty}$ normalized by permanent income

- Prices $\left(r_t, r^a_{t+1}, i_t, q^b_t, w_t, \kappa^h_t, \pi_t, \tau_t\right)_{t=0}^{\infty}$

- Aggregates $(C_t, Y_t, N_t, \Theta_t, B_t, A_t)_{t=0}^{\infty}$

Such that:

$(c_{it}(m))_{t=0}^{\infty}$ solves the household's maximization problem given $(w_t, \eta_t(X), r^a_t, \tau_t)_{t=0}^{\infty}$.

The final goods producer and intermediate goods producers maximize their objective function.

The nominal interest rate is set according to the central bank's Taylor rule.

The tax rate is determined by the fiscal rule and the government budget constraint holds.

The value of assets is equal to the value of government bonds.:

$$A_t = q^b_t B_t$$

The goods market clears: [8]

$$C_t = w_t \int_0^1 h_{it} n_{it} \, di + G_t$$

where $C_t \equiv \int_0^1 p_{it} c_{it} \, di$

[8]Note if profits were not held by firms then the goods market condition would be $C_t + G_t = Y_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$. In particular, since firm profits are $D_t = Y_t - w_t \int_0^1 h_{it} n_{it} \, di - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$, then the goods market condition would become $C_t + G_t = w_t N_t + D_t = Y_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$.

The labor demand of intermediate good producers equals labor supply of labor agency:

$$L_t = \int_0^1 h_{it} n_{it} \, di$$

1.3 Calibration

The model is calibrated to a quarterly frequency. There are three goals to the parameterization of households. The first is to match the earnings loss following job displacement documented in Davis and Wachter [2011a]. The second is to simultaneously match a large aggregate MPC consistent with micro estimates while also matching aggregate liquid wealth in the 2007 Survey of Consumer and Finances. I choose the 2007 survey as I aim to match The Great Recession in section 7. The third is to match labor market transition probabilities of permanent layoffs, temporary layoffs, other types of unemployment from estimated in Gertler et al. [2022]. The parameterization of households is broken into two steps. I first calibrate all parameters excluding the discount factors. I then estimate three uniformly distributed discount factors to match the aggregate liquid wealth from the 2007 SCF and a quarterly MPC of 0.21 as in Kekre [2023a]. The remaining parameters are calibrated to standard values in the New Keynesian and search and matching literatures.

1.3.1 Households

Labor transition probabilities The job separation rate ω is set to 0.1 in line with JOLTS. I set the job finding probability of households separated in the current period, $\eta_{r,t}$, to 0.675 to target an employment to unemployment (EU) transition probability of 4.1%, the estimate of the monthly EU probability in Gertler et al. [2022] (henceforth GHT) aggregated to a quarterly frequency. The probabilities of becoming a permanent layoff γ_P, a temporary layoff γ_P, and a quitter/other γ_O, are calibrated to match the EU probabilities of entering each unemployment state estimated in GHT and Graves et al. [2023][9]. The job finding proba-

[9] Gertler et al. [2022] estimate the E to U probability of entering a permanent separation and a temporary layoff while Graves et al. [2023] estimate the E to U probability of entering as a layoff or as a quitter/other.

bilities of each unemployment state $\eta_t(X)$ is calibrated the estimated monthly job finding probabilities in GHT, aggregated to a quarterly frequency. I let the job finding probability of permanent layoffs and quits/others to equal the estimate of the job finding probability of permanent separators in GHT as they do not distinguish between permanent layoffs and quits/others. The probability of transitioning from temporary layoff to permanent layoff, P_{TLPL}, is set to 0.47 which follows from the estimate in (GHT). The resulting steady state unemployment rate is 6.2%, equal to the mean unemployment rate estimated from the Current Population Survey in GHT. I calibrate ζ_P, ζ_T, and ζ_O such that permanent layoffs, temporary layoffs, and quits/others, account for 63%, 20%, and 17%, respectively, of an increase in the unemployment rate. GHT estimate the distribution of the increase in the unemployment rate from trough to peak across permanent separations and temporary layoffs for during the Great Recession. Their estimates indicate that the average increase in unemployment that is attributed to temporary layoffs is 17%. For increases in the unemployment rate attributed to quits/others and permanent layoffs, I use the decomposition of unemployment by reason constructed by Fujita and Moscarini [2017] using data from the BLS. Using the Fujita and Moscarini [2017] series, I calculate that during the Great Recession, 20% of the increase in the unemployment rate from trough to peak are attributed to reentrants and use this as my target for the quits/others group as my model does not include inactive/out of the labor force as a state. I assign the remaining proportion of the increase in the unemployment rate is attribute to the permanent layoffs unemployment type.

Human Capital Dynamics I use an equally spaced grid with the maximum value of human capital, $\bar{h}$, to 1.8 and the minimum value, $\underline{h}$, to 0.2 as in Birinci [2019]. I set the number of human capital grid points to 20 and assume $\Delta_L = 0.1$ so that when an employed

Both papers use the CPS from 1976 to 2019, and the same methodology, to estimate the transition probability between both different unemployment states. In addition, the estimation of both papers yield the same mean unemployment rate, the same E to E probability, and the same E to inactive probability. The probability of E to U in both papers are similar as well. I use estimates of both papers to deduce the E to U probability of permanent layoffs, temporary layoffs, and quits/others.

household accumulates capital it increases by one grid point. The probability of human capital erosion during unemployment π_U is set to 0.75 as in Birinci [2019]. I then estimate the magnitude of human capital erosion, Δ_U and the probability of human capital accumulation during employment, π_L to minimize the distance between the earnings loss following job loss in the model and the earnings loss following job loss during recessions estimated by Davis and Wachter [2011a]. I target the estimate of earnings loss following job loss in recessions as I will later simulate all past recessions since the 1980s. The resulting estimation yields $\Delta_U = 0.3$ and $\pi_L = 0.085$.

Income process The calibration of permanent and transitory income shock distributions follow Carroll et al. [2017a] with the standard deviation of permanent shocks set to 0.06 and the standard deviation of transitory shocks set to 0.2. The real wage is normalized to 1.0 and the real wage rigidity parameter $\phi_w = 0.837$ as in Gornemann et al. [2021]. The unemployment insurance replacement rate is set to 50%. The income parameters that dictate the amount of non-UI income and government transfers, ω_1, ω_2, and T^s, are calibrated to match microeconomic moments on household income throughout unemployment documented in Kekre [2023a]. In particular, these parameters are calibrated such that total income of unemployed households who receive UI is 76% of pre job loss income, total of income of unemployed households who do not receive UI is 55% of pre job loss income, and government transfers capture 13% of pre job loss income of households who have been unemployed for longer than two quarters.

Discount Factor Estimation Following Carroll et al. [2017a], households are ex-ante heterogenous in their discount factors. I let three discount factors, $(\bar{\beta} - \nabla, \bar{\beta}, \bar{\beta} + \nabla)$, be uniformly distributed across the population. I estimate the mean discount factor, $\bar{\beta}$, to target the aggregate liquid wealth to aggregate quarterly permanent income ratio in the 2007 Survey of Consumer Finances and the spread, ∇, to target an aggregate quarterly MPC of 0.21 as in Kekre [2023a]. Following Kaplan et al. [2014], I define liquid wealth as checking, saving, money market and call accounts as well as directly held mutual funds, stocks, corporate bonds, government bonds less credit card balances. I restrict my sample of liquid wealth to households with nonnegative liquid wealth as the model does not feature borrowing. I also remove all households with zero permanent income. Table 1 presents the estimated discount factors. [10]

Discount Factors		
.937	.964	.991

Table 1-I. Discount factor estimates

Remaining Parameters I let $U(c) = \frac{c^{1-\rho}}{1-\rho}$ and I set the CRRA parameter, ρ, to 2 and the probability of death to .00625 match a 40 year work life. The real rate is 3% annualized.

1.3.2 Rest of the Economy

The quarterly vacancy filling rate is 0.71 as in Ramey et al. [2000]. The matching elasticity is 0.65 following Ravn and Sterk [2017b] and the vacancy cost is set to 7% of the real wage as in Christiano et al. [2016][11]. The elasticity of substitution is set to 6. The price adjustment cost parameter is set to 96.9 as in Ravn and Sterk [2017b]. The tax rate is set to 0.3 and government spending is set to clear the government budget constraint. I follow Auclert et al. [2019] in calibrating the fiscal adjustment parameter as well as the decay rate of government coupons by setting $\phi_b = 0.1$ and $\delta = 0.95$ to match a maturity of 5 years[12].

[10] This is consistent with the work of Allcott et al. (2021) and Skiba and Tobacman (2009), who estimate discount factors of 21% at a 2 week frequency and discount factors between 0.74 to 0.83 at a 8 week frequency, respectively. Although both papers assume hyperbolic discounting, the point is that a very low discount factor is needed to match the proportion of the population who are willing to take out payday loans at very high interest rate.

[11] The range of plausible values lie between 4% and 14% as documented in Silva and Toledo [2009a]

[12] The duration of bonds in the model is $\frac{(1+r)^4}{(1+r)^4-\delta}$

Description	Parameter	Value	Source/Target
CRRA	ρ	2	Standard
Real Interest Rate	r	$1.03^{\frac{1}{4}} - 1$	3% annualized real rate
Probability of Death	D	0.00625	40 Year Work Life
$\frac{\text{Liquid Wealth}}{\text{Quarterly Permanent Income}}$	$\frac{A}{\Phi}$	4.4	2007 Survey of Consumer Finances
Prob. of human capital accumulation	π_L	0.085	See text
Prob. of human capital erosion	π_U	0.75	Birinci [2019]
Human capital accumulation step	Δ_L	0.1	Normalized
Human capital erosion step	Δ_U	0.3	See text
Tax Rate	τ	0.3	Kaplan et al. [2018]
Real Wage	w	1.0	Normalized
UI replacement rate	b	0.5	50% replacement rate
Non UI income parameter 1	ω_1	0.182	$\frac{\text{HH income w. UI}}{\text{pre job loss income}} = 0.76$
Non UI income parameter 2	ω_2	0.294	$\frac{\text{HH income w.o. UI}}{\text{pre job loss income}} = 0.55$
Gov. transfers	T_s	0.091	$\frac{\text{SNAPS and Soc. Security Inc}}{\text{Pre Job Loss Income}} = 0.13$
Std Dev of Log Permanent Shock	σ_ψ	0.06	Carroll et al. [2017a]
Std Dev of Log Transitory Shock	σ_θ	0.2	Carroll et al. [2017a]

Table 1-II. Household Calibration

Description	Parameter	Value	Source/Target
Job Separation Prob.	ω	0.1	JOLTS
Job Finding Prob. of recently separated	$\eta_{r,t}$	0.59	EU probability of 4.1%
Job Finding Prob. of perm. layoff	$\eta_t(P)$	0.51	Gertler et al. [2022]
Job Finding Prob. of temp. layoff	$\eta_t(T)$	0.82	Gertler et al. [2022]
Job Finding Prob. of quit/other	$\eta_t(O)$	0.51	Gertler et al. [2022]
Prob. of perm. layoff in steady state	λ^P_{ss}	0.35	35% of EU from perm. layoffs
Prob. of temp. layoff in steady state	λ^T_{ss}	0.31	31% of EU from temp. layoffs
Prob. of quit/other in steady state	λ^O_{ss}	0.33	33% of EU prob. quit/other layoffs
Perm. layoff deviation param.	ζ^P	10.3	63% of Δ Urate from perm layoffs
Temp. layoff deviation param.	ζ^T	-4.4	17% of Δ Urate from temp layoffs
Quits/other layoff deviation param.	ζ^O	-5.9	20% of Δ Urate from quits/other

Table 1-III. Labor Transition Calibration

Description	Parameter	Value	Source/Target
Elasticity of Substitution	ϵ_p	6	Standard
Price Adjustment Costs	φ	96.9	Ravn and Sterk [2017b]
Vacancy Filling Rate	ϕ	0.71	Ramey et al. [2000]
Matching Elasticity	α	0.65	Ravn and Sterk [2017b]
Real Wage Rigidity parameter	ϕ_w	0.837	Gornemann et al. [2021]
Vacancy Cost	κ	0.056	$\frac{\kappa}{w\phi} = 0.07$
Government Spending	G	0.38	Gov. budget constraint
Decay rate of Government Coupons	δ	0.95	5 Year Maturity of Debt
Taylor Rule Inflation Coefficient	ϕ_π	1.5	Standard
Response of Tax Rate to Debt	ϕ_b	0.1	Auclert et al. [2019]

Table 1-IV. Rest of Economy Calibration

1.4 Model Validation: Persistent Earnings Loss Following Unemployment

In this section, I verify the model generates persistent earnings loss following job displacement that matches the estimates in Davis and Wachter [2011a].

To evaluate the path of earnings loss following job displacement, I run a regression similar to Davis and Wachter [2011a] with the same sample restrictions on model simulated data. Since the model is calibrated to a quarterly frequency, I aggregate the simulated data to a yearly frequency. For a given year b, the sample of displaced workers constitutes households who enter unemployment in year $b, b+1$, or $b+2$. Households who do not enter employment during year $b, b+1$, or $b+2$ constitute the sample of non displaced workers. I restrict the the sample to households who have been continuously employed for 6 years prior to year b[13].

[13] When aggregating to annual frequency, a worker who was unemployed for at least one quarter is denoted

With these sample restrictions, I run the following regression on simulated data.

$$log(z_{iy}^b) = c^b + \Sigma_{k\geq -6}^{20} \delta_k^b D_{iy}^k + \epsilon_{iy}^b$$

where z_{iy} is labor income, D_{iy}^k is a indicator denoting a household that was displaced k years ago, and c is a constant in the regression. The regression features no fixed effects as human capital is exogenous with respect to becoming unemployed. δ_k for $k = 1, 2, ..., 20$ are the key estimates that capture the earnings of an individual who was displaced k years ago compared to an individual who was not displaced k years ago.

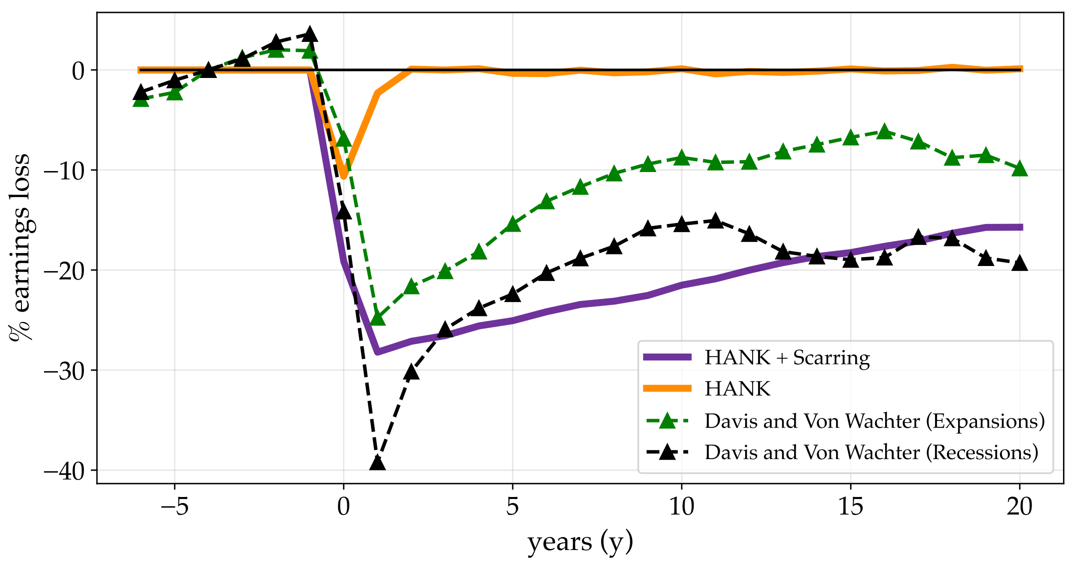


Figure 1-2. Earnings loss following job loss in $y = 0$: Model vs Data

Figure 1-2 illustrates the path of earnings loss following displacement for the baseline model with scarring (HANK + Scarring) and the model without scarring (HANK). Scarring is eliminated by assuming the probability of accumulation or erosion in human capital is eliminated. The baseline model produces a severely persistent earnings loss that is missing in the model without human capital dynamics. As in the data, these losses remain after 20 years.

as displaced for that year. and is therefore not considered as employed for that year.

1.5 Consumption Response to an Increase in Unemployment in Partial Equilibrium

In this section, I show in partial equilibrium that the aggregate consumption response to a transitory increase in the unemployment rate is deeply persistent in the presence of scarring. I simulate the consumption response to a transitory 1% increase in the unemployment rate in $t = 0$. To capture the effects of scarring on consumption, I compare the simulated path of consumption in the baseline model to the simulated path of consumption to a version of the model where scarring is eliminated. I eliminate scarring by setting the probability of human capital accumulation π_L and the probability of human capital erosion π_U to zero. Figure 1-3 plots the simulated path of consumption to this experiment with and without scarring. Even with 55% of the increase in unemployment rate accounted for by permanent layoffs who are subject to scarring, the response of consumption is significantly more persistent than the response of the unemployment rate.

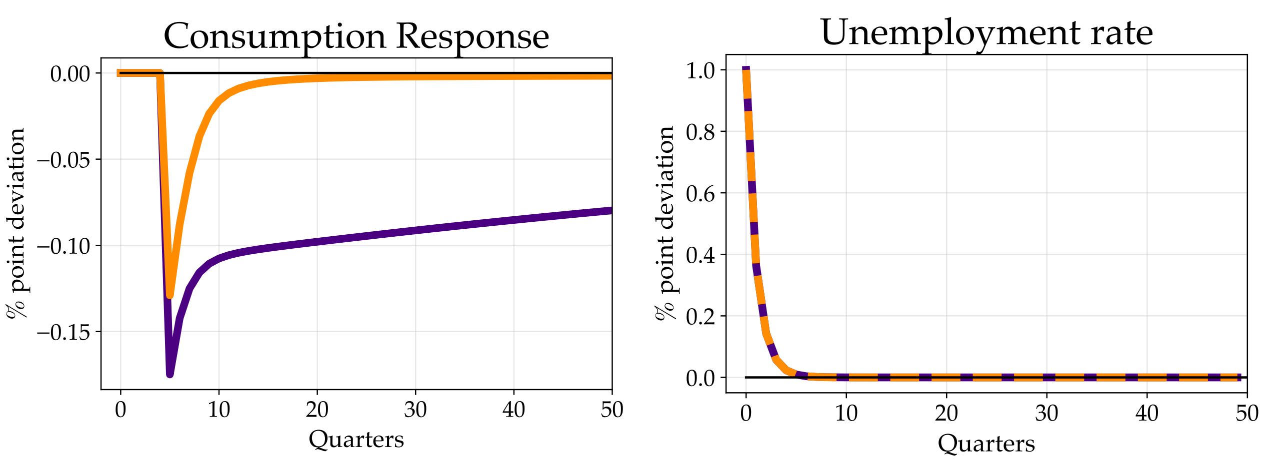


Figure 1-3. Consumption response to a transitory increase in the unemployment rate

Note: The exercise above plots the consumption response to a one time negative shock to the job finding probability in $t = 0$. The size of the one time shock is calibrated to increase the unemployment rate by one percentage point on impact.

1.6 Business Cycle Implications

1.6.1 Macroeconomic Hysteresis

In this section, I show that unemployment scarring generates hysteresis in macroeconomic fluctuations. To illustrate this, I solve for the impulse responses to a negative demand shock, modeled as a positive discount factor shock. For simplicity, the size of the shock is the same for all ex-ante discount factor groups. The impulse responses to key aggregate variables is plotted in figure 1-4. In response to this demand shock, increased patience reduces aggregate consumption leading to decreases in output and labor demand. As a result, firms post less vacancies lowering the job finding probability and raising the unemployment rate. As households lose their jobs, on average, they find jobs at a lower wage leading to persistent losses in mean human capital. This causes consumption, output, and labor income to exhibit hysteresis while the unemployment rate recovers with the demand shock. Notably, the responses of output, and aggregate labor productivity (mean human capital) still do not recover after 100 quarters, long after the recovery in the unemployment rate. Since unemployment does not exhibit hysteresis, wages nor the vacancy filling rate will either. As a result marginal costs, and therefore inflation, do not exhibit any persistence.

1.6.2 Unemployment Scarring and Inequality

With unemployment scarring, an increase in unemployment leads to a persistent rise in income inequality. Figure 1-5 plots the impulse response of the labor income gini index across households to the negative demand shock under the baseline model and under the model without scarring. In the baseline model, the initial increase in the gini index is attributed to the rise in unemployment and the decline in the aggregate wage. The persistence of the gini index response is due to the recomposition of the distribution of human capital of employed households. In particular, as unemployed households find reemployment at lower levels of human capital. Since the human capital of newly employed households accumulates slowly,

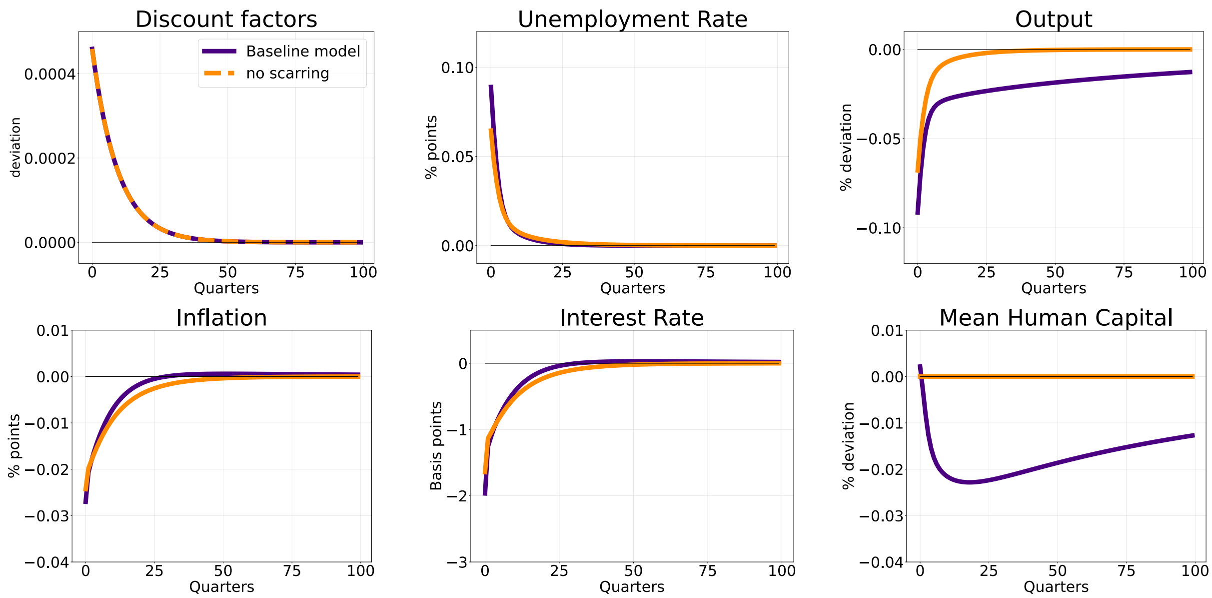


Figure 1-4. Impulse responses to a negative demand shock

Note: The exercise above plots the impulse responses to a positive discount factor shock. The quarterly persistence of the shock is 0.9 and the size of the shock is then calibrated to generate a 0.1 percentage point increase in the unemployment rate.

this causes hysteresis in the gini index. In the model without scarring, the increase in income inequality is transitory as it is only affected by transitory changes in the unemployment rate and the aggregate wage.

1.6.3 Scarring and Debt to GDP

Unemployment scarring increases the pressure that recessions place on national debt. Figure 1-6 plots the responses of debt to GDP and debt to the demand shock from previous section. The figure demonstrates that the debt to GDP and debt increase much more persistently in the presence of scarring. This is due to the pressure that scarring places on tax revenues. As households lose their jobs and find reemployment at a lower effective wage, the tax base is scarred. This persistent decline in tax revenues require the government to borrow substantially more to maintain their expenditures.

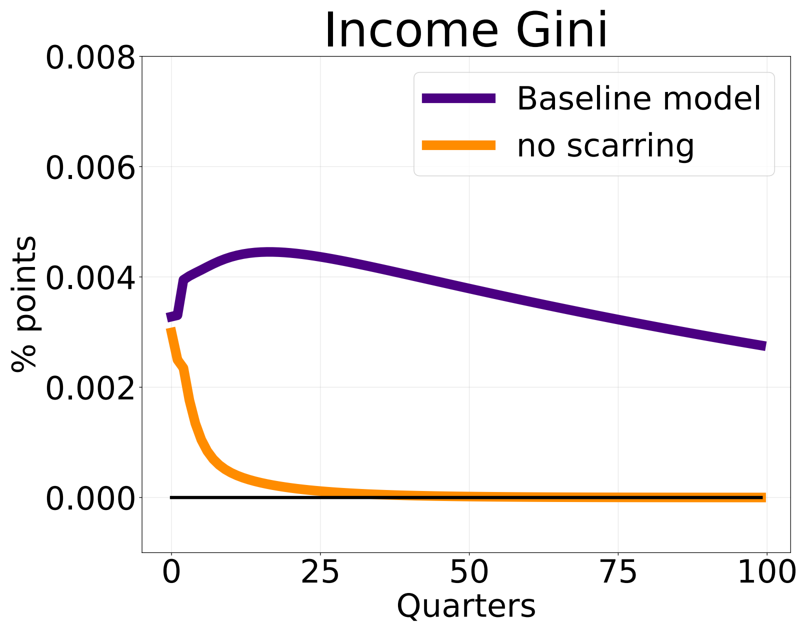


Figure 1-5. Response of income Gini index to negative demand shock.

Note: This exercise plots the impulse response of the Gini index from the negative demand shock in 1-4.

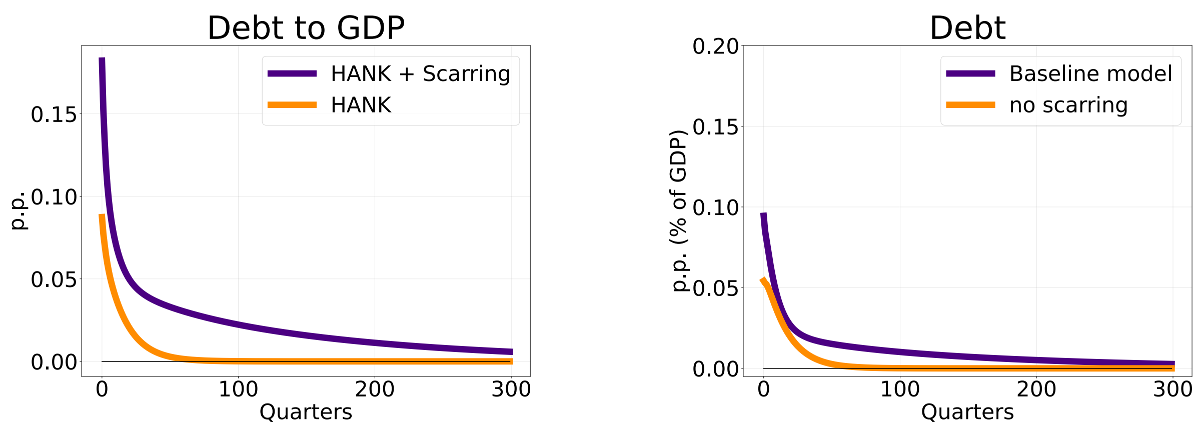


Figure 1-6. Responses of debt and debt to GDP to negative demand shock

Note: This exercise plots response of the debt-to-GDP and debt from the negative demand shock in 1-4.

1.7 Scarring and the Transmission of Fiscal Policy

Having established that in the presence of unemployment scarring, aggregate shocks lead to persistent responses in output. In this section, I show that fiscal multipliers are substantially larger and rise with the horizon because of unemployment scarring. To do so, I consider a negative government spending shock in the baseline model and the model without scarring and compute the multipliers across the horizon. In particular the multiplier is defined as:

$$\text{Multiplier} = \frac{\Sigma_{t=0}^{H} \frac{1}{R^t} \Delta Y_t}{\Sigma_{t=0}^{H} \frac{1}{R^t} \Delta G_t}$$

where H is the horizon of the mulitplier.

Figure 1-7 plots the fiscal multipliers to a contractionary government spending shock across the horizon of the multiplier under the baseline model and model without scarring.

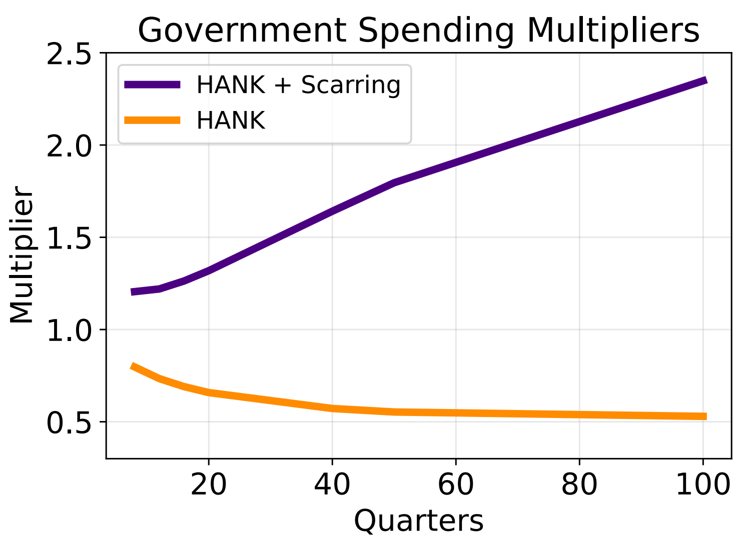


Figure 1-7. Fiscal Multipliers to a negative government spending shock.

Note: This figure plots the multiplier out of negative government spending shock with a quarterly AR(1) persistence of 0.933 across the horizon H of the multiplier. For example, a point on the purple line at quarters = 20 represents the fiscal multiplier: $\frac{\Sigma_{t=0}^{20} \frac{1}{R^t} \Delta Y_t}{\Sigma_{t=0}^{20} \frac{1}{R^t} \Delta G_t}$.

The multipliers under the baseline model rise sharply with the horizon while the multipliers in the model without scarring falls gradually with the horizon. This is because unemployment scarring leads the decline in output in response to the fall in government spending to persist long after the government spending shock recovers.

1.8 Simulating The Great Recession

1.8.1 Model vs Data

In this section, I quantify the extent to which unemployment scarring explains the sluggish recovery from the Great Recession. In particular, I demonstrate that unemployment scarring explains a large share of the sluggish recovery from the Great Recession. To illustrate this, I simulate consumption and output during and after The Great Recession by estimating a sequence of negative demand shocks that allows the model to match the path of unemployment from 2008 to 2018. I perform this exercise in both the baseline HANK model with scarring and the HANK model without scarring. I then compare the untargeted paths of consumption and output to their empirical counterparts. I use data on consumption (real PCE), output (Real GDP), prices (PCE deflator), nominal wages (average earnings of private production employees), real hourly and real aggregate labor compensation (labor compensation from wages and salaries). I de-trend each series from the first quarter of 1990 to the last quarter of 2019 and then scale them down such that they represent deviations from the first quarter of 2008.

For the estimation, I follow Kekre [2023a] and jointly estimate a sequence of discount factor shocks to match the path of unemployment from 2008 to 2018 monetary policy shocks to account for the zero lower bound. I use discount factor shocks for parsimony as the goal of this exercise is not to answer what caused The Great Recession but to answer why did The Great Recession lead to such a slow recovery[14]. For these discount factor shocks, I set the fiscal adjustment parameter to $\phi_b = 0.015$, the lower bound of the estimates documented by Auclert et al. [2019], and assume that the government cannot adjust taxes for 40 quarters to obtain a more accurate assessment of the effects of the Great Recession on debt. When estimating these discount factor shocks, I assume all discount factors follow an AR(1) with quarterly

[14]The same simulation exercise can be reproduced with shocks to the household borrowing limit or to the job separation rate and would not affect the results below as unemployment scarring is present in the responses to all aggregate shocks in the model.

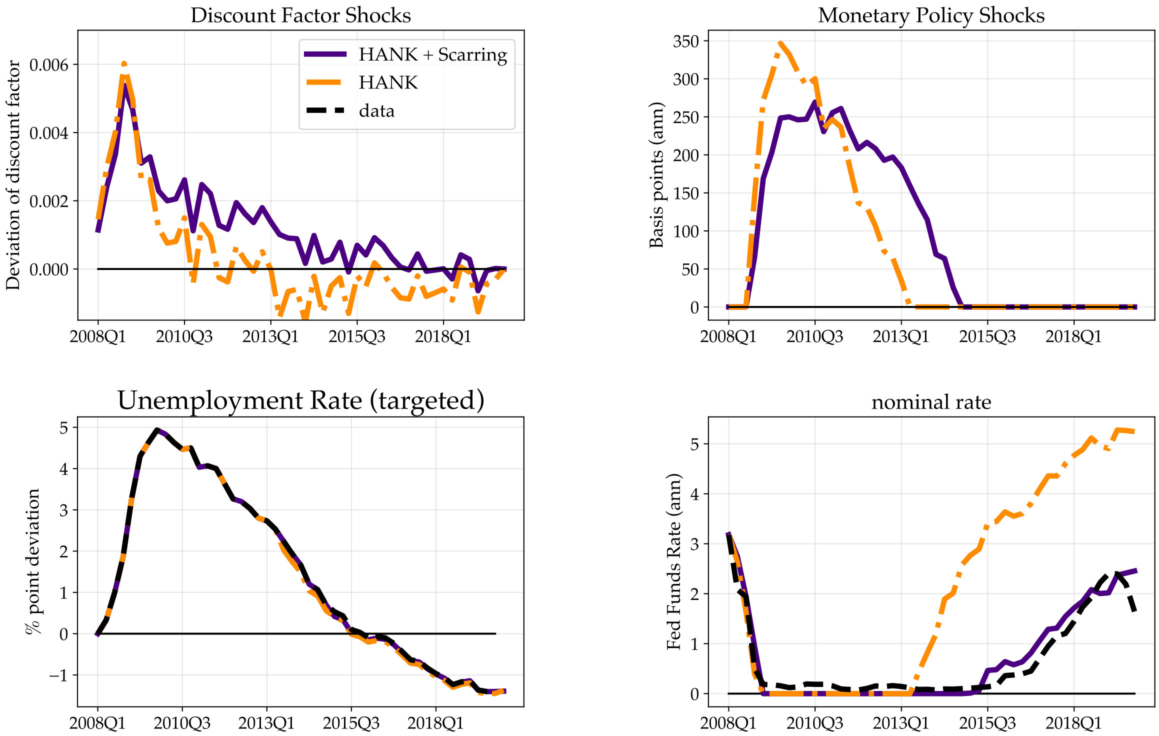


Figure 1-8. Estimated shocks to discount factor and nominal rate

persistence 0.95. As noted in Kekre [2023a], the chosen AR(1) persistence does not alter the results as a different persistence will alter the estimated sequences of shocks but not the path of unemployment as that is what is targeted. The monetary policy shocks are assumed to have no persistence. I repeat this procedure over a grid of different wage rigidities ϕ_w and choose the wage rigidity parameter that minimizes the squared distance between the response of price index and its counterpart in the data. To capture the effects of unemployment scarring, I repeat this procedure for the version of the model where unemployment scarring is turned off in the same manner as in section 6.

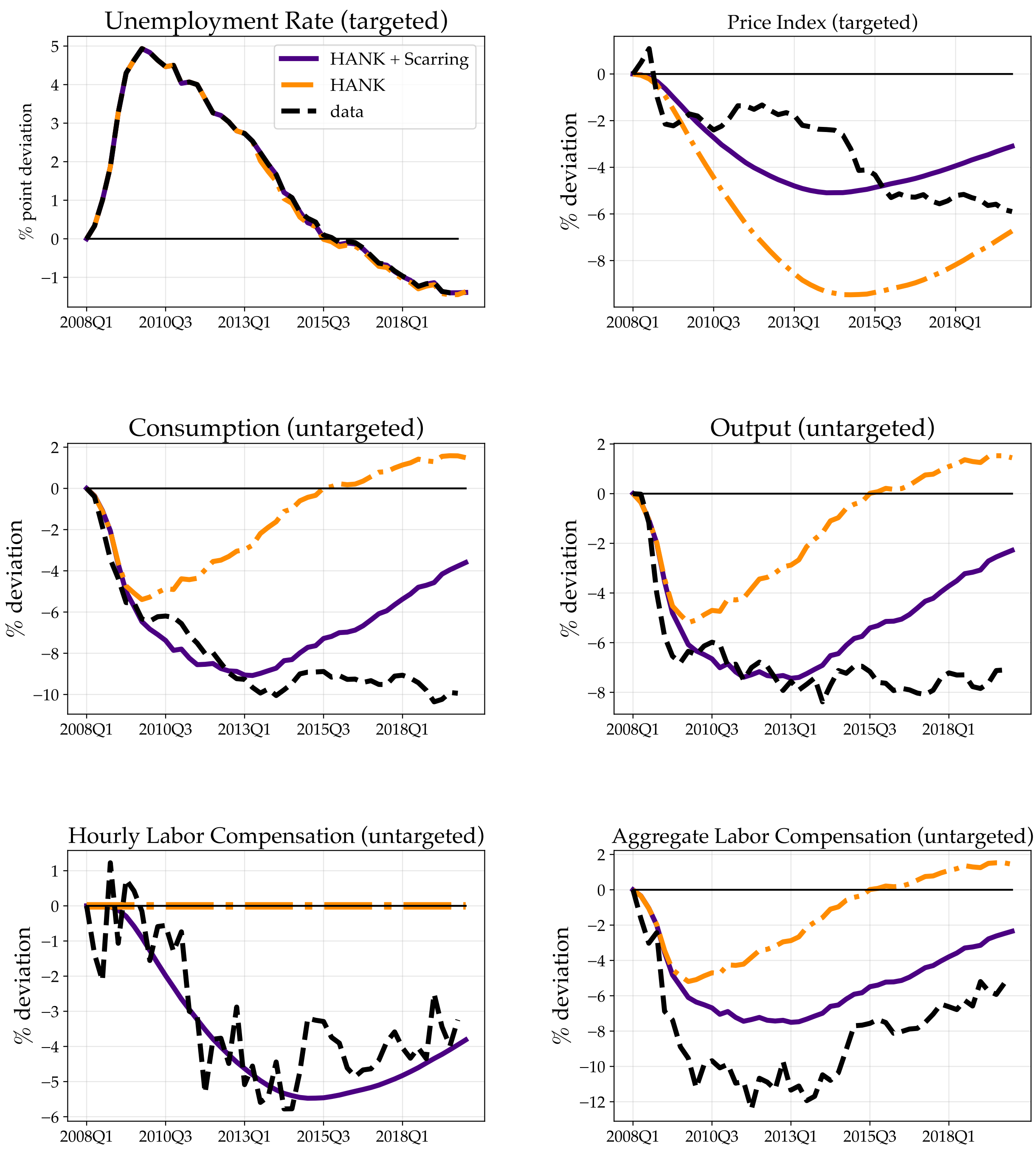


Figure 1-9. Great Recession: Model vs Data (detrended)

Note: This figure compares the paths of various aggregates in the model with and without unemployment scarring to the data. The series display deviation from steady state for the model and from 2008Q1 for the data. In the data, real PCE, PCE deflator, real GDP, real hourly labor compensation, aggregate labor compensation are detrended from 1990Q1 to 2019Q4 and then rescaled such that the data represent deviation from 2008Q1.

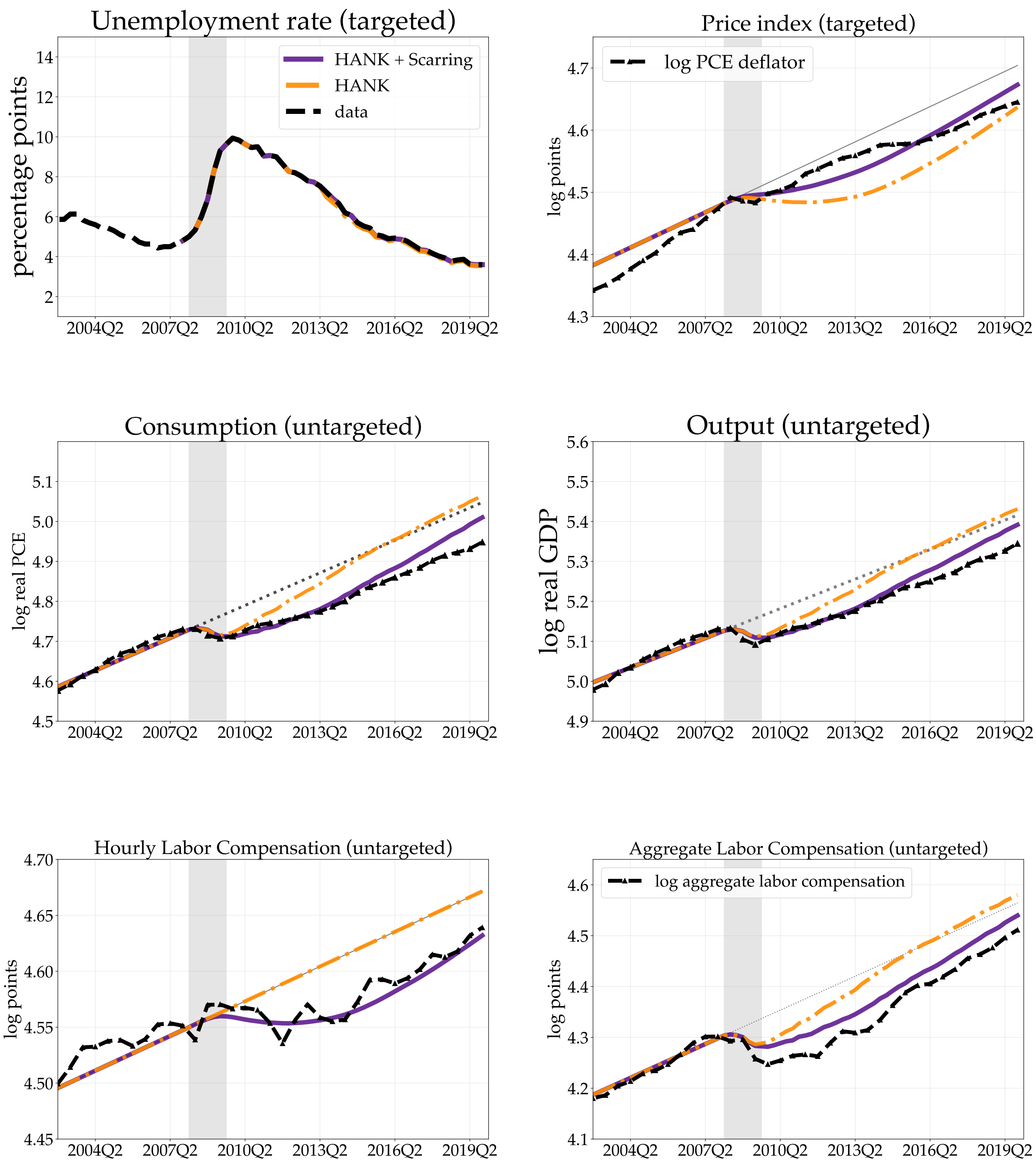


Figure 1-10. Great Recession: Model vs Data (with trend)

Note: This figure plots the responses from figure 1-9 with the trend.

Figure 1-8 plots the estimated shocks, the unemployment rate, and the nominal rate against the data under the baseline model and the model without scarring. Figure 1-9 plots the key aggregate variables against their detrended observed counterpart in the data and 1-10 plots the model responses against the data without detrending. Only the unemployment rate and price index are targeted.

Overall, unemployment scarring explains a substantial share of slow recovery following the Great Recession. In particular, scarring allows the model to match the path of the PCE and GDP until the beginning of 2015. Furthermore, the model under predicts the response of aggregate labor compensation likely due to the absence of labor force participation in the model. The path of hour labor compensation is matched especially well and provides macroeconomic validation that for unemployment scarring. Without unemployment scarring, the response of PCE, GDP, and aggregate labor compensation exhibit a 'V' shaped recovery as it mirrors the response of the unemployment rate. Unemployment scarring generates a persistent decline in labor productivity without a prolonged increase in the unemployment rate. This allows model to produce an income response that is significantly more persistent than the response of unemployment.

1.8.2 Debt to GDP during the Great Recession

Having shown that the model can replicate the sluggish recovery from The Great Recession, in this section I evaluate the extent to which human capital losses increased debt to GDP during and after the Great Recession. Figure 1-11 plots the simulated path of debt to GDP and tax revenues under the baseline model and the model without scarring. The model suggests that, by 2019, unemployment scarring increased debt to GDP by 5.5 % points. Human capital losses cause persistent losses in GDP as well as tax revenues which in turn increases debt.

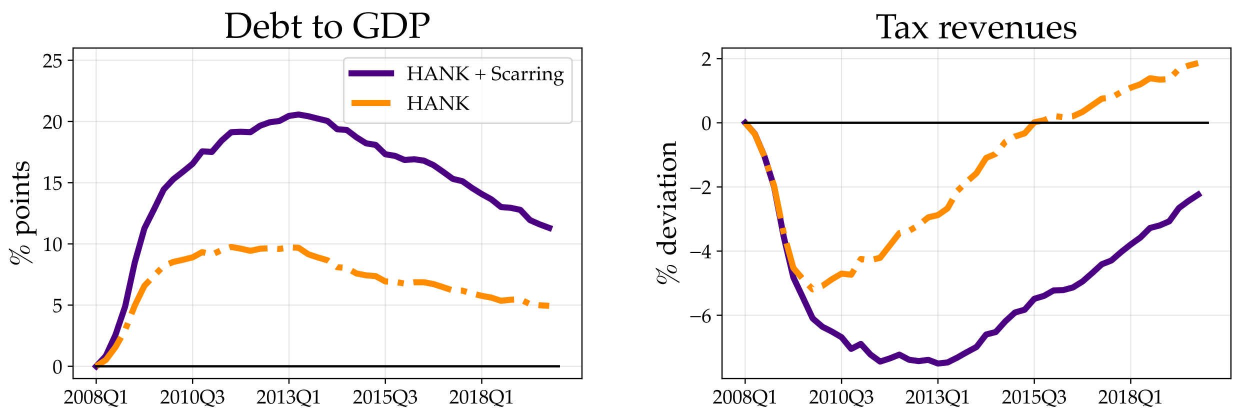


Figure 1-11. The response of debt to GDP and tax revenues

1.8.3 Income Inequality during the Great Recession

Unemployment scarring increases the dispersion in human capital during a recession. As households become unemployment and later find reemployment at a lower wage, the variance of the distribution of wages increases persistently as the re-accumulation of human capital is slow. Figure 1-12 shows that unemployment scarring allows the model to generate a near-permanent response in the Gini index of income that is consistent with the data.

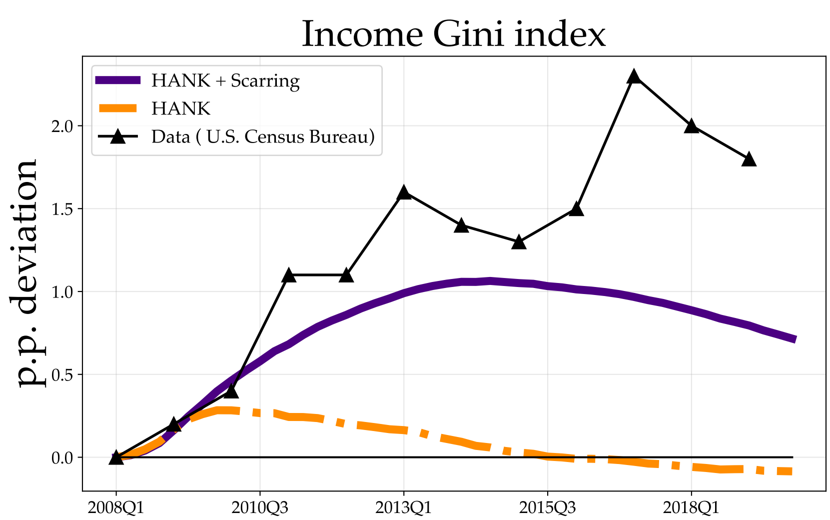


Figure 1-12. Gini Coefficient: Model vs Data

1.9 The COVID Recession and Temporary Layoffs

1.9.1 The COVID Recession and the Absence of Scarring

The behavior of unemployment during the COVID recession was unprecedented due to various reasons. One of these reasons is that 97.7% of the increase in the unemployment rate was attributed to temporary layoffs [Gertler et al., 2022]. In this section, I show that, during the COVID recession, unemployment scarring did not translate to macro scarring because of the unprecedented fraction of temporary layoffs . Further, this section also shows that the model can explain both recessions with sluggish recoveries as well as recessions with quick recoveries. I repeat the estimation procedure of the previous section and recalibrate ζ^X for each unemployment state X to maximize the proportion of temporary layoffs that is attributed to a change in the unemployment rate. Further I assume that temporary layoffs cannot transition to a permanent layoff by setting $P_{TLPL} = 0$.[15] At best, the model can attribute 78.5% of an increase in the unemployment rate to temporary layoffs. Figure 1-13 plots the responses of unemployment rate, Gini index for income, consumption, output under the model with scarring calibrated to maximize the proportion of temporary layoffs (purple), and the version of the model without scarring (orange). With a large mass of temporary layoffs, the effects of unemployment scarring are effectively eliminated as temporary layoffs are reemployed at their pre-job layoff wage. The effective absence of unemployment scarring reduces the persistence of the responses of consumption and output in the baseline model leading leading the model to be consistent with the empirical paths of consumption and GDP. Further, the response of the Gini index is transitory, similar to the data.

1.9.2 Temporary Layoffs and Swift Recoveries

In this section, I demonstrate that temporary layoffs, following the COVID recession, were instrumental in both accelerating the swift recovery of GDP and in preventing a permanent

[15] Gertler et al. [2022] note that 98% of these temporary layoffs do not transition to a permanent layoff.

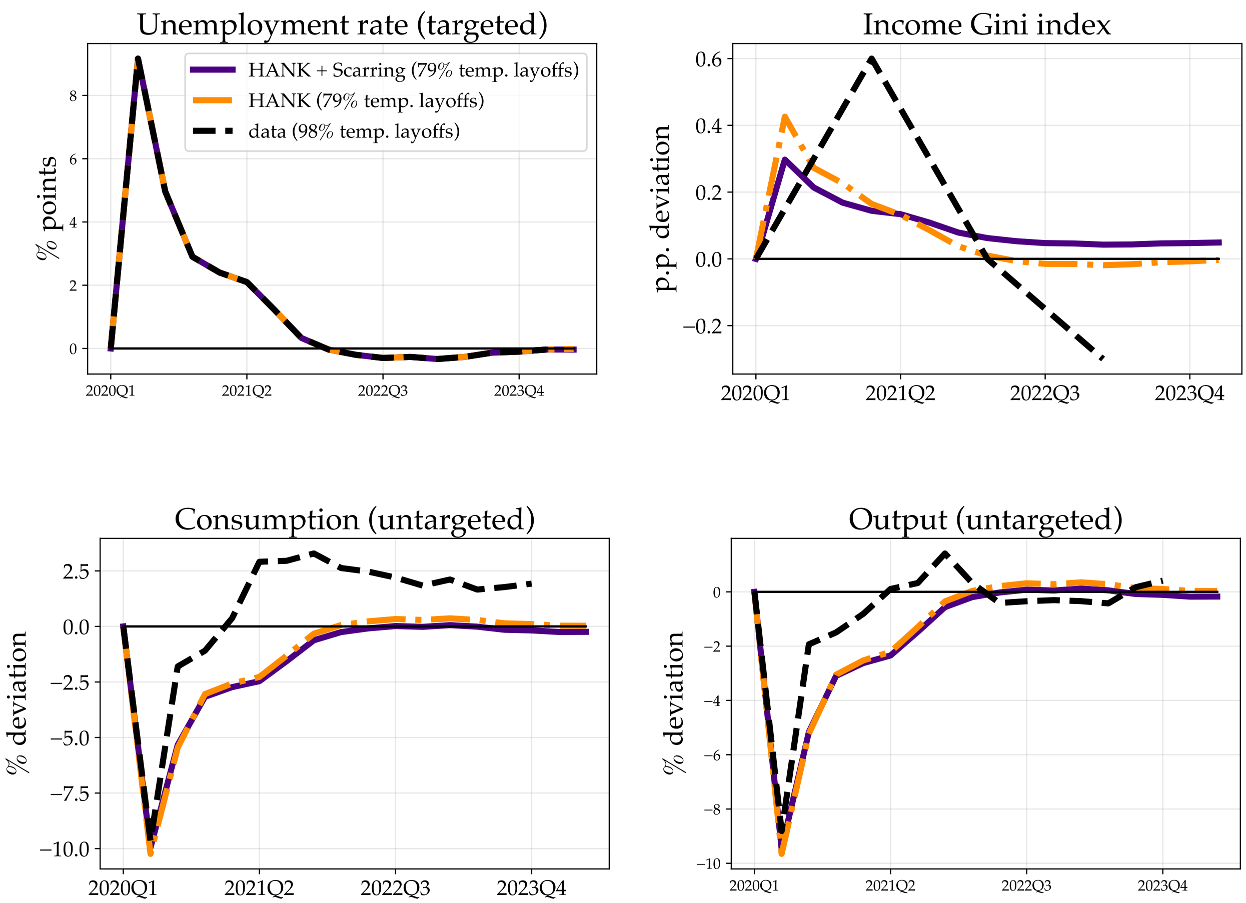


Figure 1-13. Model vs data: The COVID Recession

Note: In this exercise, the effects unemployment scarring are eliminate when the model is recalibrated to match the large proportion of temporary layoffs that explain the rise in unemployment. In particular, for this calibration, 78.5 % of the increase in the unemployment rate is attributed to temporary layoffs. Empirically, 97.7% of the increase in the unemployment rate is due to temporary layoffs. The model is unable to account for such a large proportion of temporary layoffs because the fall in labor market tightness during the simulation lowers the job finding probability of those who were already in a permanently layoff prior to the recession. Thus, the duration of those permanent layoffs rises.

rise in income inequality. To show this, I repeat the estimation procedure of matching the unemployment rate during the COVID Recession but recalibrate the model to maximize the fraction of permanent layoffs that can be attributed to an increase in the unemployment rate. Because the job probabilities of workers who are in temporary layoff falls endogenously with the unemployment rate, the duration of a temporary layoff rises therefore preventing the model from producing an increase in an unemployment rate that is entirely explained by permanent layoff.[16]

Figure 1-14 and figure 1-15 compares the path of output and income Gini, respectively, under the original calibration (from section 9.1) against the counterfactual scenario with a large fraction of permanent layoffs. In all lines in each figure, the path of unemployment remains identical and instead only differs in the composition of the unemployment rate between permanent and temporary layoffs. Figure 1-14 demonstrates that if the rise in unemployment has been primarily due to permanent layoffs, GDP would not have returned to its pre-recessionary trend. Although the long run difference between the counterfactual and the data may appear small —due to the sharp initial contraction in GDP— the percentage deviation of the counterfactual from the trend reaches 2 % by the second quarter of 2023. This magnitude is within range of long run output deviations observed after the 1990-1991 and 2000s recessions. Moreover, emphasizing the role of temporary layoffs does not diminish the significance of fiscal policy in shaping the recovery from the pandemic. Fiscal measures may have contributed to the large proportion of temporary layoffs during the COVID Recession. Overall, temporary layoffs were a key factor in enabling GDP to return to its pre-recessionary trend and likely complemented the effectiveness of fiscal stimulus during this period. Similarly, Figure 1-15 illustrates that temporary layoffs prevented the permanent rise in the Gini index for income. Notably, the red line demonstrates that if the majority of the increase in the unemployment rate was due to permanent layoffs, then the Gini index for income would have permanently risen.

[16] In other words, even if the increase in the EU probability in this simulation is completely captured by permanent layoffs, the UE probability of workers who were in temporary layoff prior to the recession must also fall.

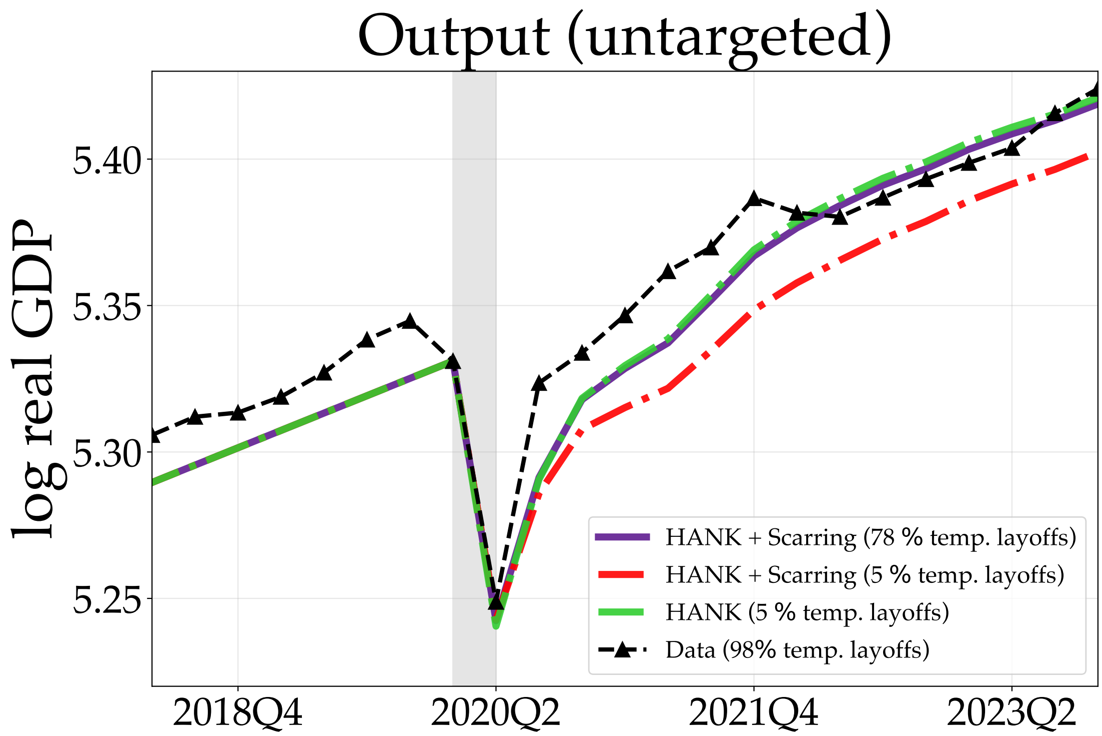


Figure 1-14. Counterfactual for GDP: What if the rise in unemployment during the pandemic was due to permanent layoffs?

This figure plots the paths of output with trend from the HANK + Scarring model (purple) under the baseline COVID calibration (with 78% temporary layoffs) against a counterfactual (red) where the rise in unemployment during COVID is largely explained by permanent layoffs. Note that for both paths of output, the unemployment rate is identical. Only the composition of the unemployment rate differs.

1.10 What if the US had pursued fiscal consolidation during the Great Recession?

1.10.1 A Reductions in Government Transfers in 2010

During The Great Recession, while the US pursued fiscal stimulus, European countries engaged in large fiscal consolidations. These austerity measures led to large contractions in GDP [Jorda and Taylor, 2016, Fatás and Summers, 2018, House et al., 2020]. Further, unemployment scarring has been shown to be very much present, and slightly worse, in Europe.[17] In this

[17] Bertheau et al. [2023]

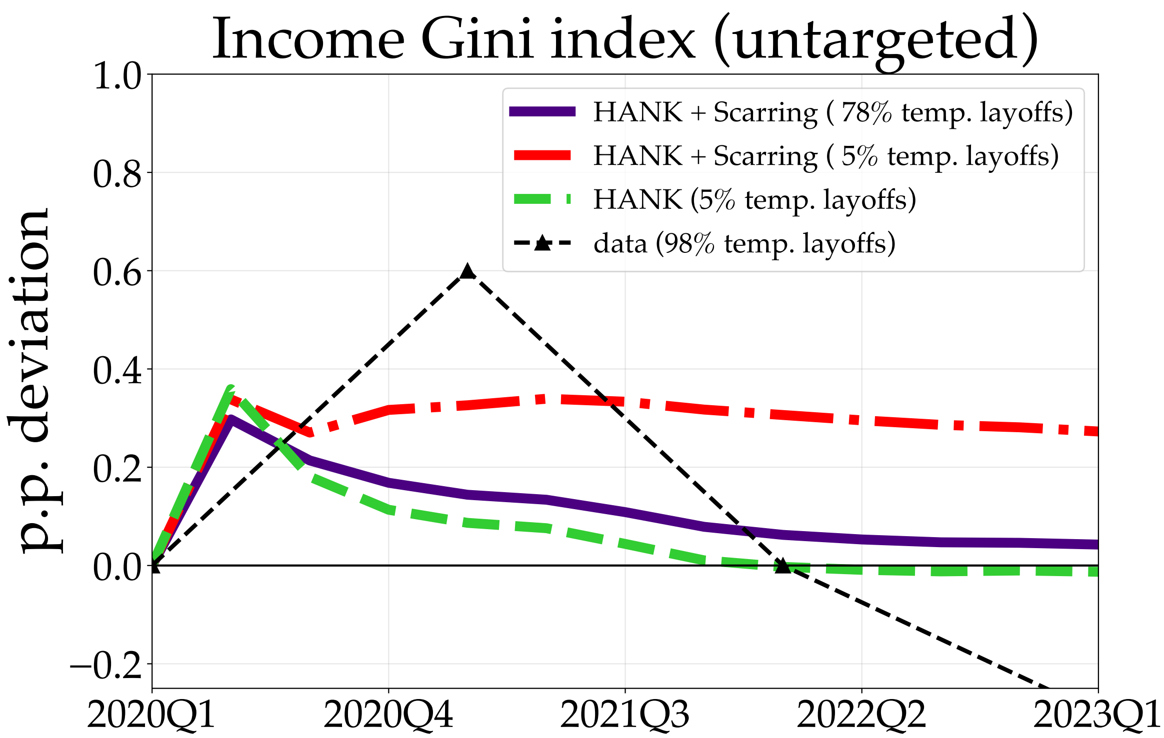


Figure 1-15. Counterfactual for Gini index: What if the rise in unemployment during the pandemic was due to permanent layoffs?

This figure plots the paths of the income Gini index from the HANK + Scarring model (purple) under the baseline COVID calibration (with 78% temporary layoffs) against a counterfactual (red) where the rise in unemployment during COVID is largely explained by permanent layoffs. Note that for both paths of the income Gini index, the unemployment rate is identical. Only the composition of the unemployment rate differs.

section, I consider the path of the US economy had it engaged in similar austerity measures. I augment the simulation in the previous section by simulating a counterfactual where the US reduces government spending by 2% of GDP at the beginning of 2010. I assume the shock has a quarterly persistence of 0.9 such that its path fades by 2016. As in the Great Recession simulation, the tax rate cannot adjust for 10 years and set $\phi_b = 0.015$. To account for the zero lower bound, I set the the coefficients of the Taylor rule on output, ϕ_Y, and inflation, ϕ_π, to zero such that the central bank fixes the nominal rate in response to this shock. I augment the estimated demand and monetary policy shocks from the previous section with this fiscal consolidation shock and simulate the path of the economy. Figure 1-16 plots the deviation in government spending, GDP, debt to GDP, and debt in the baseline simulation (purple), the simulation with fiscal consolidation (red), and the path of these aggregates without human capital losses (green dashed). In figure 1-16, fiscal consolidation causes a persistent decline in GDP while only generating a slight decline a debt and debt to GDP. In particular, the decrease in government spending of 2% of GDP only decreases debt to GDP by 1 percentage point. In the absence of human capital losses from scarring, the green dashed line demonstrates that debt to GDP would have fallen by 2.4 percentage points. Overall, fiscal consolidation during the Great Recession would have generated a large and persistent decline in GDP while being ineffective at reducing debt to GDP.

1.10.2 Fiscal Consolidation and the Zero Lower Bound

What are the effects of the zero lower bound on the counterfactual fiscal consolidation in section 7.3? To do so, I redo the experiment in section 7.3 but allow for an active Taylor rule. In particular, I set the Taylor rule coefficient on output, ϕ_Y, to 1/12 and the Taylor rule coefficient on inflation, ϕ_π, to 1.5. Further, to illustrate the effect of an aggressive monetary authority, I also perform this experiment again with $\phi_Y = 0.2$ Figure 1-17 plots the fiscal consolidation exercise with and without the zero lower bound under the baseline Taylor rule and the more aggressive Taylor rule. Without the zero lower bound, fiscal consolidation becomes significantly more effective at reducing debt to GDP. The dashed blue and orange lines demonstrates that the decline in debt to GDP is substantially larger without the zero lower bound. The increased effectiveness of fiscal consolidation in reducing debt to GDP in the absence of the zero lower bound stems from decreasing the cost of debt. Decreasing the interest rate alleviates the fiscal authority's cost of borrowing, and therefore decreases the upward pressure that lost tax revenues place on debt.

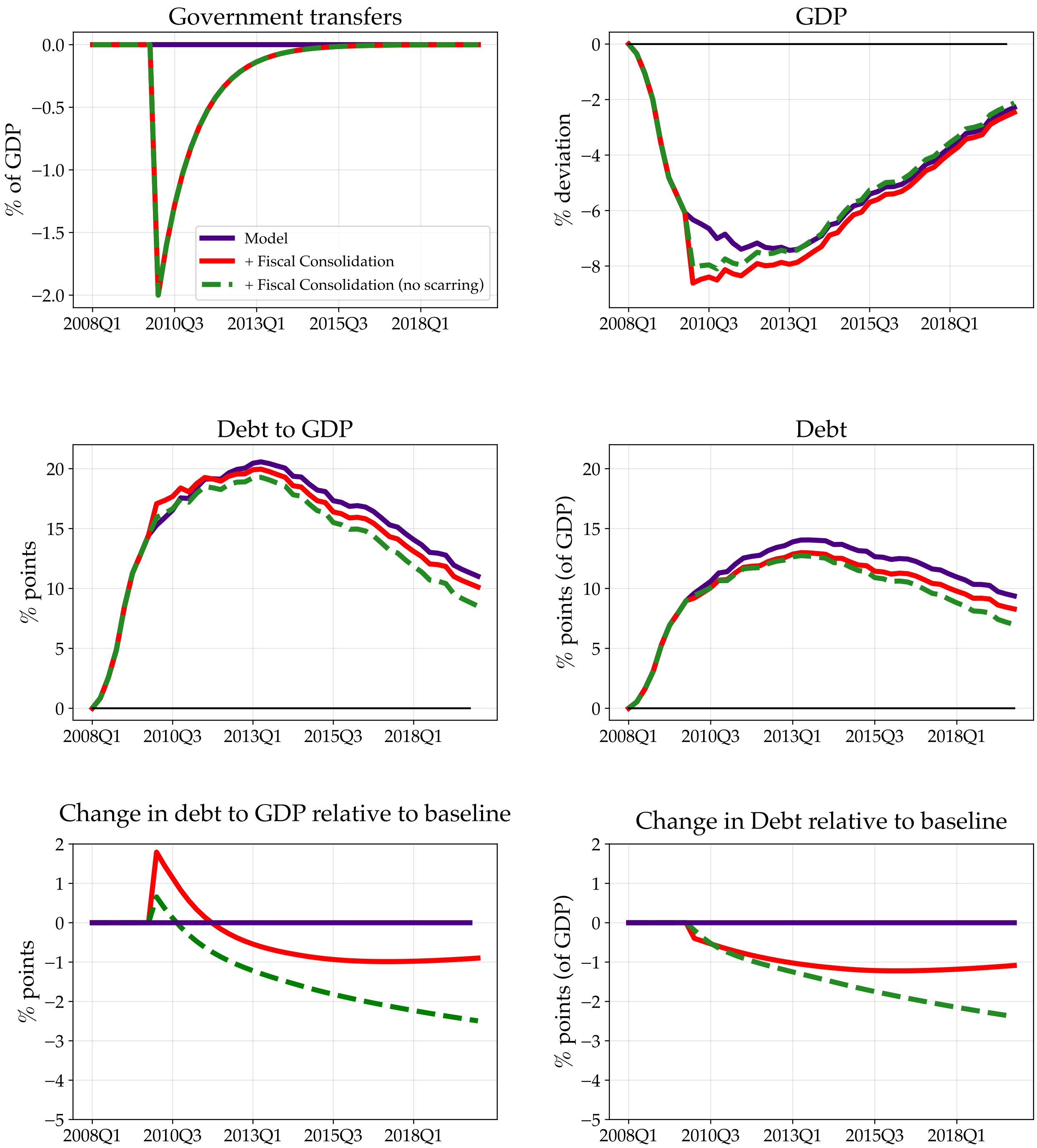


Figure 1-16. Counterfactual: Fiscal Consolidation in the US

Note: This exercise plots the simulated paths of of macro aggregates during the Great Recession from figure 1-9 with a fiscal consolidation shock that begins in 2010Q1 under the baseline model and the model without scarring.

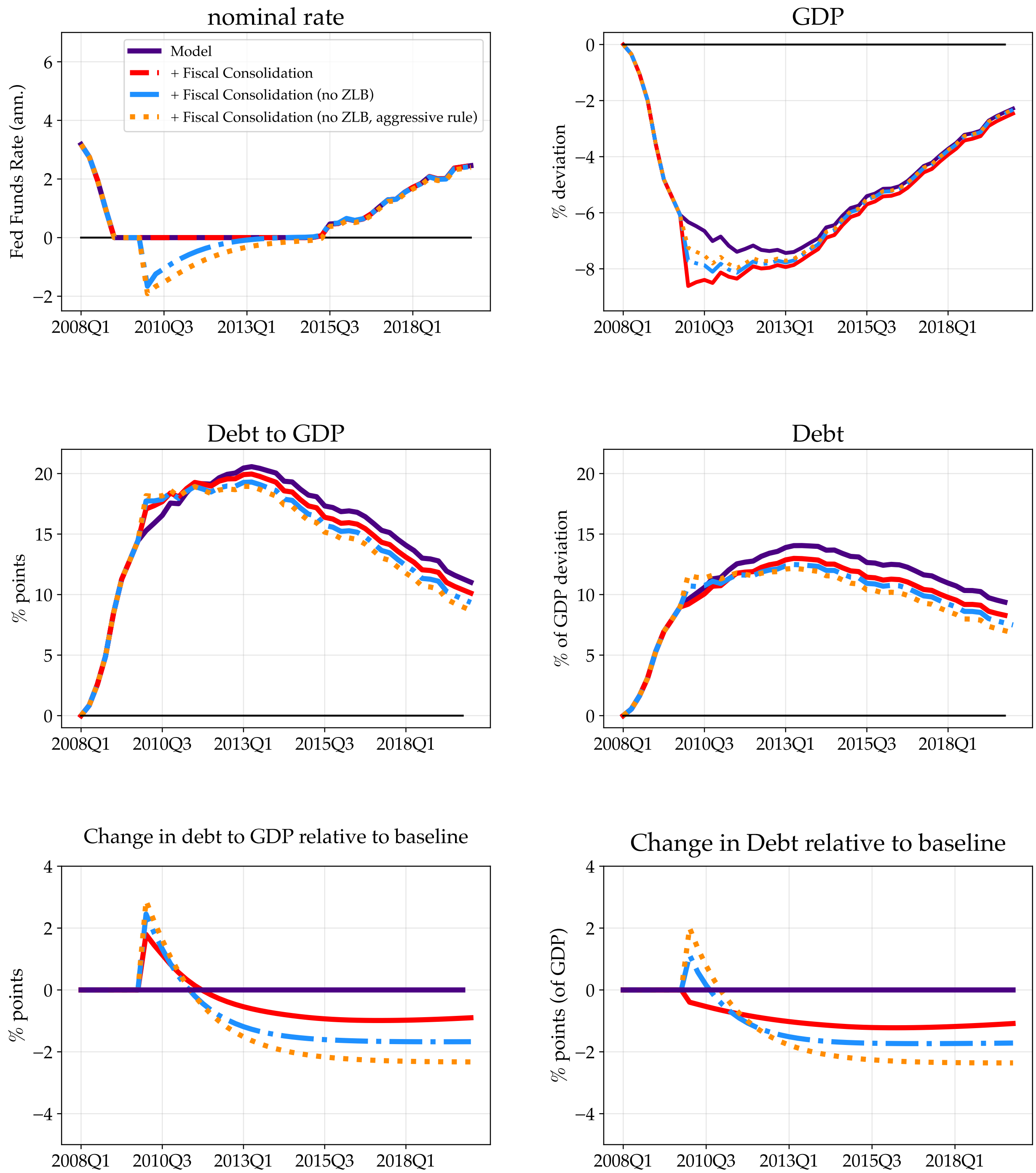


Figure 1-17. Counterfactual: Fiscal Consolidation in the US and the effects of the zero lower bound

1.11 Conclusion

This paper quantifies the macroeconomic role of a well-documented microeconomic fact, that job loss leads to scars on wages. Incorporating these microeconomic scars into a heterogeneous agent New Keynesian model with search and matching frictions introduces a novel channel that emerges as a key determinant of the speed of macroeconomic recovery from a recession. When estimated to match the microeconomic estimates on scarring, and calibrated to match the fraction of temporary layoffs in each recession, the model is able to quantitatively capture *both* the sluggish recovery from the Great Recession and the swift rebound from the COVID Recession. During a recession, the extent to which micro unemployment scarring translates to macro scarring hinges on the share of temporary layoffs driving the rise in the unemployment rate. In particular, had the majority of layoffs during the COVID Recession been permanent rather than temporary, GDP would not have returned to its pre-2020 trend, even when accounting for the large fiscal response during the pandemic.

In addition, the transmission of fiscal austerity changes considerably in the presence of these scars. Given a reduction in government spending, scarring erodes future tax revenues, increasing pressure on the fiscal deficit. Quantitatively, the decline in debt to GDP from a fiscal consolidation is four times smaller because of unemployment scarring and leads to a near permanent rise in income inequality as scarring increases the dispersion in wages.

The role of unemployment scarring in business cycle dynamics and macroeconomic policy presents many promising avenues for future research. First, the root causes of these scars remain an active area of research. Incorporating the origins of this microeconomic phenomenon into macroeconomic analysis could offer clearer guidance for designing policies to mitigate scarring. Additionally, the connection between unemployment scarring and sluggish recoveries highlights the potential of job retention schemes, like those implemented in Europe during the COVID recession, as an area for future research. As emphasized by Lachowska et al. [2020] and Jacobson et al. [1993], "something intrinsic to the employment relationship itself...

is lost when workers are displaced." Job retention policies may serve as the most effective hedge against scarring, given the inherent challenges of finding a strong employer-employee match. I leave these important questions for future research.

Chapter 2

Perceived Unemployment Risks over Business Cycles[1]

– joint with Adrian Monninger, Xincheng Qiu, and Tao Wang

2.1 Introduction

In the state-of-the-art incomplete markets model with search and matching frictions, countercyclical fluctuations unemployment amplifies business cycle fluctuations through two key channels.[2] The first is an expectations-driven precautionary channel whereby heightened *fears* of unemployment lead to increased saving and reduced consumption, which in turn depresses aggregate demand. The second is an income channel, where realized income losses from unemployment directly reduce consumption.[3]

These two channels are typically disciplined by the observed rate at which workers transition between employment and unemployment. However, the true share of workers moving from employment to unemployment does not necessarily reflect the true ex-ante risk of job loss that dictates a worker's precautionary behavior. Realized separation rates are shaped by unforeseen macroeconomic shocks. For instance, workers in 2019 did not anticipate

[2] Counter-cyclical idiosyncratic job risks are one of the important drivers of aggregate business cycle fluctuations[Bayer et al., 2019, Den Haan et al., 2018, Broer et al., 2021a, Graves, 2020]. Other papers study the role of unemployment insurance in stabilizing such fluctuations and its distributional impacts[McKay and Reis, 2021, Boone et al., 2021, Kekre, 2023b].

[3] The distinction between ex-ante and ex-post responses is also relevant to the dynamics of durable consumption. [Harmenberg and Öberg, 2021]

the COVID-19 pandemic, so their perceived risk of job loss for 2020 was far lower than the actual separation rate observed that year.

Furthermore, the risk of job loss that is perceived by households does not necessarily align with the actual real-time risk of job loss given prevailing macroeconomic conditions. A large literature documents systematic deviations between household expectations and full-information rational expectations (FIRE). This raises a natural question: do households accurately perceive their risk of job loss? If households underreact to rising unemployment risk, they may fail to adequately insure themselves against income shocks, leading to insufficient consumption smoothing. Conversely, an overreaction could trigger a sharp decline in aggregate demand.[4]

This paper separately measures how (a) perceived unemployment risk, (b) objective unemployment risk, and (c) job transition rates vary over the business cycle, and shows that these measures differ substantially in their cyclical dynamics. The conventional approach to studying expectation formation using survey data relies on a direct comparison between (a) and (c)–i.e., forecast errors–to identify deviations from full-information rational expectations (FIRE). By incorporating measure (b), we can characterize the gap between subjective perceptions of job risk and their ex-ante rational benchmark. This extends existing studies that identify biases in job risk beliefs based solely on ex-post comparisons.[5]

In particular, our measure of perceived risk (a) is derived from survey expectations of job risk in the New York Fed's *Survey of Consumer Expectations* (SCE), which is available only since 2013. To extend the series back to 1978,[6] we employ machine learning algorithms trained on a rich set of expectation-related indicators from the Michigan Survey of Consumers (MSC). We also externally validate our imputation method by confirming that the backcasted versions of several benchmark series by the same procedure align closely with actual observed values. This backcasted series enables us to analyze multiple business cycles and empirically

[4] See, for instance, Den Haan et al. [2018].

[5] See, for instance, Stephens Jr [2004], Spinnewijn [2015], Mueller et al. [2021], Balleer et al. [2021], etc.

[6] Many series from the Michigan Survey of Consumers begin in 1978.

assess the strength of precautionary behavior over a much longer history.

We create a proxy for (b) using a real-time machine-learning forecast framework following the methodology of Bianchi et al. [2022]. Specifically, at each point of time in our sample, we perform a LASSO (least absolute shrinkage and selection operator) estimation to select a subset of variables from a set of 600 real-time series of macroeconomic conditions and forward-looking expectations by households and professionals that best predict subsequent labor market flows. We then generate a one-step-ahead forecast using the machine-efficient model that is selected from cross-validation. Real-time predicted job transition rates approximate the best possible risk forecast of the labor markets, hence, serving as a good proxy for the objective ex-ante risks.

Two main findings emerge from comparing these measures. First, the comparison between (a) perceived unemployment risk and (c) realized job transition rates shows that households' ex-ante subjective beliefs–especially about job-finding probabilities–are strong predictors of actual labor market transitions. This suggests that individuals form expectations using meaningful private information, consistent with micro-level evidence that workers possess advance signals about their employment prospects.[7] Second, the comparison between (a) and (b) reveals a systematic gap between subjective beliefs and machine-learning-based forecasts: perceptions respond sluggishly to changes in real-time job risk. While the algorithmic forecasts accurately predict job transitions over a three-month horizon (with the exception of crisis onsets like COVID), average subjective expectations underreact and fail to incorporate available predictive signals indicating a deviation from rational expectations.

We propose two explanations for why average perceived job risks underreact to real-time macroeconomic labor market conditions. First, information rigidity–households update their beliefs about macroeconomic conditions sluggishly. Second, risk heterogeneity–households face differing levels of job risk, either conditionally or unconditionally, implying that not all households respond equally to aggregate labor market shifts. We find that workers across

[7]See, for instance, Hendren [2017].

the distribution of perceived job risks respond to true real-time risks with varying intensity and degrees of stickiness. This underscores the importance of heterogeneity in both actual and perceived job risks over the business cycle. It aligns with a growing body of research showing that heterogeneity in job risk exposure amplifies aggregate demand fluctuations through unemployment risk channels. Since households are unevenly affected by rising job risks in recessions, the unequal mapping from aggregate labor market flows to individual risk perceptions helps explain why average perceived job risks respond less than one-for-one to actual labor market dynamics.

Lastly, we incorporate our measures of perceived and objective unemployment risk, along with observed job transition rates, into a heterogeneous agent model with persistent unemployment. This framework allows us to quantify the extent to which fluctuations in aggregate consumption over the business cycle are driven by precautionary saving versus income losses caused by actual changes in unemployment. We simulate the path of aggregate consumption starting in 1988 under two scenarios. In both, the actual unemployment rate evolves according to observed job transition rates; however, workers' perceptions of job risk differ. In the first scenario, perceptions follow our measure of perceived unemployment risk. In the second, they are aligned with our measure of rational (objective) unemployment risk. Finally, to isolate the precautionary saving channel in each scenario, we simulate a benchmark path of aggregate consumption driven solely by observed job transition rates. The difference between this benchmark and the consumption paths that incorporate workers' perceptions of unemployment risk captures the contribution of precautionary behavior.

Our simulations of aggregate consumption beginning in 1988 show that the precautionary channel is sharp and substantial when workers are assumed to have rational (objective) perceptions of job loss risk. In contrast, when we use workers' actual risk perceptions—which tend to underreact to macroeconomic dynamics—the strength of the precautionary channel is notably attenuated. Interestingly, this underreaction leads workers to under-insure, resulting in a smaller initial drop in consumption during recessions but a more sluggish recovery afterward, as there is less precautionary savings to draw down.

We also highlight the important interaction between job risk heterogeneity and belief distortions. Low-educated workers, who are disproportionately exposed to cyclical job risks, exhibit the stickiest beliefs and are therefore the most underinsured when unemployment shocks materialize. This underinsurance amplifies the effects of unemployment risk over the business cycle.[8] Taken together, this evidence suggests that the strength of unemployment and unemployment risk as amplification channels critically depends on how heterogeneous households perceive fluctuations in job risk.

Related Literature

Our paper builds on the empirical evidence of biases in job-finding expectations as documented by Mueller et al. [2021], which studies the microdata on job-finding expectations in the SCE. In comparison to their work, we study the job-finding expectations at the macro level. We corroborate their finding by showing that individuals' job-finding expectations underreact to changes in the actual job-finding probability over business cycles, in addition to the underreaction to changes over the unemployment duration. In addition, several other studies based on a comparison of the perceived job risks and realized job transitions, as surveyed in Mueller and Spinnewijn [2023], provide divergent evidence between over-optimism and over-pessimism in job expectations. For instance, Arni [2013], Spinnewijn [2015], Conlon et al. [2018], Mueller et al. [2021] all found that workers over-perceive the job-finding probability, with a stronger bias with longer duration of unemployment. Conlon et al. [2018] shows such bias is due to over-optimism in perceived offer arrival rates and wage offers. Balleer et al. [2021] explores the consequences of over-optimism bias. Unlike these papers, we primarily focus on the variability of the business cycle fluctuations of these perceptions relative to their realizations, instead of a possibly constant bias.

[8] For example, Patterson [2023] shows that workers with the most cyclical incomes also have the highest marginal propensities to consume. Similarly, **?** identifies the conditions under which the interaction between beliefs, disagreement, and heterogeneity amplifies business cycle dynamics.

On job separation perceptions, Stephens Jr [2004]'s evidence suggests that workers over-perceive the job loss probability compared to the realization. However, the author cautions on the possible selection bias in interpreting this finding, as higher perceived job loss probability might induce workers to opt out of high-risk jobs, lowering the realized job loss probability. The same issue may also be relevant in the scenario of overoptimism in job findings. A few follow-up studies suggest similar upward biases in job loss perceptions.[Dickerson and Green, 2012, Balleer et al., 2023] Despite such biases, Dickerson and Green [2012], Hendren [2017], Pettinicchi and Vellekoop [2019], Hartmann and Leth-Petersen [2024] suggest that workers' perceived job risks predict the unemployment outcome reasonably well indicating advance information.

This paper builds on the literature that adopts real-time forecasting to approximate ex-ante uncertainty/risks. This is also closely related to using machine-efficient forecast as the rational benchmark instead of a constructed benchmark under a specific assumption of data-generating process [Bianchi et al., 2022]. Our use of the approach in Bianchi et al. [2022] is to proximate not just FIRE, but also *ex-ante* job risks. The notion that ex-ante risks are different from ex-post outcomes is also made clear by Jurado et al. [2015], Rossi and Sekhposyan [2015] in measuring the macroeconomic uncertainty instead of specifically labor income risks.

Our paper directly contributes to several papers that incorporate subjective job risk perceptions in otherwise standard macroeconomic models featuring uninsured job risks. [Pappa et al., 2023, Bardóczy and Guerreiro, 2023]. In addition, Morales-Jiménez [2022], Menzio [2022], Rodrıguez [2023] incorporate informational frictions in standard search and matching models to resolve the volatility puzzle in the aggregate unemployment rate. Different from their work, we explore the implications of perceived unemployment risks on consumption/saving and aggregate demand fluctuations. Our findings of the heterogeneity in job expectations also relate to Broer et al. [2021b], which relies on endogenous information choice to account for empirical evidence that information frictions in household macroeconomic expectations non-monotonically depend on their wealth. Our finding that rigidity in job beliefs of workers does not often decrease with the cyclical exposure of their job risks, seems to suggest that mechanisms beyond optimal information choices may play a role in causing such belief stickiness.

2.2 Perceived job risks predict realized job transitions

2.2.1 Data

The data on perceived job risks is derived from the Survey of Consumer Expectations (SCE) by the Federal Reserve Bank of New York. The SCE is a nationally representative online survey conducted with a rotating panel of approximately 1,300 household heads. The specific questions used to elicit perceived job finding and job separation probabilities are as follows:

> *What do you think is the percent chance that you will lose your main (for those with multiple jobs) or current (for those with single job) job during the next 12 months?*
>
> *Suppose you were to lose your main job this month, what do you think is the percent chance that you will find a job within the following 3 months?*

The realized rates of job transitions are calculated using data from the Current Population Survey (CPS) [e.g., Fujita and Ramey, 2009], which tracks the movement of workers between unemployment, employment, and non-participation statuses based on panel records of individual work histories. The job finding (JF_t) and job separation (JS_t) rates are defined as

$$JF_t = \frac{UE_t}{U_{t-1}}, \quad JS_t = \frac{EU_t}{E_{t-1}},$$

where UE_t is the number of transitions from unemployment to employment in month t, EU_t is the number of transitions from employment to unemployment in month t, U_{t-1} is the number of individuals unemployed in month $t-1$, and E_{t-1} is the number of individuals employed in month $t-1$. We directly obtain the data on realized transition rates across various demographic groups, such as by education and income, from the labor market tracker provided by the Federal Reserve Bank of San Francisco.[9]

2.2.1.0.1 Time Aggregation. The perceived transition probabilities are reported for different horizons from the realized flow rates. For consistency, we convert all these rates into 3-month horizons using the following procedure. Consider the flow rates for three consecutive months, denoted p_1, p_2, p_3. The aggregated flow rate over the 3-month window is then given by $1-(1-p_1)(1-p_2)(1-p_3)$. For the 1-year horizon job separation probability, we first convert it into a continuous-time Poisson rate and then re-convert it into a 3-month horizon.

2.2.2 Perceived risks versus realized outcomes

Figure 2-1 directly compares perceived risks and realized job transitions for the sample period since 2013. It shows that perceptions predict realizations reasonably well at the aggregate level. This is evident not only in the similarity of the magnitudes of the two series but also in the highly positive correlation coefficients between them. Specifically, the 3-month-ahead perceived job-finding rate accounts for approximately 70% of realized job transitions, while the perceived job-separation rate accounts for 37% of its realization.

The correlation between perceived risks and realized flow rates would have been even higher without the COVID pandemic crisis, which introduced the most significant deviations of perceived risks from subsequent realizations. At the onset of the pandemic, the perceived job-finding rate dropped sharply, but the actual job-finding rate increased initially. This discrepancy was partly driven by the rehiring of previously laid-off workers through recalls. Similarly, while perceived separation risk spiked at the onset of the crisis, the spike was dwarfed by a much higher increase in the realized job separation rates. Such deviations highlight the unexpected nature of the COVID shock. However, the dynamics of perceived

[9] Available at www.frbsf.org/research-and-insights/data-and-indicators/sf-fed-data-explorer/.

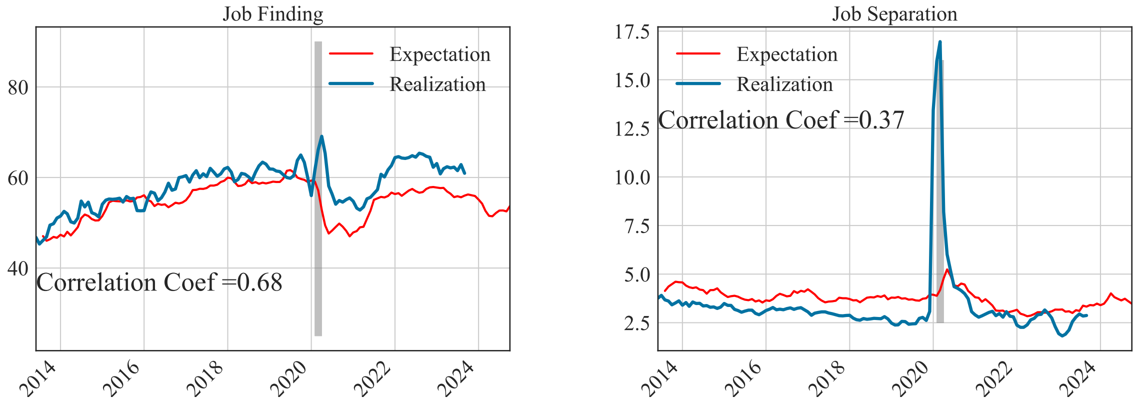


Figure 2-1. Perceived versus realized job transitions

This figure plots the perceived job transition probabilities over next three months, $\widetilde{JF}_{t+3|t}$ and $\widetilde{JS}_{t+3|t}$ and the realized job flow rates three months later JF_{t+3} and JS_{t+3}. All rates are in the units of percent chance.

risks and corresponding realizations moved in tandem again within two months following the initial outbreak. The unusual labor market dynamics during the COVID crisis were unprecedented even for professional economists in real-time, and continue to be a subject of current and future studies. Therefore, it is noteworthy that average perceptions of job risks could still partially predict ex-post labor market flow rates, despite the unprecedented crisis.

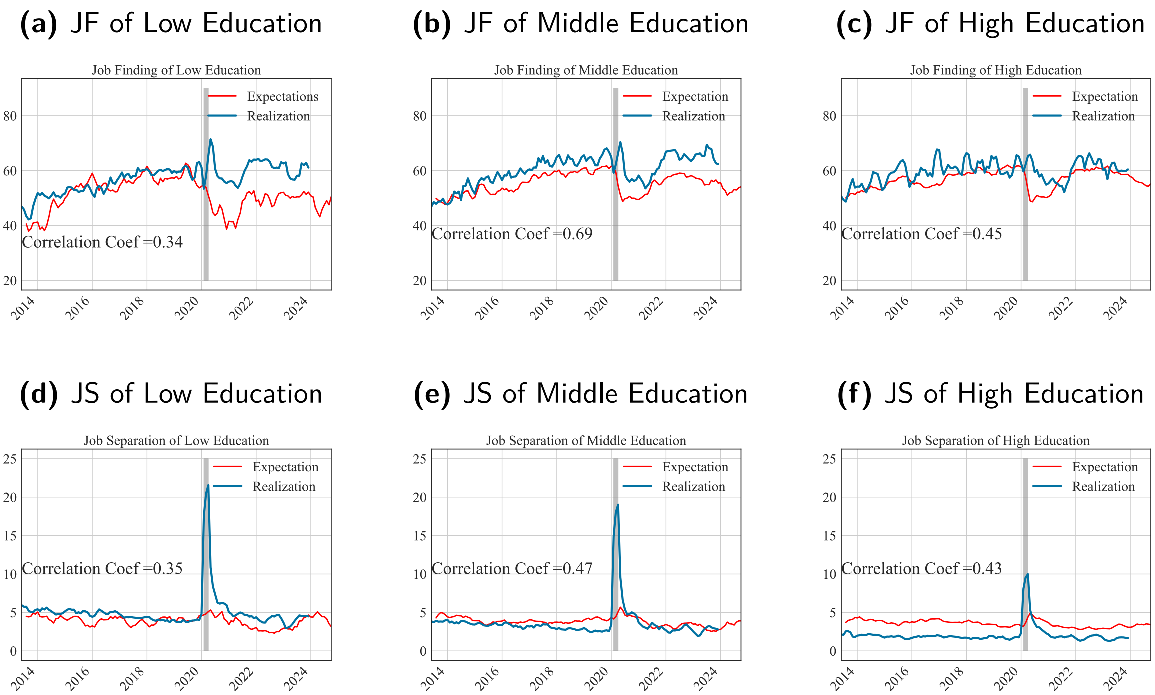
The fact that perceived risk predicts subsequent changes in the labor market is, on one hand, surprising, and on the other hand, reassuring. Growing survey evidence suggests that households' macroeconomic expectations, especially regarding inflation and unemployment rates, tend to contain systematic forecast errors. However, the average perceived job risks reported based on individuals' situations appear to capture predictable movements in subsequent labor market flows. This is encouraging for our analysis of perceived job risks, as it suggests that these measured beliefs contain meaningful time variations that reflect the underlying state of the economy. On the other hand, the correlation between ex-ante perceived job risks and ex-post realized transitions, while positive, is far from perfect, indicating a deviation from perfect foresight. Regardless of what the ex-ante perceptions are, realized job flow rates inevitably incorporate the realization of ex-ante unexpected macroeconomic shocks or idiosyncratic shocks.

2.2.2.0.1 Within-Group Comparison.

The results presented above are based on average rates across all households in the survey. One potential concern when generalizing these findings is how perceptions and realizations compare within demographic groups. Several studies such as Hall and Kudlyak [2019], Gregory et al. [2021], Patterson [2023] show the importance of heterogeneity in job risks in driving aggregate labor market dynamics, while Broer et al. [2021b] provide indicative evidence that information frictions are heterogeneous along the wealth distribution. Therefore, we also calculate both perceptions and realizations separately for low, middle, and high education groups, separately, as plotted in Figure 2-2. The figure reveals that, within each education group, the dynamics of perceived risk and realized rates closely mirror those observed at the aggregate level, exhibiting a high correlation during normal times. There is, however, substantial heterogeneity by education level in the realized rates, both in terms of overall levels and time-series volatility. Not surprisingly, low-education workers face higher job separation and lower job-finding rates than high-education ones. The differences in perceived job risks, especially in job separation rates, are relatively small across education groups. Interestingly, low-education workers appear to particularly underforecast their job separation rates at the onset of the pandemic, with the subsequent increase in separation rates being much larger than for the other two groups. Additionally, while low-education workers were notably more pessimistic about their job-finding prospects, the dynamics of realized job-finding rates were similar across all education groups. These patterns underscore the importance of considering heterogeneity in both the job risks faced by different groups and the perceptions of those risks. We explore these two points in the later part of the paper.

2.2.3 Forecast errors of perceived job risks

To systematically assess the relationship between perceived risks and realized job transitions, we adopt a widely used metric in the literature: forecast errors (FE), defined as the difference



(a) JF of Low Education **(b)** JF of Middle Education **(c)** JF of High Education

(d) JS of Low Education **(e)** JS of Middle Education **(f)** JS of High Education

Figure 2-2. Perceived versus realized job transitions: by education

This figure plots the 3-month-ahead job risk expectations, measured as perceived job finding and separation rates in SCE, by different education groups, $\widetilde{JF}^{Educ}_{t+3|t}$ and $\widetilde{JS}^{Educ}_{t+3|t}$ $\forall Educ \in \{High, Mid, Low\}$, along with their respective realization 3 months later obtained from the San Francisco Fed, JF^{Educ}_{t+3} and JS^{Educ}_{t+3} $\forall Educ \in \{High, Mid, Low\}$. All rates are in the units of percent chance.

between the perceived risk and realized flow rate.

$$\mathrm{FE}^{JF}_{t,t+3} = \widetilde{\mathrm{JF}}_{t+3|t} - \mathrm{JF}_{t,t+3}, \tag{2.1}$$

where the expectation is formed over a 3-month horizon. Here, $\widetilde{\mathrm{JF}}_{t+3|t}$ represents the perceived job-finding rate for 3 months ahead at time t and $\mathrm{JF}_{t,t+3}$ is the realization over the same horizon.

To test the informational efficiency of perceived job risks, we perform a 3-month-apart auto-regression of forecast errors with an intercept term, which is commonly used in the literature on expectation formation, e.g., Coibion and Gorodnichenko [2015], Fuhrer [2018], and Coibion et al. [2018].

$$\mathrm{FE}^{JF}_{t,t+3} = \alpha + \beta \mathrm{FE}^{JF}_{t-3,t} + \gamma X_{t-3} + \epsilon_t, \tag{2.2}$$

where X_{t-3} denotes information available at time $t-3$. A key null hypothesis under FIRE is that agents do not fully react to new shocks to the underlying variable. A significantly positive β implies predictable forecast errors based on past forecast errors.[10] In particular, $\beta > 0$ suggests that past errors persist into future forecasts in the same direction, reflecting the presence of information rigidity.

The estimation results for forecast errors in job-finding and separation perceptions are reported in Table 2-I. They overwhelmingly reject the null hypothesis of full efficiency ($\beta = 0$). Specifically, the 3-month-apart auto-regression coefficient of average forecast errors in job-finding is 0.256. Education-specific estimates range from 0.183 for the high-education group to 0.535 for the low-education group. For job separation, although the auto-correlation of average forecast errors is not significant, forecast errors of education-specific perceptions all show significantly positive auto-correlations, with regression coefficients ranging from 0.20 for the low-education group to 0.55 for the high-education group.

[10] A related null hypothesis in the same spirit is based on a regression of forecast errors on past information X_{t-3}, which states that γ being statistically different from zero means information available at $t-3$ predicts future forecast errors, implying that they are not fully utilized when the forecasts are made. We provide additional results of such tests in the Appendix A.3.

	JF	JF LowEdu	JF MidEdu	JF HighEdu	JS	JS LowEdu	JS MidEdu	JS HighEdu
Constant	-0.027***	-0.027***	-0.038***	-0.024***	0.003*	0.076***	0.079***	0.051***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.002)	(0.009)	(0.010)	(0.009)
lag_FE_jf	0.256***	0.545***	0.272***	0.183**				
	(0.087)	(0.076)	(0.084)	(0.088)				
lag_FE_js					0.131	0.202**	0.267***	0.554***
					(0.091)	(0.089)	(0.088)	(0.075)
Observations	121	124	124	124	121	124	124	124
R^2	0.068	0.295	0.079	0.034	0.017	0.040	0.070	0.308
Adjusted R^2	0.060	0.289	0.071	0.026	0.009	0.032	0.062	0.302
F Statistic	8.628***	51.049***	10.452***	4.297**	2.062	5.103**	9.197***	54.322***

*p<0.1; **p<0.05; ***p<0.01

Table 2-I. Forecast Error Regression

The table reports the auto-regression results of average and various education groups' respective average forecast errors of expectations of job finding and separation rate with their respective 3-month-lagged values, as defined in Equation 2.2.

These estimates of auto-correlation of non-overlapping forecast errors suggest the presence of information rigidity in perceived job transition risks. However, the fact that the estimates are not close to one indicates that the information rigidity is moderate. This is particularly the case if the shocks to job finding and separation are relatively persistent, which means that only a mild degree of information rigidity sufficiently leads to non-zero auto-correlation of forecast errors.

Besides a non-zero serial correlation of forecast errors, as revealed in estimated β, it is worth noting that the constant term α in the auto-regression is also informative. Under FIRE, a positive (negative) α indicates an upward (downward) bias in the average forecasts. Its estimates in Table 2-I are significantly different from zero. Forecast errors of job-finding perceptions are on average positive and that of job separation is negative. At face value, this implies that ex-ante perceptions of job risks underestimates the job finding, and overforecasts the job separation rates. Although it is tempting to conclude that job risk perceptions are biased based on such evidence, as argued in several papers, we only focus in this paper on the dynamic rigidity of risk perceptions instead of its constant bias in levels with a cautionary note that the sign of the latter is sensitive to the exact procedure of aggregation of individual beliefs.[11]

2.3 Measuring subjective versus objective risks

2.3.1 Proxy of objective job risks using real-time machine-learning

In the previous section, we directly compare perceived risks with the ex-post realization of job transitions. We reject the perfect foresight assumption, as ex-ante perceived risks differ from realized job flow rates. However, this gap cannot be fully interpreted as a deviation from a full-information-rational-expectations benchmark from an ex-ante point of view. Even if perceived job risks are fully rational ex-ante, conditional on real-time economic conditions, newly realized shocks due to changes in the macroeconomy may still induce a gap between them. We would need a proxy for true ex-ante job risks to characterize the deviations of perceived job risks from a FIRE benchmark.

We adopt the methodology of Bianchi et al. [2022] to use machine-learning efficient forecasts of labor market transition rates to proxy the true ex-ante job transition risks. Specifically, for each month t in our historical sample, we use a Lasso model to select the set of variables that makes the best in-sample prediction of realized flow rates over a 10-year window up to t, as defined in Equation 2.3. Note that the coefficients are time-specific due to the real-time nature of this estimation procedure, i.e., the prediction model is estimated using only historical information up to time t.

$$\begin{aligned} JF_{t+3|t} &= \beta_0^t + \sum_{i=1}^{p} \beta_i^t X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\beta_i^t| \leq \lambda. \end{aligned} \tag{2.3}$$

Next, we generate a 3-month-ahead out-of-sample predicted value, $\widehat{\mathrm{JF}}^*_{t+3|t}$, based on the optimally chosen coefficient estimates, β^{t*}, obtained through k-fold cross-validation.

[11] Arni [2013], Conlon et al. [2018], Mueller et al. [2021], based on a comparison of average survey perceptions and realization, concluded that workers over perceive job finding probability. Meanwhile, Stephens Jr [2004], Dickerson and Green [2012], Balleer et al. [2023] found that workers overperceive job separation probabilities relative to their realizations.

(Equation 2.4)

$$\widehat{JF}^{*}_{t+3|t} = \beta_0^{*t} + \sum_{i=1}^{p} \beta_i^{*t} X_{t,i} \tag{2.4}$$

Approximately 600 time series are considered as candidate predictors of job flow rates. They include not only real-time macroeconomic variables but also forward-looking expectations of households and professional forecasts. Specifically, the following categories of predictors are included:

- Real-time macroeconomic data, such as inflation, unemployment rate, GDP growth, etc. We ensure that these series are real-time data rather than retrospectively revised figures.

- Household expectations from the Michigan Survey of Consumers (MSC).[12] We use disaggregated indices instead of composite indices in the survey. These indices contain rich information on how average households perceive the macroeconomy and their personal finances. Notably, we include survey questions that elicit respondents' recent exposure to macroeconomic news, their intentions to purchase durable goods, and the reasoning behind their reported expectations (e.g., "it is not a good time to buy a car because the price is too high.").[13]

- Realized job-finding and separation rates calculated from the Current Population Survey (CPS) [Fujita and Ramey, 2009]. Given the persistence of flow rates, recent job flow realizations may serve as strong predictors of future transitions.

- Consensus professional forecasts of the macroeconomy from the Survey of Professional Forecasters (SPF). Even professional forecasters have often been shown to deviate from the FIRE benchmark due to information rigidity and overreaction [Coibion and Gorodnichenko, 2015, Bordalo et al., 2020, Bianchi et al., 2022]. Nonetheless, professional

[12] Codebook: `https://data.sca.isr.umich.edu/subset/codebook.php`.

[13] Survey questions that ask about not only "what" but also "why" contain useful information in understanding household expectations [Colarieti et al., 2024, Haaland et al., 2024].

forecasts' views reflect one of the most sophisticated and informed perspectives on the macroeconomy in real time. Indeed, Carroll [2003] treats professional forecasts as a proxy for real-time rational forecasts. Here, however, we do not make such an assumption, instead recognizing their potential, as part of the broader real-time information set.

In theory, there is no restriction to what series we can use as long as it was measured in real time and could have been, in principle, in the information set of agents making forecasts standing at t. In practice, we cannot exhaustively account for all potentially relevant real-time information. However, given the extensive coverage of our selected series, they collectively serve as a reasonable proxy for the hypothetical complete real-time information set.

One particularly important input in real-time forecasting is the directly reported perceived job risks. A large body of literature has shown that individuals have advance information, or superior information, about their future job changes which economists bystanders might have otherwise attributed to unexpected shocks [Hendren, 2017]. Using average perceived risks is therefore meant to take care of this fact. If household expectations indeed predict subsequent labor market transition rates, as shown in the previous section, our machine-learning model would identify them as useful predictors.

In practice, however, we cannot always rely on perceived risks by households, as such data have only been available in SCE since 2013. Instead, we indirectly include all time series on household expectations in MSC, assuming that perceived job risks are ultimately correlated with other household expectations. Alternatively, we also explicitly impute perceived risks using such an assumption in Section 2.3.2. Both approaches yield similar results.

2.3.1.0.1 Real-time job risks. The real-time machine-efficient prediction of job transition rates is plotted in Figure 2-3 against the realized job transition rates. Each point on the real-time forecast risk line corresponds to a forecast generated using only the information up to that point in time, based on a selected set of predictors with the optimally chosen penalization to prevent overfitting. Overall, the machine-efficient forecasts predict subsequent labor market movements with high accuracy, with the notable exception of major recessions, particularly the COVID-19 crisis in the first quarter of 2020.

This suggests that near-horizon labor market flow rates are highly predictable as long as all the relevant information is used, especially during normal times. When it comes to sudden crisis episodes such as the COVID pandemic outbreak, machine-efficient forecasts fail to anticipate the resulting labor market disruptions, consistent with the unexpected nature of such events. Nonetheless, once the initial shock unfolds, the machine-efficient forecasts are able to predict the subsequent changes in job flows with reasonable accuracy.

Figure 2-4 highlights the importance of using real-time forecasts without relying on hindsight. In most of the sample periods, the machine-efficient real-time forecasts of job-finding and separation rates exhibit non-zero forecast errors, implying even the rational ex-ante job risks would not have perfectly anticipated the subsequent realization of macro flow rates. In contrast, one-shot retrospective machine-learning forecasts, by which we mean the forecasts made based on the hindsight of the entire sample period, produce a forecast of job transition rates that have on average zero forecast errors. This was essentially due to overfitting to latter realizations of the history. This suggests that compared to a well-informed benchmark of ex-ante risks, unexpected shocks to realized job flow rates inevitably occur.

2.3.1.0.2 What predicts labor flows? One of the commonly selected predictors in real-time forecasting is the unemployment rate. A higher current unemployment rate predicts a higher separation rate and a lower job-finding rate. This is not surprising, as the unemployment rate reflects the overall state of the labor market and impacts the subsequent transition rates.

In addition, many forward-looking variables in MSC consistently predict future labor market outcomes. The fact that many expectational variables can predict labor transitions suggests that households possess meaningful forward-looking views on job risks. It is worth noting that such predictability should not be interpreted as causal. We take it as evidence

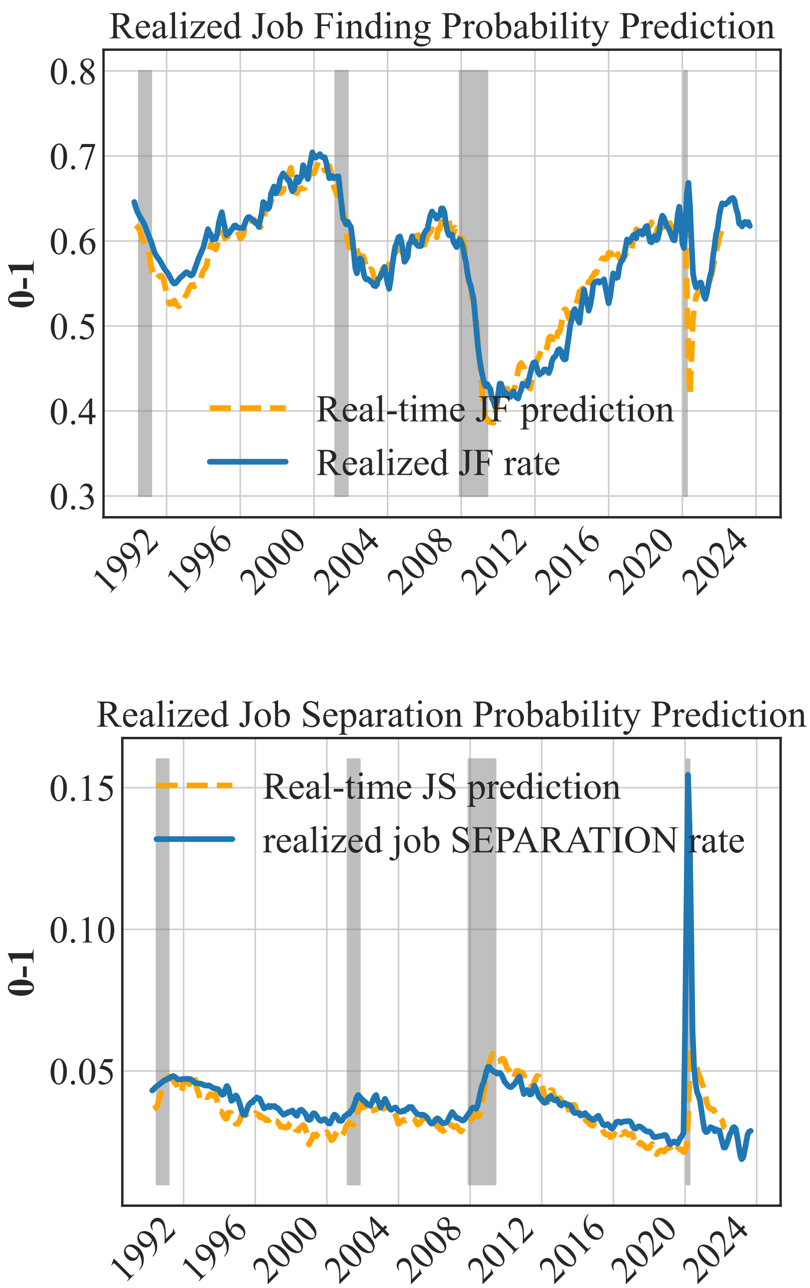


Figure 2-3. Machine prediction of labor market outcomes

3-mouth-ahead job risks generated from real-time machine-learning forecasts using real-time data for each 10-year rolling window (in scale of 0-100).

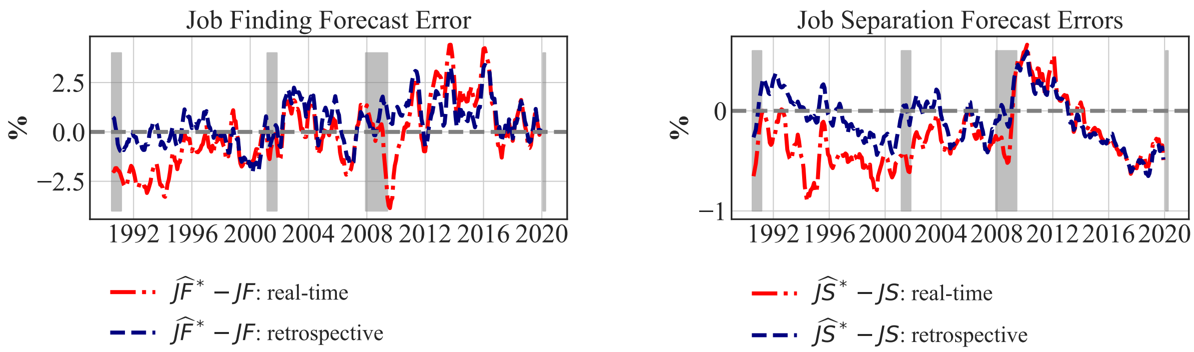


Figure 2-4. Forecast errors of real-time versus retrospective job risks

This figure compares the forecast errors of the machine-learning predictions of job finding and separation rates generated by two different approaches: real-time versus retrospective forecasting. All rates are in the units of percent chance.

that information available ex-ante and predictable for macroeconomic outcomes is indeed incorporated into households' expectations about their future employment prospects.

In particular, three types of household expectations commonly show up in the Lasso model selections. The first set of variables directly relates to the self-reported exposure to labor market news. In particular, we find that when households report having heard favorable (unfavorable) news about the labor market, it predicts subsequent increases (decreases) in job finding and decreases (increases) in job separation. The second group of expectational variables is broadly about future personal finance and its recent realizations. The third set of predictors that are constantly selected across real-time forecasting samples is forward-looking actions by households, the most notable of which is the durable goods purchase intentions. Several papers [Carroll and Dunn, 1997, Harmenberg and Öberg, 2021] have empirically established the negative relationship between job risk and the propensity to purchase durable goods, consistent with structural models predicting that costly adjustments in durable goods are highly sensitive to income uncertainty, due to both precautionary saving motives and "wait-and-see" mechanisms. Therefore, the correlation between intentions of future durable purchasing and subsequent labor market movements is likely driven by their respective correlation with ex-ante perceived job risks. In addition, durable goods demand plays a crucial role in aggregate fluctuations through general-equilibrium forces, as shown in McKay and Wieland [2021].Interestingly, survey questions that directly elicit rationales by households on their expectations, such as "not buying a durable due to high uncertainty", also help predict future job transition rates. This confirms the finding by Leduc and Liu [2016] also based on the uncertainty question elicited in the MSC.

2.3.1.0.3 Comparing Machine-Learning Forecasts with Simple Time Series Models. Are these predictions as good as simply one univariate time series prediction? Given the persistence and time-series correlation of flow rates, the answer is not necessarily yes. We therefore compare the mean squared errors (MSE) of real-time forecasts using all datasets with a real-time forecast that is only using an AR(1) model. We show that the Lasso prediction based on a large time series dataset slightly outperforms the AR(1) model in terms of MSEs. Figure II-1 in the Appendix compares the risk forecast based on Lasso and AR(1). In most of the sample period, the two track each other quite well. The most noticeable divergence occurred during the pandemic where AR(1) forecast overforecast job separations due to the historical persistence of separation rate while Lasso model-based separation risk is predicted to have a more temporary reversal following the initial dramatic spike.

2.3.2 Backcasting perceptions: what were people thinking then?

Directly observed perceived risks have only been available in SCE since 2013. Meanwhile, a wide range of expectations have been surveyed in MSC for a much longer time span, some of which go back to as early as the 1960s. Under the assumption that the correlations between different expectations have been stable[14], we can utilize the estimated correlation between perceived job risks in SCE and other expectations in MSC in the overlapping sample period to impute the out-of-sample perceived risks back in earlier history. We use a Lasso model to

[14]We reject the null hypothesis of a structural break based on the test by Andrews [1993].

select among many contemporaneous variables that best predict the measured perceived job risks, as specified below.

$$\begin{aligned} \widetilde{\mathrm{JF}}_{t+3|t} &= \gamma_0^t + \sum_{i=1}^{p} \gamma_i^t X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\gamma_i^t| \leq \lambda. \end{aligned} \tag{2.5}$$

where $\widetilde{JF}_t$ is the average 3-month job-finding expectations at month t. The regressor vector X_t includes both EXP_t, a vector of contemporaneous belief variables, and REAL_t, a vector of real-time macro aggregates. The reason why we also include real-time aggregate realizations, not just expectational variables, is that in theory, this information may have been in the information set of the agents forming expectations. We again use cross-validation to determine the optimal degree of regularization of the Lasso model and obtain the optimal model coefficients of the selected list of predictors, we denote as $\gamma_i^{*t} \forall i = 1, 2...p$.

We externally validate our imputation methodology utilizing the fact that the expectations about 1-year-ahead inflation, and 5-year horizon job separation probability are measured in MSC for a much longer period. Figure II-2 in the Appendix suggests that the imputation based on only 2013-2022 in-sample can generate out-of-sample backcasts of these two expectations that almost mimic the observed data by a correlation of 80%-99%. [15]

What are the most important covariates of the perceived risks? It turns out that numerous expectation variables in MSC, such as durable purchase, news heard about economic conditions, recent experience, and future expectations of personal finance. In Figure II-6 in the Appendix, we list the top predictors of perceived finding and separation rates, respectively. The directions of these correlations all have sensible and intuitive interpretations.

In addition to expectations, real-time macroeconomic realizations are also found to be important covariates of perceived job risks. In particular, the recent unemployment rate

[15] Figure II-3 further validates that the imputed unemployment rate expectation in SCE almost perfectly correlates with the unemployment rate expectation index in MSC, although the two are not measured in the same way. This suggests that even across the two surveys the imputation methods yield valid backcasts of beliefs.

stands out as the most important variable that comoves with the contemporaneous perceived separation rate. The role of inflation and inflation expectations also deserves a special discussion. For instance, a higher recent realization of inflation is positively associated with a higher perceived separation rate. Meanwhile, higher inflation expectations, as measured by the share of those who expect higher inflation above 15%, are also associated with lower job finding perceptions. The positive association of inflation (and inflation expectations) with job risks is consistent with the finding by Hou and Wang [2024].

Figure 2-5 plots the in-sample and out-of-sample imputation model fit from the optimal Lasso model selected from such a procedure. One of the advantages of a Lasso model is that it optimally penalizes the over-fitting in the sample, as indicated by the difference between the in-sample prediction of the belief and the actual belief. We favor this approach over traditionally used linear models such as OLS because of our primary focus on achieving a great prediction of the beliefs even out of the sample. The backcast of perceived risks before 2013 exhibits reasonable cyclical movements. Throughout most of the five recessions since the 1980s, the imputed perceived job finding rate dropped significantly compared to normal times, and the perceived job separation rate significantly increased.

With the imputed belief, we confirm the findings in Section 2.2.2 based on directly observed beliefs that job findings perceptions predict job finding outcomes quite well, while the job separation expectations are much less predictive of realized outcomes. The imputed belief on job finding and separation have a correlation coefficient of 0.81 and 0.16, respectively, with their realization 3 months later.

Our benchmark imputation in-sample includes the 2013-2022 period, which witnessed drastic movements in the labor markets. In Appendix A.2.3, we examine if the choice of including the Covid era has significant impacts on the dynamics of the imputed beliefs. In particular, we show that the belief imputation based on pre-Covid sample would have implied a much more dramatic drop in the job-finding perceptions than the actual perceptions observed in SCE during this period, and the imputed job-separation perceptions turned out to be overly optimistic than the actual perceptions. Since our final goal in this exercise is to produce the best backcast of the belief to an earlier period in which such beliefs are not observed, we decide to maximize the in-sample size to include the variations in beliefs during this period, despite its possible peculiarity.

2.4 Perceived versus "true" risk

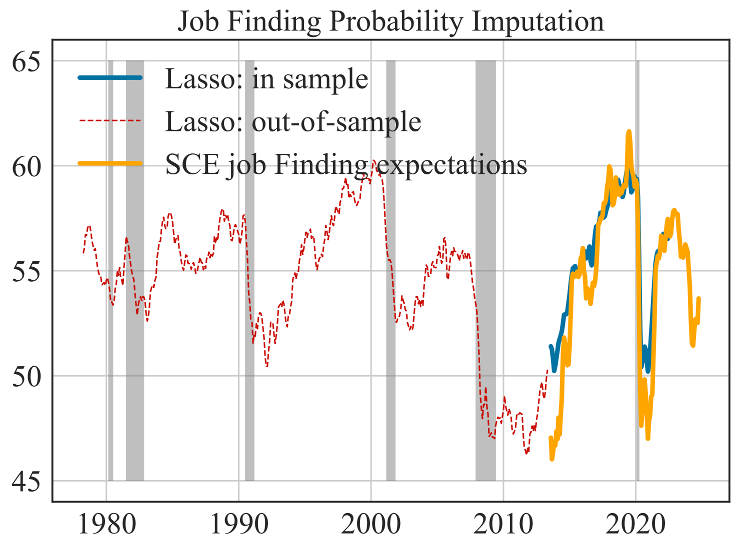
With the true risk proxy from the real-time machine-learning forecasting, denoted as $\widehat{JF}^*$ and $\widehat{JS}^*$, respectively, we can directly estimate the degree of belief distortion, namely the extent to which perceived job risks $\widetilde{JF}$ and $\widetilde{JS}$ deviate from rational ex-ante job risks. In particular, we regress $\widetilde{JF}$ and $\widetilde{JS}$ on the machine-efficient risk forecasts, $\widehat{JF}^*$ and $\widehat{JS}^*$, respectively. We use the log values in both sides of the equation so that the coefficient can be interpreted as the elasticity of beliefs with respect to changes in real-time risk. A coefficient of unity corresponds to the situation where perceived job risks fully react to real-time rational risk, e.g. no under/overreactions.

For each one percentage point increase in real-time job-finding forecast, the average perceived job-finding rate increases by 0.5 percentage points. This suggests that perceived job finding follows real-time job finding rate forecasts relatively well. But a coefficient of only half is still indicative of underreaction in job finding expectations. Figure 2-6 plots the perceived risk, real-time machine-efficient risk forecasts, and ex-post transition rates.

$$\log(\widetilde{JF}_{t+3|t}) = 1.92 + \mathbf{0.51} \log(\widehat{JF}^*_{t+3|t}) + \epsilon_t \tag{2.6}$$

Perceived job-separation probabilities are less correlated with the real-time risk, with a regression coefficient $\widehat{JS}^*_{t+3|t}$ being 0.31, implying a one-third percentage point increase in response to each one percentage point increase in machine forecasts. Perceived job separation fails to incorporate about 80% of the predictable job separation transitions.

In addition, similar to perceived job finding, the constant term of the regression is positive,



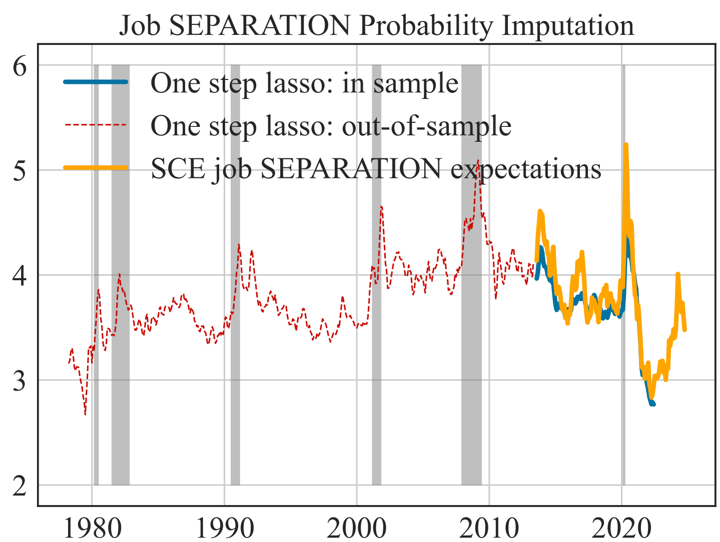


Figure 2-5. Imputed Perceived Job Risks

the two charts plot imputed perceived job risks (in scale of 0-100) that are predicted using the selected Lasso model based on in-sample cross-validation.

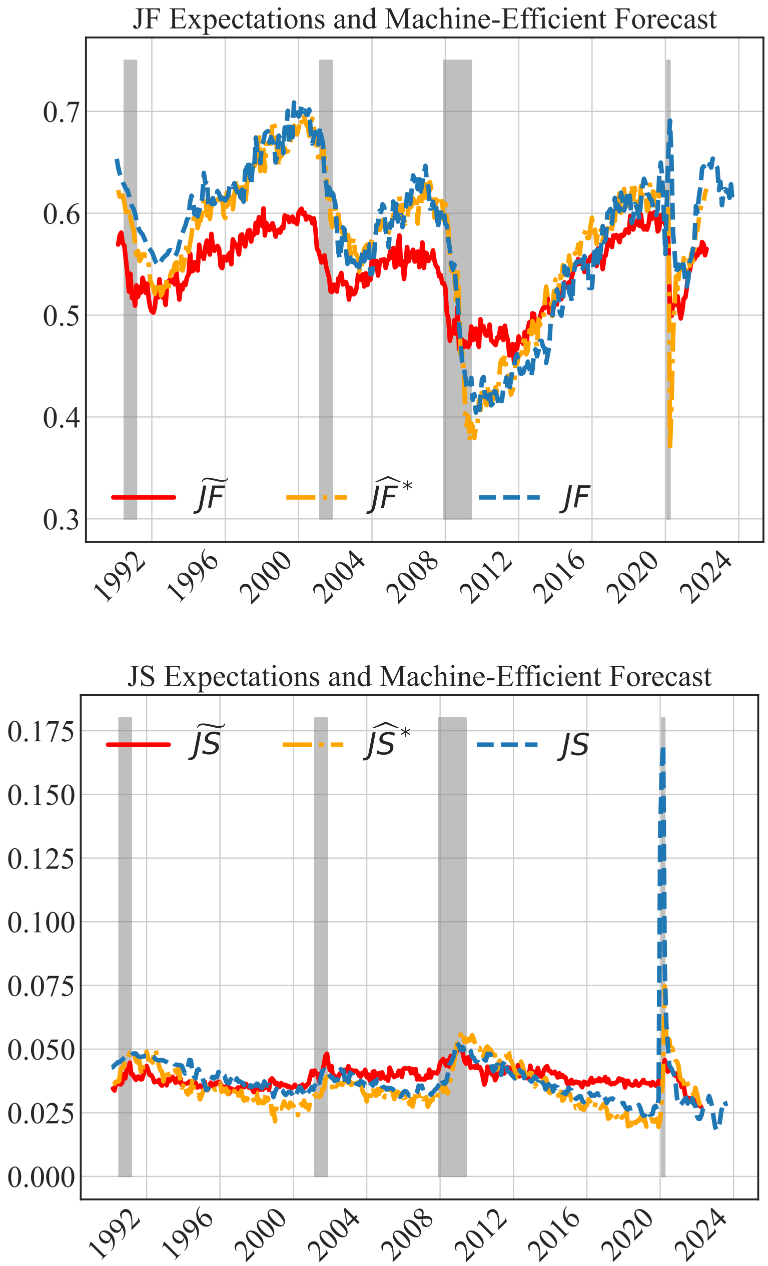


Figure 2-6. Survey perceived job risks versus machine-efficient risk forecasts (0-1)

the charts plot (in the scale of 0-1) perceived job risk, real-time machine-efficient forecast, and realized job flow rates.

implying on average an upward bias in the perceived job separation rate.

$$\log(\widetilde{JS}_{t+3|t}) = 1.13 + \mathbf{0.19}\log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \tag{2.7}$$

2.4.1 Information rigidity in job beliefs

The tests presented in the previous section using forecast errors reject the null of FIRE and imply information rigidity, but it does not give us an exact degree of information rigidity that can be used to generate quantitative model implications. To do so, we follow a large body of literature to specify a widely used model of expectation formation capturing information rigidity: Sticky Expectations (SE).[16]

Sticky Expectation posits a very tractable mechanism of underreaction mechanism of beliefs in the population average. In particular, in each period, each agent learns about the most up-to-date information regarding the aggregate economy (the true underlying real-time job-finding probability) at a constant and time-independent rate of λ. Therefore, the average belief under SE mechanism follows a recursive formula as below.

$$\widetilde{JF}_{t+3|t} = (1-\lambda)\widetilde{JF}_{t+3|t-1} + \lambda JF^{*}_{t+3|t} \tag{2.8}$$

The intuition behind this equation is that the average expectation depends on both the average expectation of the $(1-\lambda)$ fraction of agents who did not update at time t and the FIRE expectation of the λ fraction of updated agents. In the special case of full-updating, $\lambda = 1$, the above equation collapses into the FIRE case.[17]

Our estimated Equation 2.6 and Equation 2.7 can be almost squarely interpreted within

[16] Mankiw and Reis [2002], Carroll [2003], and Coibion and Gorodnichenko [2015].

[17] A number of studies have estimated the updating rate λ to be significantly lower than one, based on survey expectations of inflation, unemployment and other macroeconomic variables, e.g. Mankiw and Reis [2002], Carroll [2003], Coibion and Gorodnichenko [2012], etc. In the literature, such information rigidity can be also microfounded by another class of models, namely the noisy information, where agents learn about the true state of the world via noisy public and private signals. Like SE, it generates a serial correlation of forecast errors as shown at the beginning of the paper, but it does not exactly have a prediction as in Equation 2.8.

the SE framework. In particular, the updating rate of job-finding expectations is about $\widehat{\lambda}^{JF} = 0.51$ and $\widehat{\lambda}^{JS} = 0.19$ for job separations. Both are significantly different from unity, rejecting the null hypothesis of perfect updating.

When the lagged perceived job risks are controlled in the same regression, the coefficient remains in a similar range. In addition to the true real-time risks, we also control past information such as the realized job finding and separation flow rates or aggregate economic variables. The estimated rigidity does not vary much.

Although the information rigidity as formulated by SE model fits the correlation between perceived job risks and true real-time risks well, there remains the big gap between the SE-model-implied time series of perceived job risks $\widetilde{JF}^{SE}$ versus the observed perceived job risks $\widetilde{JF}$ as plotted in Figure 2-7 where we plug in the estimated $\hat{\lambda}^{JF}$ and $\hat{\lambda}^{JS}$ into the Equation 2.8. The perceived job risk sequences more or less center around the true real-time risks, with mild deviations. It shows less time-variations, which does capture the underreaction of perceptions to real-time conditions.

2.4.2 Heterogeneity in job risks

Our analysis so far assumes homogeneous job risks, which means that the perceived job risks by different workers are supposed to react to the true aggregate risk by the same degree in the absence of belief distortion. But in reality, job risks are widely heterogeneous across workers Hall and Kudlyak [2019], Ahn and Hamilton [2020], Gregory et al. [2021]. So are the perceived risks, as shown in Mueller et al. [2021], Wang [2023]. Guvenen et al. [2014] shows that heightened income risks during recessions can be in part predicted by observable factors measured prior to recessions. Patterson [2023] shows that the positive correlation between workers' marginal propensity to consume (MPCs) and the cyclicality of their income amplifies recessions compared to a world with equal income exposure. A similar argument can be made in the space of job risks. We therefore consider it to be important to study ex-ante heterogeneity in job risks. Unlike the common countercyclical risks that drive time-varying

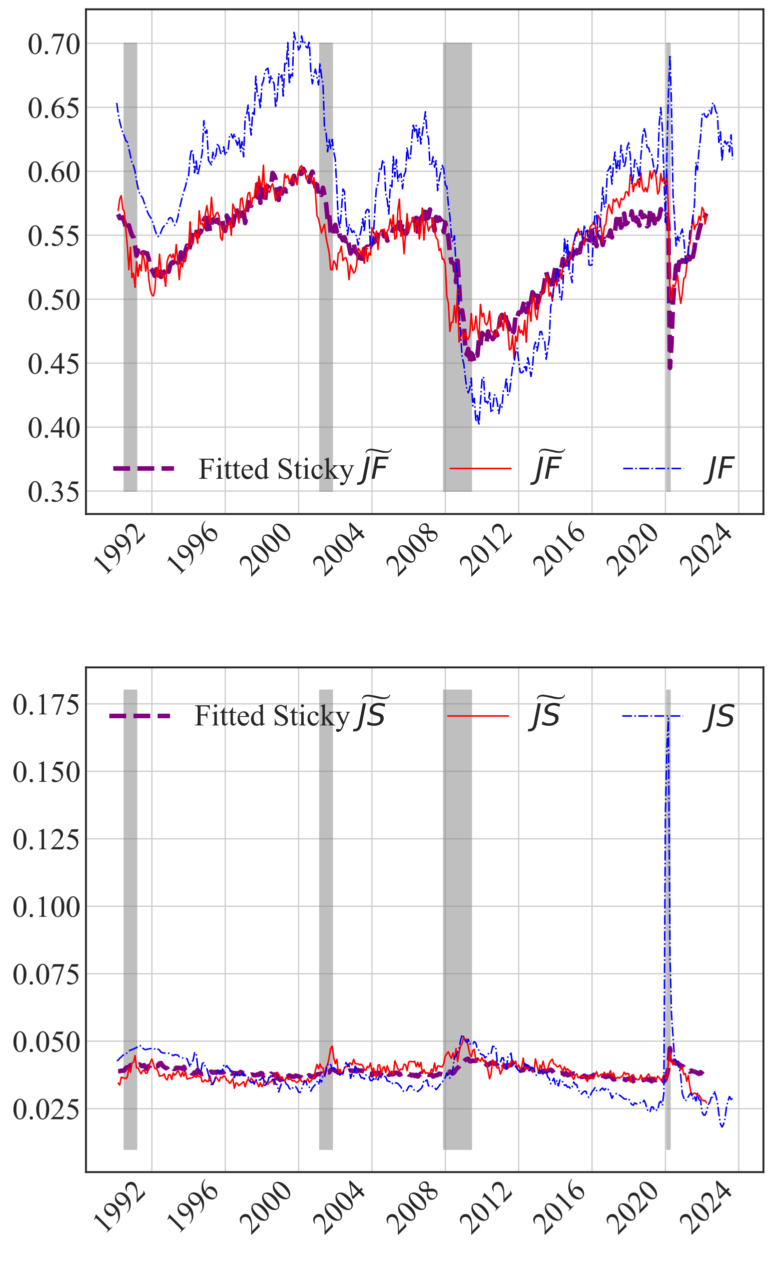


Figure 2-7. The Estimated Sticky Expectation Model of Perceived Job Risks (0-1)

the figures plot the perceived job risk ($\widetilde{JF}$ and $\widetilde{JS}$) versus their fitted value based on the estimation of Equation 2.6 and 2.7, in addition to the realized job transition rates (JF and JS.), respectively. All rates are on a scale of 0-1.

fluctuations, the presence of risk heterogeneity causes business cycle fluctuations via its heterogeneous incidences.

Meanwhile, the fact that workers face different degrees of job risks is naturally another important reason for why average perceptions underreact to the real-time conditions. To see this point clearly, assume an individual worker i's JF has an idiosyncratic loading $\eta_{i,t}$ from the aggregate job finding rate JF_t. (Equation 2.9). Where each individual i has their respective expectations of their own heterogeneous risk $\widetilde{JF}_{i,t}$. We further make the assumption that people know perfectly about their heterogeneous factor $\eta_{i,t}$, which makes the last equality hold in the second line of the Equation 2.9.

$$\begin{aligned} \mathrm{JF}_{i,t} &= \eta_{i,t}\mathrm{JF}_t \\ \widetilde{\mathrm{JF}}_{i,t} &= \mathbb{E}_i(\mathrm{JF}_{i,t}) = \mathbb{E}_i(\eta_{i,t}\mathrm{JF}_t) = \eta_{i,t}\mathbb{E}_i(\mathrm{JF}_t) \end{aligned} \tag{2.9}$$

If the following equation holds, namely if average perceived job risks across agents converge to the aggregate job risks JF_t depends on at least two factors. The first is the cross-sectional distribution of $\eta_{i,t}$. The second is the expectation patterns of individuals toward aggregate job risk. Even if all workers correctly perceive JF_t, which implies $\mathbb{E}_i(\mathrm{JF}_{i,t}) = JF_t \forall i$, the heterogeneity in job risks still matter for the behaviors of average perceived job risk.

$$\widetilde{JF}_t = \frac{\sum \mathbb{E}_i(\mathrm{JF}_{i,t})}{N} = \frac{\sum \eta_{i,t}}{N} JF_t \overset{?}{=} \mathrm{JF}_t \tag{2.10}$$

Such an aggregation through the distributional effects of aggregate job risk on individual workers, even in the absence of belief distortion, would also potentially imply a wedge between average perception and true aggregate risk. Imagine the shocks to JF_t are highly persistent while the idiosyncratic loadings $\eta_{i,t}$ are entirely transitory and agents perceive these components correctly. That would imply that the average perceived risks $\widetilde{JF}_t$ are less responsive to aggregate risks JF_t by a degree less than unity.

The importance of heterogeneity in job risks in understanding perceived job risks is emphasized by Mueller et al. [2021]. They show that both ex-ante heterogeneity and underreaction to variations in job-finding rate *across workers* and *over unemployment spells* are important to explain the patterns of job-finding perceptions. To the extent that such beliefs induce self-insurance behaviors through job search, underreaction to the heterogeneity and duration-dependent variations results in a larger dispersion in job-finding outcomes. What this paper has shown so far is essentially that such underreaction to variations in job risks also exists along the variations of job risks over business cycles at the aggregate level.

To formally shed light on the role of heterogeneity, we estimate the belief-distortion regression for different percentiles of the perceived job risks. The key assumption is that at any point in the business cycle, workers face different degrees of job risks and are affected by the same aggregate conditions unevenly.

In particular, instead of the mean perceived job risks in the survey as in Equation 2.6, we regress the q-th percentile perceived job risks $\widetilde{JF}^q$ and $\widetilde{JS}^q$ $\forall q = \{25, 50, 75\}$ (Equation 2.11) on the same aggregate common real-time risk measure. By doing so, we are asking a very intuitive question: whose expectations are the most reactive to the change in real-time risks?

$$
\begin{aligned}
\log(\widetilde{JF}^{0.25}_{t+3|t}) &= -1.55 + \mathbf{1.22} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{0.5}_{t+3|t}) &= 1.54 + \mathbf{0.63} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{0.75}_{t+3|t}) &= 3.62 + \mathbf{0.20} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t
\end{aligned}
\tag{2.11}
$$

The job-finding perceptions of the 25 percentile worker in terms of their perceptions react to the real-time job-finding rate by a much larger degree than the rest, as implied by the coefficient estimates of 1.22 for this group, as opposed to a 0.63 for the median worker and 0.20 for the worker at the 75 percentile. To put it bluntly, those who usually believe that they cannot easily find a job are the marginal workers whose belief reacts to the real-time job-finding rate the most. A higher-than-one elasticity of beliefs suggests that the beliefs are overreactive to the market finding conditions.

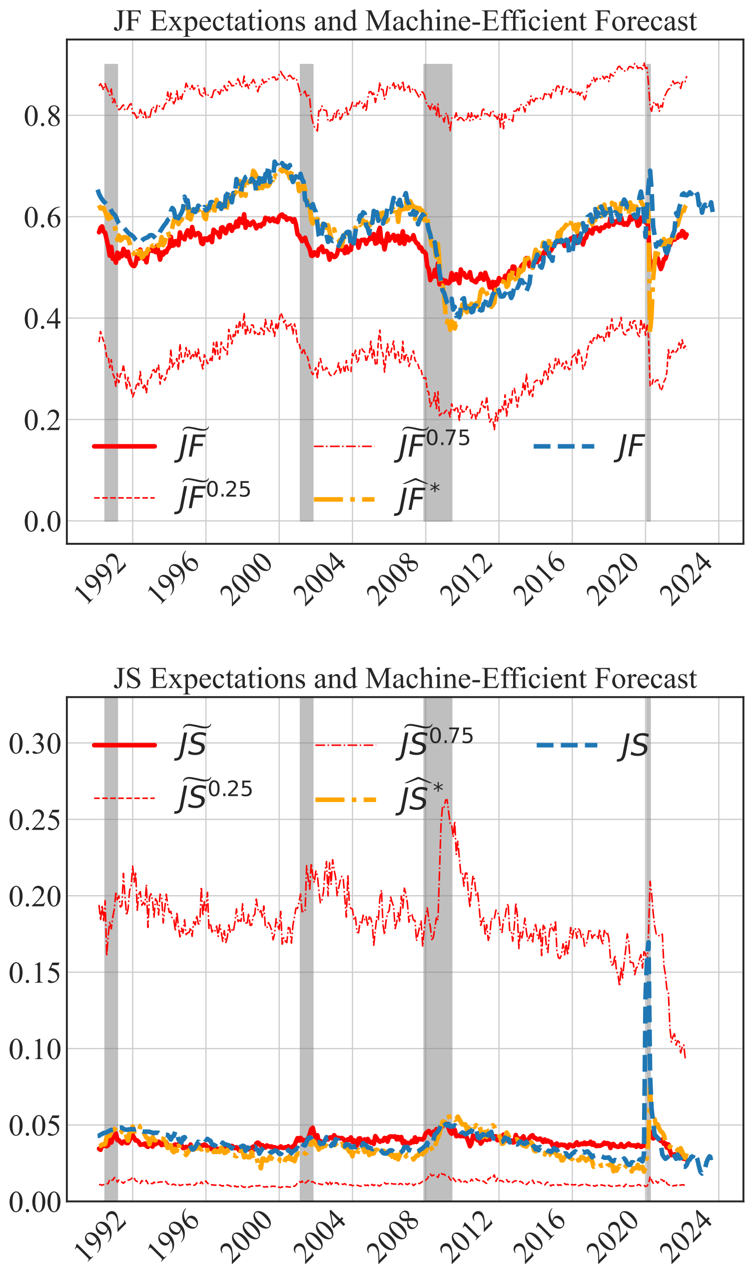
$$
\begin{aligned}
\log(\widetilde{JS}^{0.25}_{t+3|t}) &= -0.42 + \mathbf{0.46}\log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{0.5}_{t+3|t}) &= 1.06 + \mathbf{0.68}\log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{0.75}_{t+3|t}) &= 2.57 + \mathbf{0.27}\log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t
\end{aligned}
\tag{2.12}
$$

In terms of job separation, it is the median-risk workers that have the most sensitive reactions to aggregate real-time job separation rate. The estimates of responses range from 0.46 for 25 percentile workers (almost non-reaction) to 0.68 and 0.27 for the median and 75 percentile workers, respectively.

Taken all together, these estimates suggest conditional on individual heterogeneity in risk exposures, the information rigidity is not as severe as the average perceived job risks. Both overreaction and underreaction in perceptions exist, depending on where the worker is located in the distribution of heterogeneous job risks.

The heterogeneous sensitivities of perceptions with respect to common aggregate risk are probably sensible. In particular, the perceptions of those who perceive high job risks (high separation and low finding risk perceptions) show the highest sensitivity. Business cycles are not just characterized by the change in aggregate job risks, it is probably more accurately seen as a shift in the location of the marginal workers who face the job risks. For instance, in recessions, the marginal worker who faces job loss risk shifts downward from the top 10 percentile of perceived job risk to the 50th percentile. The sensitivity in perceptions helps reveal who is the marginal worker.

The idea that distributional expectations contain information about the aggregate economy also echoes a few papers that show distributional expectations of households/firms improve the predictions of subsequent aggregate outcomes. It is not always the average agent, but the *marginal* one, whose expectations matter for the macroeconomic outcomes, because the same aggregate shock has different footprints on heterogeneous agents in the economy.



Note: The figures plot the average and heterogeneous perceived job risks at different quantiles, real-time job risks, and realized job transition rates.

Figure 2-8. Survey perceived job risks versus machine-efficient risk forecasts by distribution (0-1)

2.4.3 Heterogeneous perceptions of job risks

Is there heterogeneity in terms of belief distortions in addition to the heterogeneity in true job risks faced by different workers? If the workers who face the most cyclical movements in job risks tend to underperceive such movements – therefore underinsure – total consumption fluctuations amplify due to the heterogeneous footprints of uninsured job risks.

We can shed light on this question along a few observable dimensions, such as education, relying upon the fact that we can create group-specific risk forecasts specifically for each education group, e.g. $\widehat{JF}^{HighEdu*}$,$\widehat{JF}^{MidEdu}$,$\widehat{JF}^{lowEdu*}$, respectively. Using group-specific risk forecasts admits the ex-ante heterogeneous risk exposures of different education groups.

The estimates are reported below. In terms of job finding, the middle-education group is the most rigid relative to their real-time risk than the low- and high-education workers. Meanwhile, with job separation, low-education workers underreact to the real-time risks the most, exhibiting the largest degree of information rigidity. Such patterns are consistent with the patterns in Figure 2-2 that different low-education groups underestimate the spike in job separation rate and more strongly react to the decline in job finding at the outbreak of the pandemic than the high-education group. Assuming a strong correlation between education and liquid wealth, Broer et al. [2021b] would predict a U-shaped pattern as poor and rich households have the highest incentives to know the current state of the world. Our results support such a claim for job finding, but contradict it for job separation rates. In fact, workers without a high school degree have the weakest reaction in beliefs to changes in realized job separation rates, even though they would have the largest utility penalties of non-optimal precautionary savings.

Despite the differences across workers, however, it is worth emphasizing that overall, all beliefs by all types of groups exhibit rigidity, with the coefficient always below 60 percent.

$$
\begin{aligned}
\log(\widetilde{JF}^{LowEdu}_{t+3|t}) &= 1.28 + \mathbf{0.66}\log(\widehat{JF}^{*LowEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{MidEdu}_{t+3|t}) &= 2.53 + \mathbf{0.36}\log(\widehat{JF}^{*MidEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{HighEdu}_{t+3|t}) &= 1.87 + \mathbf{0.53}\log(\widehat{JF}^{*HighEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{LowEdu}_{t+3|t}) &= 1.1 + \mathbf{0.17}\log(\widehat{JS}^{*LowEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{MidEdu}_{t+3|t}) &= 0.95 + \mathbf{0.35}\log(\widehat{JS}^{*MidEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{HighEdu}_{t+3|t}) &= 1.08 + \mathbf{0.33}\log(\widehat{JS}^{*HighEdu}_{t+3|t}) + \epsilon_t
\end{aligned}
\tag{2.13}
$$

2.5 Macro implications of perceived job risks

2.5.1 Shocks or risks?

In the previous sections, with the three measures in hand, namely (a) perceived risks, $\widetilde{JF}/\widetilde{JS}$, (b) objective risks $\widehat{JF}^*/\widehat{JS}^*$, and (c) realization of job flow rates JF/JS, we have established two major findings. The first is a rejection of perfect foresight, in that even ex-ante rational and fully informed forecasts of risks don't fully predict ex-post realizations. This is indicated by the gap between (b) and (c). The second is the deviation of ex-ante perceived job risks from its true ex-ante counterpart, at least partially due to information rigidity.

But do the distinctions between (a), (b), and (c) matter for aggregate fluctuations? We can assess empirically the relative importance of ex-ante precautionary saving motives resulting from perceived job risks (a), responses due to misperceived risk ((a)- (b)), and ex-post responses due to truly unexpected income shocks ((b)-(c)), by comparing the cyclical properties of (a), (b) and (c) across business cycles.

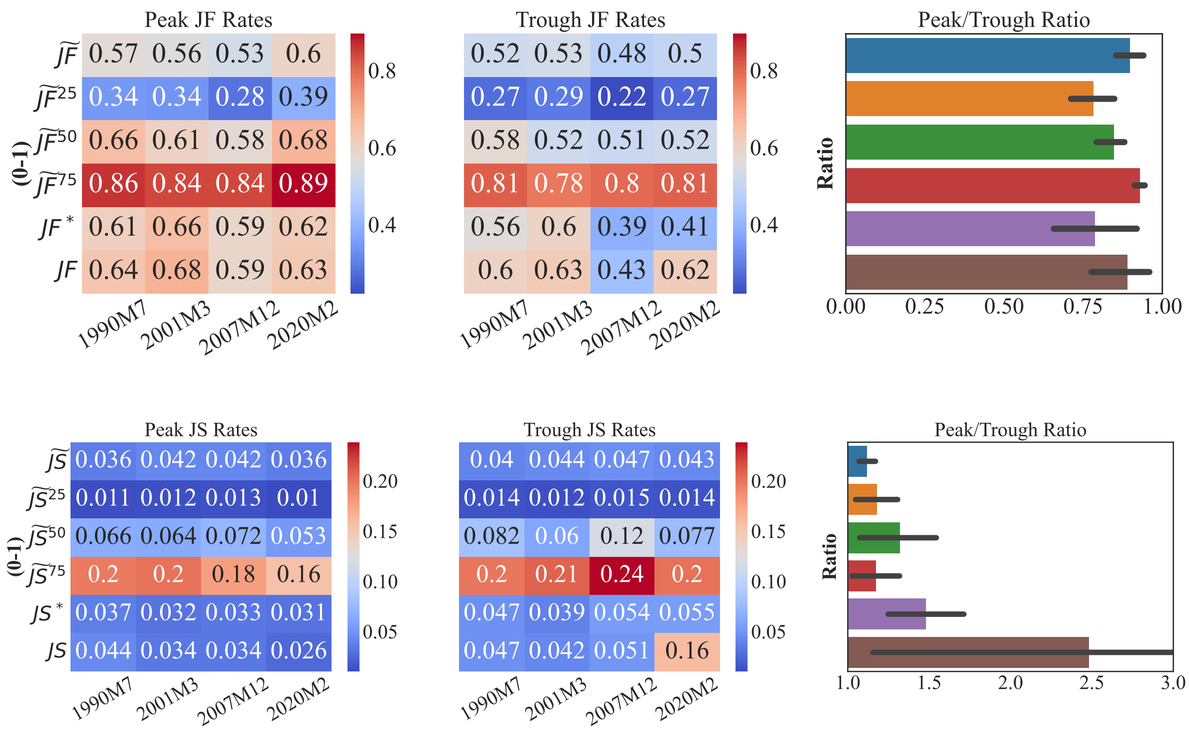
We use two sets of metrics to evaluate the relative importance of the three channels. The first one is the unconditional standard deviation of (a), (b), and (c). The second metric is the ratio between the onset and the end of each recession in our sample. More intuitively, they reflect the changes in these rates from the peak to the trough of each cycle.

Throughout our data sample 1990-2024 which covered four recessions and experienced sizable cyclical movements of unemployment risks, the unconditional standard deviation of realized job-finding rates is approximately 7.2 percentage points. Most of these variations are reflected in real-time finding probabilities, whose standard deviation was about 6.9 percentage points. In contrast to these cyclical movements of realized job finding rates, the perceived finding rates exhibit milder fluctuations and have a standard deviation of 4 percentage points. In the domain of job separation, the unconditional standard deviations of perceptions, risk forecast, and realizations are 1.0, 0.9, and 0.3 percentage points, respectively. Both finding and separation perceptions move significantly less than the realized job risks.

Such rankings of the relative volatility of perceptions and realizations also can be seen in Figure 2-9 which reports the peak and trough rates in each of the four recessions in the sample period. From the onset of each recession to its end month, the real-time job finding drops by 25%, while the perceptions of job finding only decrease by 15%.

Meanwhile, average job separation perceptions are much more sluggish than job finding expectations, which is again confirmed by on average a 16% increase from the start to the end of each recession, as opposed to a 50% average increase in job separation risk forecast and 150% in realized job separation rates. The increase in realized job separation rates remains high with the pandemic recession excluded, which was not reflected in the change in perceptions.

Such average patterns mask substantial heterogeneity in job risks and perceptions. Figure 2-9 also plots the movements of perceptions over business cycles by agents at different percentiles of perceived job risks. In terms of job-finding, although an average worker's perceived job finding probability drops by 15% from the peak to trough of a recession, more or less comparable to the realized job finding, it is the low-finding rate worker, at 25 percentile who perceive a much sharper drop by about 25%, compared to a drop of 10% for the worker at the 75th percentile. In terms of job separation, although an average worker's job loss perceptions only increase by 15 percentage points in recessions, the *median* worker's perceptions increased much more sharply by about 35 percentage points. Recessions hit



Note: The left tables report the perceived job risks, perceived job risks at different quantiles, real-time job risks, and realized job transition rates at the beginning and the end month of each one of the four recessions. The bar chart on the right plots the peak-to-trough ratios of these rates. The sample period is 1990-2024.

Figure 2-9. Business Cycle Patterns of Risks and Perceptions: Start versus End of Recessions agents in the economy unevenly in terms of their job risks. Such heterogeneity in perceptions reveals the uneven footprints of business cycle fluctuations via job risk changes. Heterogeneity in risk exposure implies different degrees of ex-ante precautionary saving behaviors and their consequent ex-post shock responses, a topic we turn to in the next section.

2.5.2 Quantifying the aggregate consumption impacts of unemployment risks

In this section, we show that the strength of the unemployment risk channel changes substantially when household beliefs are instead disciplined by survey data on workers' expectations of finding and losing a job instead of the realized counterparts of these probabilities. Furthermore, we demonstrate that the magnitude of this channel differs significantly across education groups.

To assess the extent to which consumption fluctuations are driven by precautionary behavior versus realized income losses from unemployment, we simulate the path of aggregate consumption dynamics by feeding our time series of perceived and objective unemployment risk, and our measures of observed (un)employment transition rates into a standard heterogeneous agent model with persistent unemployment.

The model is set to a monthly frequency. In the model, workers make a consumption-saving decision in the face of both idiosyncratic productivity shocks and stochastic transition between employment and unemployment. Transitions between (un)employment states are dictated by the job separation and job finding probability. Workers' perceptions of job finding and separation probabilities are distinct states, separate from the probabilities that govern their actual transitions between employment and unemployment. Self-insurance is achieved by saving money on a risk-free asset. Finally, during unemployment, households receive unemployment insurance. Figure 2-10 illustrates the timeline of the model. Details of the model specifications are found in Appendix A.5. The calibration of the model can be found in table III-IV.

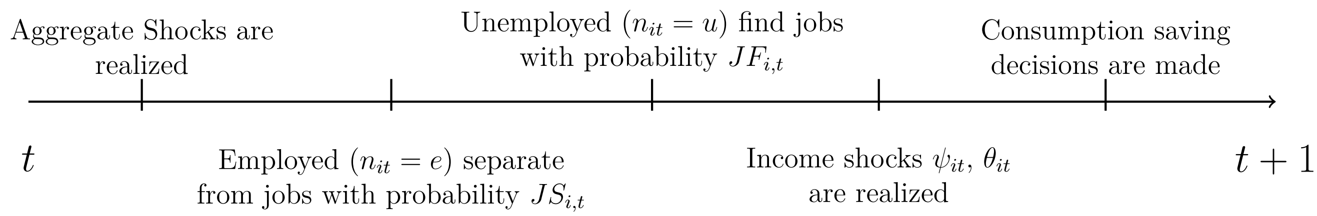


Figure 2-10. Timeline of the Model

Decomposition of consumption Jacobians

We first decompose the sequence space consumption Jacobians—following the approach of Auclert et al. [2021a]-with respect to job separation probability into a precautionary effect and an income effect stemming from changes in unemployment to highlight that a greater degree of aggregate precautionary saving dampens the income effect. Furthermore, we utilize these decomposed jacobians to simulate the path of aggregate consumption under different counterfactual.

Figure 2-11 illustrates the consumption response to an increase in the job separation probability at horizon $t + h$, with $h = 10$. The black line corresponds exactly to the 10^{th} column of the consumption Jacobian with respect to the job separation probability. The *ex-ante* component captures the anticipatory behavior reflected in the black line—that is, the self-insurance response of workers leading up to the increase in separation risk at $t = 10$, under the assumption that the risk itself does not actually materialize. In contrast, the *ex-post Jacobian* captures the consumption response to the realized increase in unemployment resulting from an actual rise in the separation probability, assuming workers do not anticipate this change.

Figure 2-12 illustrates how underreactive beliefs—as documented in survey expectations about both job finding and job loss probabilities—weaken the precautionary channel while amplifying the income loss channel associated with unemployment. The figure includes two additional consumption responses under the assumption of sticky belief updating. The purple line shows the *subjective* consumption response to an increase in the job separation probability

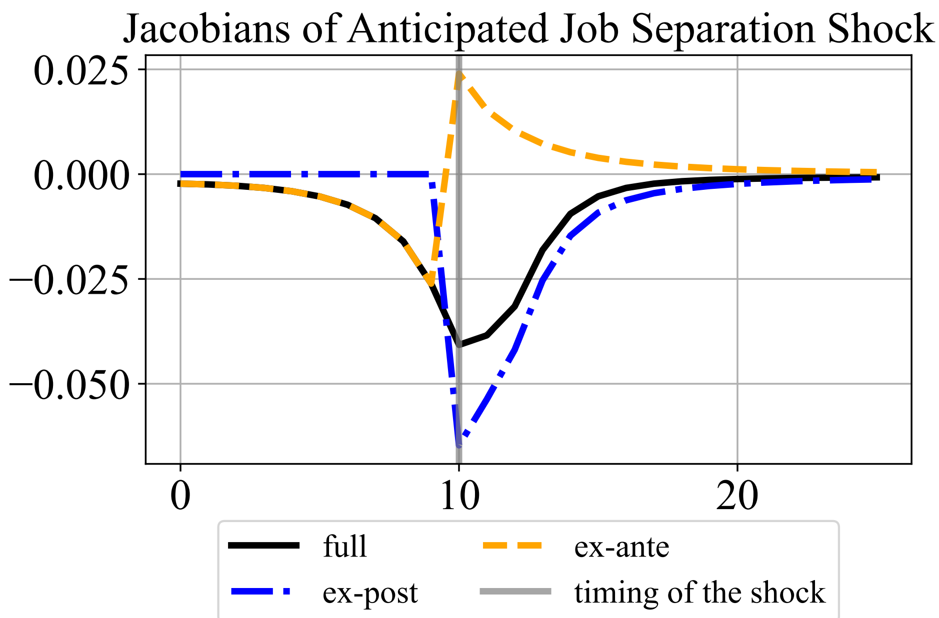


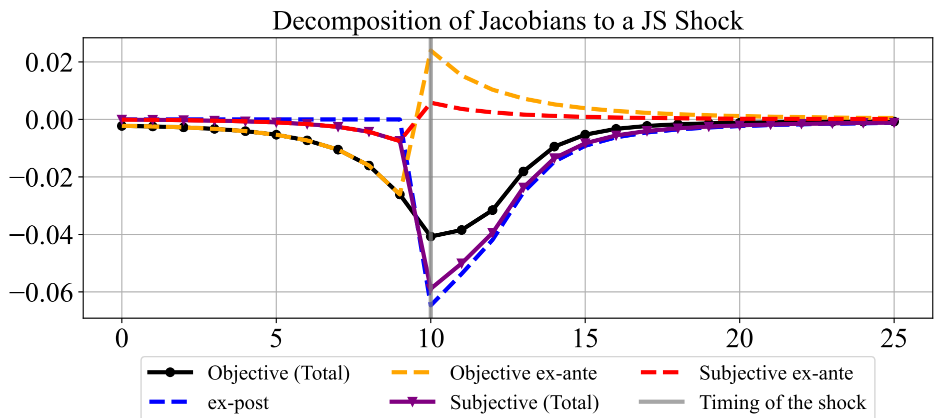
Figure 2-11. Consumption Jacobian to an anticipated 10-period-ahead shock to the job separation

This figure plots the total and decomposed Jacobians of the aggregate consumption with respect to an anticipated shock to job separation probability at $t+10$. The Jacobian is defined exactly as in Auclert et al. [2021a].

at $t = 10$, assuming that in each period from $t = 10$ onward, 10% of workers update their expectations. The red line shows the same response with the additional assumption that the job separation probability never effectively increases. The *ex-ante* component of the response is significantly muted relative to the full (objective) response shown in black. However, the consumption drop at $t = 10$ and beyond is substantially larger, reflecting a lack of precautionary saving and thus a lack of self-insurance.

Quantification of consumption impacts

With the decomposed Jacobians, we simulate of the path of aggregate consumption from 1988 to 2020. Specifically, we estimate AR(1) processes for both our survey-based expectations and the constructed rational expectations of job separation and job finding probabilities, and recover the corresponding shocks that replicate their observed paths from 1988 to 2020.



Note: The figure shows the aggregate consumption Jacobian concerning a future shock to job-separation rate that is broken down into those driven by ex-ante perceived risk and that is caused by ex-post shock response in full-information versus subjective/sticky perceptions of job separation risk.

Figure 2-12. Subjective Consumption Jacobians with Sticky Expectations

We apply the same procedure to the realized job finding and job separating probabilities estimated from the CPS. These shocks are then fed into the model: household perceptions evolve according to the respective expectation shock series, while actual job transition rates follow the shocks estimated from realized data. This approach generates a simulated path of aggregate consumption that reflects the assumptions underlying each scenario.

We conduct this simulation under four different scenarios. The first assumes that workers do not perceive changes to the job finding and job separation probabilities are only subject to realized changes to the unemployment rate. This simulation isolates the income loss channel of consumption induced from an increase in the unemployment rate. The second assumes that workers' expectations follow our survey based measure of job finding and job loss expectations. The third assumes that workers expectations follow our constructed measure of rational expectations. Finally, the fourth simulation assumes workers have perfect foresight and perfectly anticipate the actual shocks to the job transition probabilities.

Figure 2-13 shows simulated paths of aggregate consumption from the 1980s through 2020. The two panels isolate the effects of fluctuations in the job separation and job finding probabilities, respectively. Figure 2-14 presents the combined effect of both the job finding probability and job separation probability on aggregate consumption.

Three key findings emerge from the figure. First, when considering job separation alone, the stickiness in separation beliefs leads to a minimal ex-ante precautionary saving response during recessions. Consequently, the total consumption response based on subjective perceptions closely mirrors the ex-post impact and falls short of the response implied by objective risk. Finally, as workers engage in a substantially smaller magnitude of precautionary saving, the recovery of consumption exhibits a more sluggish recovery under subjective beliefs.

Second, in the case of job-finding risk, precautionary saving plays a non-trivial role in driving consumption. However, because beliefs on job finding adjust only partially to the true underlying risk, there is a large a gap between the simulation with objective risk or perfect foresight versus subjective expectations. In the Great Recession, the objective response implies an even larger drop—roughly 1 percentage point more—than the subjective estimate. Just as sluggish job separation beliefs induce a slower recovery, the slow adjustment in job-finding beliefs also contributes to a delayed recovery in aggregate consumption.

Third, the combined impact of job separation and job finding in figure 2-14 is largely driven by the job-finding channel. This reflects two main factors. First, consistent with Fujita and Ramey [2009] and the broader search and matching literature, fluctuations in job finding account for a larger share of unemployment dynamics over the business cycle, though the precise contribution is debated. For instance, Broer et al. [2021a] argue that job separations shape the short-term response, while job finding drives longer-term dynamics. Second, in our model, job finding risk matters not only for the unemployed but also for the employed, as workers face the possibility of job loss followed by difficulty finding re-employment. Importantly, beliefs about job finding are also more responsive than those about separation, amplifying the precautionary saving motive. Since our model focuses on non-durable consumption, these estimates likely represent a lower bound. As noted by Carroll and Dunn [1997] and Harmenberg and Öberg [2021], the impact of unemployment risk on durable goods consumption is considerably larger.

Allowing for heterogeneous risks and beliefs

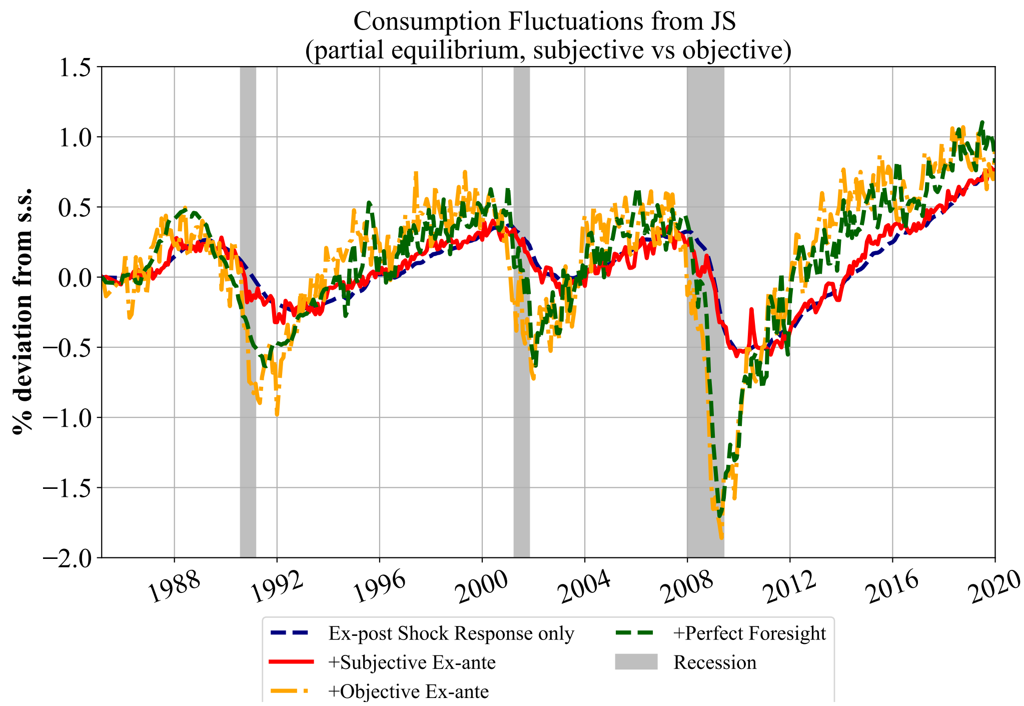
Figure 2-15 simulates consumption fluctuations for each education group separately, under the alternative assumption that job risks vary ex-ante by education level. This assumption is motivated by the findings in Section 2.4.3, which show that lower-education groups are slower to adjust their perceptions of separation risk, despite facing larger fluctuations in those risks. In contrast, it is the middle-education group whose beliefs about job finding are the most sluggish in responding to real-time changes. We quantify the role of both misperceived risks and overall precautionary saving motives for each group. We calibrate the discount factors for the low- and middle-education groups to target a quarterly marginal propensity to consume (MPC) of 0.34, and for the high-education group to 0.27–values consistent with the estimates reported by Fuster et al. [2020] for individuals without and with a bachelor's degree, respectively.

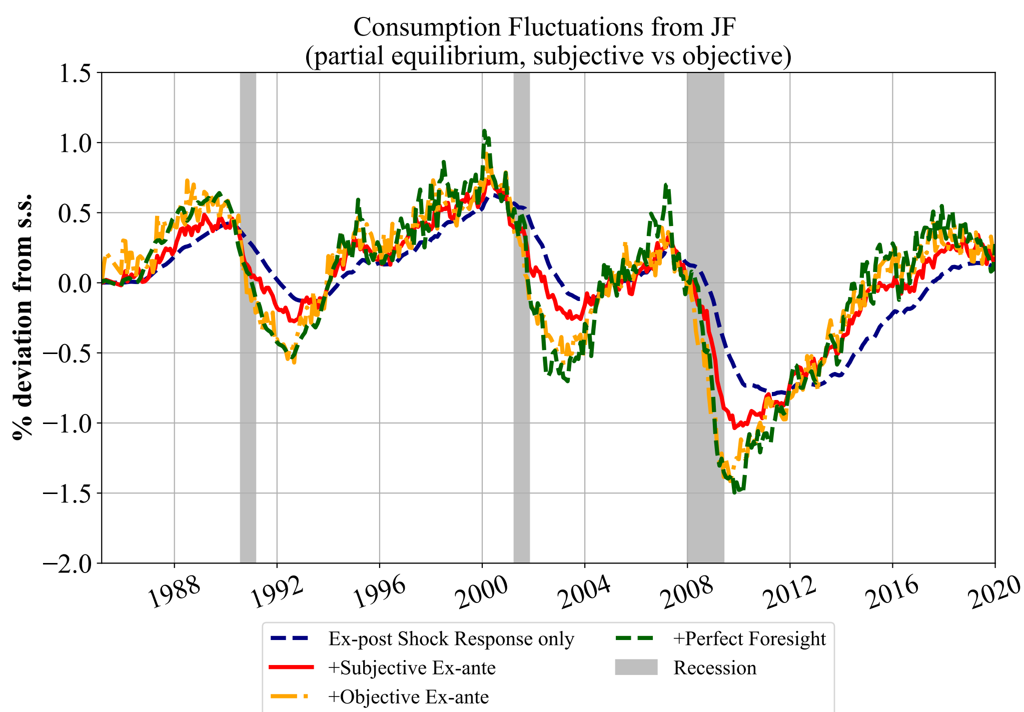
We make two findings. First, as expected, the low-education group exhibits the largest ex-post consumption response during recessions, reflecting the interaction between the higher volatility of their realized job transitions and their higher MPC. Second, the high-education group shows a stronger precautionary response overall, driven by their greater sensitivity in updating beliefs. This is evidenced by a smaller gap between their subjective and objective responses, and a larger gap between their subjective and ex-post responses. Our group-specific anatomy bears aggregate implications. To the extent that the most cyclically exposed groups in job risks are also the ones that have the least sensitivity in reacting to their beliefs and carrying out self-insurance behaviors, which means a larger cut in spending at the moments of the shock, this introduces a potentially important amplification mechanism in the aggregate consumption that is not via its counter-cyclicality per se, but via its heterogeneous footprints. Although heterogeneous risk exposures do not, in general necessarily amplify job risks' impacts on aggregate consumption, they could do so when the heterogeneous workers' risk exposures are positively correlated with their degree of underinsurance. Our results seem to suggest this mechanism is empirically feasible, particularly because workers facing more cyclical risks tend to underreact to such movements in job risks.

Our group-specific analysis has important aggregate implications. When the workers most exposed to cyclical job risks are also the least responsive in updating their beliefs and engaging in self-insurance, the result is a sharper drop in consumption at the onset of shocks. This creates a potential amplification mechanism for aggregate consumption—not through its overall cyclicality, but through the uneven distribution of responses across groups. While heterogeneous risk exposure does not inherently amplify the aggregate impact of job risks, it can do so when exposure is positively correlated with underinsurance. Our findings suggest this condition holds empirically, as those facing more cyclical risks appear especially prone to underreacting to changes in job risk.

2.6 Conclusion

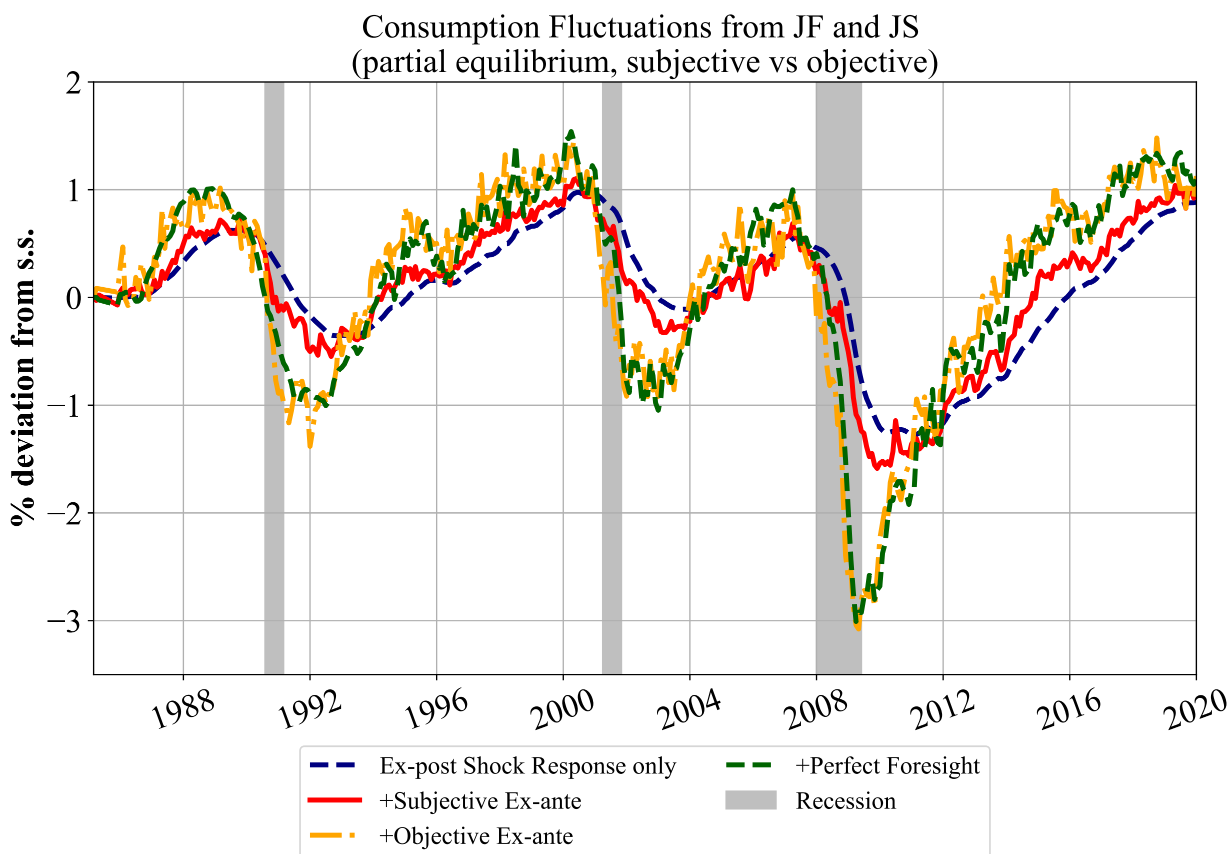
Recessions lead to more job losses and fewer job gains—but do households anticipate these shifts in labor market risk? This paper investigates whether business cycle fluctuations in the probability of finding and losing a job are actually perceived by the average household. Understanding the extent to which these risks are anticipated is crucial for distinguishing between consumption declines driven by precautionary behavior and those caused by actual income losses from rising unemployment. The analysis reveals that households' perceptions of the probability of finding and losing a job adjust slowly to changing economic conditions. Unsurprisingly, this sluggish adjustment in perceived job loss risk diminishes the role of precautionary behavior in driving consumption declines, instead emphasizing the quantitative importance of realized income losses from rising unemployment. However, while a muted precautionary response results in a smaller initial drop in consumption during a recession, it also dampens the recovery, as most households—those who remain employed—have smaller precautionary buffers to draw down once unemployment declines. Household perceptions on the probability finding and losing a job also vary widely across the population, reflecting substantial heterogeneity in how households interpret labor market signals. It is not the average worker, but rather the marginal worker—those most exposed to cyclical job risk—that drives fluctuations in aggregate demand.





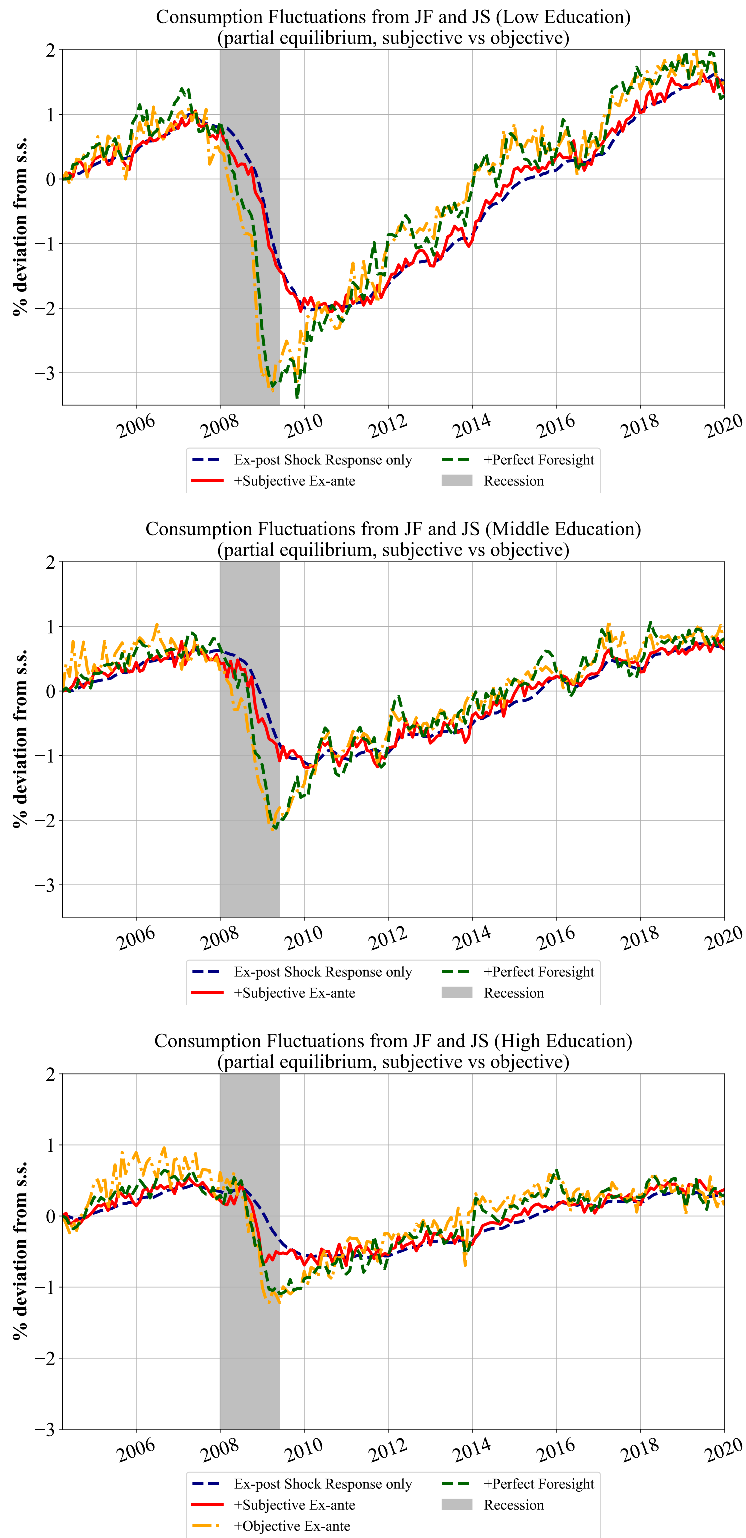
Note: The figure compares the partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates.

Figure 2-13. Consumption fluctuations due to changes in the job finding probability and to changes in the job separation probability



Note: The figure compares the partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates.

Figure 2-14. Consumption Fluctuations due to Unemployment Risks



Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates.

Figure 2-15. Consumption Fluctuations due to Unemployment Risks: by Education

Chapter 3

Welfare and Spending Effects of Consumption Stimulus Policies[1]

– joint with Christopher Carroll, Edmund Crawley, Ivan Frankovic, and Håkon Tretvoll

3.1 Introduction

Fiscal policies that aim to boost consumer spending in recessions have been tried in many countries in recent decades. The nature of such policies has varied widely, perhaps because traditional macroeconomic models have not provided plausible guidance about which ones are likely to be most effective—either in reducing misery (a 'welfare metric') or in increasing output (a 'GDP metric').

But a new generation of macro models has shown that when microeconomic heterogeneity across consumer circumstances (wealth; income; education) is taken into account, the consequences of an income shock for consumer spending depend on a measurable object: the intertemporal marginal propensity to consume (iMPC) introduced in Auclert et al. [2018]. The iMPC extends the notion of a marginal propensity to consume to account for the speed at which households spend. Fortuitously, new sources of microeconomic data, particularly from Scandinavian national registries, have recently allowed the first high-quality measurements of the iMPC (Fagereng et al. [2021]).

Even in models that can match a given measured iMPC pattern, the relative merits of alternative policies depend profoundly both on the metric (welfare or GDP) and on the quantitative structure of the rest of the model – for example, whether multipliers exist and whether the degree of multiplication is different under different economic conditions. Here, after constructing a microeconomically credible heterogeneous agent (HA) model, we examine that model's implications for how effects of stimulus policies depend on the existence and timing of any "multipliers," which, following Krueger et al. [2016], we model in a clean and simple way, so that the interaction of the multiplier (if any) with the other elements of the model is reasonably easy to understand. This partial equilibrium analysis allows us to transparently incorporate the possibility that multipliers may be larger in recessions. But we understand that a richer general equilibrium framework could introduce transmission channels absent from the partial-equilibrium-plus-multiplier analysis, so we also analyze a standard HANK-and-SAM general equilibrium model modified to embed our households' consumption responses.[2]

By "microeconomically credible," we mean, at a minimum, a model that can match both the cross-sectional distribution of liquid wealth (following Kaplan and Violante [2014]'s definition of liquid wealth) and the entire pattern of the iMPC from Fagereng et al. [2021] (see Figure 3-1a for their data and our model's fit to it).

Standard HA models can match both the pattern of spending in years 1-4 (for a shock that arrives in year 0) and the initial distribution of liquid wealth.[3] But even a brief look at the figure convinces the eye that spending in the initial period when the shock arrives seems out of line with the smooth declining pattern in years 1-4. The eye is not wrong: HA models that match liquid assets and the spending pattern in years 1-4 seriously underpredict the amount of immediate spending that occurs on receipt of the income shock.

[2]The Econ-ARK toolkit with which the partial equilibrium model was solved constructs the Jacobians necessary to connect a steady-state version of the model to the SSJ Toolkit. Our HANK-and-SAM model builds on Ravn and Sterk [2017a, 2021].

[3]For example, the model in Carroll et al. [2017b].

We call this initial extra spending the 'excess initial MPC.' Below, we describe a substantial and longstanding literature in which the pattern of an excess initial MPC has been documented, and a vigorous recent literature confirming the fact with different datasets and proposing various potential theoretical explanations.

If multipliers are operative only in recessions (or are more powerful in recessions), a model that fails to capture the excess initial MPC might generate the wrong answers for the effectiveness of the alternative fiscal policies.

The purpose of our paper is not to weigh in on which of the alternative models of an excess initial MPC is right. Instead we sought the simplest modeling device that would capture the empirical fact of an excess initial MPC and permit unambiguous welfare calculations. We accomplish this by adding to the standard model something we call "splurge" beahavior, in which each household has a portion of income out of which they have a high MPC, and the remainder of their income is disposed of as in standard micro models with mildly impatient but time-consistent consumers. Because the available evidence finds high initial MPCs even among wealthy households, we assume that this splurge behavior is the same across households and independent of their liquid wealth holdings.[4]

Our resulting structural model could be used to evaluate a wide variety of consumption stimulus policies. We examine three that have been implemented in recent recessions in the United States (and elsewhere): an extension of unemployment insurance (UI) benefits, a means-tested stimulus check, and a payroll tax cut.

Our first metric of policy effectiveness is "spending bang for the buck": For a dollar of spending on a particular policy, how much multiplication is induced? First, we calculate the policy-induced spending dynamics in an economy with no multiplier. We then follow Krueger et al. [2016]'s approach to modeling the aggregate demand externality, in which output depends mechanically on the level of consumption relative to steady state. But in our model,

[4]Proponents of the theoretical models described in our literature review in section 3.1.1 may choose to think of our splurge as a reduced form for a deeper explanation; we would not necessarily resist such an interpretation.

the aggregate demand externality is only switched on when the economy is experiencing a recession—there is no multiplication for spending that occurs after our simulated recession is over.

Even without multiplication, a utility-based metric can justify countercyclical policy on welfare grounds because the larger idiosyncratic shocks to income that occur during a recession may justify a greater-than-normal degree of social insurance. Because our model's outcomes reflect the behavior of utility-maximizing consumers, we can calculate a measure of the effectiveness of alternative policies: their effect on consumers' welfare. We call this "welfare bang for the buck."

The principal difference between the two metrics is that what matters for the degree of spending multiplication is how much of the policy-induced extra spending occurs during the recession (when the multiplier matters), while effectiveness in the utility metric also depends on who is doing the extra spending (because the recession hits some households much harder than others).

Because high-MPC consumers tend to have high marginal utility, a standard aggregated welfare function would favor redistribution to such consumers even in the absence of a recession. We are interested in the degree of *extra* motivation for social insurance that is present in a recession, so we construct our social welfare metric specifically to measure only the *incremental* social welfare effect of alternative policies during recessions (beyond whatever redistributional logic might apply during expansions – see section 3.4.3).

When the multiplier is active, any reduction in aggregate consumption below its steady-state level directly reduces aggregate productivity and thus labor income. Hence, any policy stimulating consumption will also boost incomes through this aggregate demand multiplier channel.

Our results are intuitive. In the economy with no recession multiplier, the benefit of a sustained payroll tax cut is negligible.[5] When a multiplier exists, the tax cut has more

[5] One reason there is any (welfare) benefit at all, even for people who have not experienced an unemployment

benefits, especially if the recession continues long enough that most of the spending induced by the tax cut happens while the economy is still in recession (and the multiplier still is in force). The typical recession, however, ends long before our 'sustained' wage tax cut is reversed—and even longer before lower-MPC consumers have spent down most of their extra after-tax income. Accordingly, even in an economy with a multiplier that is powerful during recessions, much of the wage tax cut's effect on consumption occurs when any multiplier that might have existed in a recession is no longer operative.

Even leaving aside any multiplier effects, the stimulus checks improve welfare more than the wage tax cut, because at least a portion of such checks go to unemployed people who have both high MPCs and high marginal utilities (while wage tax cuts, by definition, go only to persons who are employed and earning wages). The greatest "welfare bang for the buck" comes from the UI insurance extension, because many of the recipients are in circumstances in which they have a much higher marginal utility than they would have had in the absence of the recession, whether or not the aggregate demand externality exists.

And, in contrast to the wage-tax cut, both the UI extension and the stimulus checks concentrate most of the marginal increment to consumption at times when the multiplier (if it exists) is still powerful. A disadvantage of the UI extension relative to the stimulus checks, in terms of "spending bang for the buck," is that it takes somewhat more time until the transfers reach the beneficiaries. The stimulus checks are assumed to be distributed immediately in the same quarter as the recession starts. Countering this disadvantage is the fact that the MPC of UI recipients is higher than that of stimulus check recipients, and, furthermore, the insurance nature of the UI payments reduces the precautionary saving motive. In the end, our model says that these two forces roughly balance each other, so that the spending bang

spell, is that the heightened risk of unemployment during a recession increases the marginal value of current income because it helps them build extra precautionary reserves to buffer against the extra risk. A second benefit is that, for someone who becomes unemployed some time into the recession, the temporary tax reduction will have allowed them to accumulate a larger buffer to sustain them during unemployment. Finally, in a recession, there are more people who will have experienced a spell of unemployment, and the larger population of beneficiaries means that the consequences of the prior mechanism will be greater. But, quantitatively, all of these effects are small.

for the buck of the two policies is similar. In the welfare metric, however, there is considerable marginal value to UI recipients even if they receive some of the benefits after the recession is over (and no multiplier exists). Hence, in the welfare metric, the relative value of UI benefits is increased compared with the policy of sending stimulus checks.

We conclude that extended UI benefits should be the first weapon employed from this arsenal, as they have a greater welfare benefit than stimulus checks and a similar (multiplied) spending effect. But a disadvantage is that the total amount of stimulus that can be accomplished with the UI extension is constrained by the fact that only a limited number of people become unemployed. If more stimulation is called for than can be accomplished via the UI extension, checks have the advantage that their effects scale almost linearly in the size of the stimulus—see Beraja and Zorzi [2023] for a more detailed exposition of the relation between MPC and stimulus size. The wage tax cut is also, in principle, scalable, but its effects are smaller because recipients have lower MPCs and marginal utility than check and UI recipients. In the real world, a tax cut is also likely the least flexible of the three tools: UI benefits can be further extended, and multiple rounds of checks can be sent, but multiple rounds of changes in payroll tax rates would likely be administratively and politically more difficult.

One theme of our paper is that which policies are better or worse, and by how much, depends on both the quantitative details of the policies and the quantitative modeling of the economy.

But the tools we are using could be reasonably easily modified to evaluate a number of other policies. For example, in the COVID-19 recession in the US, not only was the duration of UI benefits extended, but those benefits were also supplemented by substantial extra payments to every UI recipient. We did not calibrate the model to match this particular policy, but the framework could accommodate such an analysis.

3.1.1 Related literature

Several papers have looked at fiscal policies that have been implemented in the U.S. through the lens of a structural model. Coenen et al. [2012] analyses the effects of different fiscal policies using seven different models. The models are variants of two-agent heterogeneous agent models and make no attempt to match the full distribution of liquid wealth as we do in this paper. We also attempt to match the microdata on household consumption behavior, much of which has come more recently. More closely aligned to the methodology of our paper are McKay and Reis [2016b], McKay and Reis [2021], and Phan [2024] which look at the role of automatic stabilizers. By contrast, we consider discretionary policies that have been invoked after a recession has begun. Another related paper is Bayer et al. [2023] who studies fiscal policies implemented during the pandemic. They find that targeted stimulus through an increase in unemployment benefits has a much larger multiplier than an untargeted policy. In contrast, we find that untargeted stimulus checks have slightly higher multiplier effects when compared with a targeted policy extending eligibility for unemployment insurance. Our results derive from the fact that—as in the data—even high liquid wealth consumers have relatively high MPCs in our model.

This paper is also closely related to the empirical literature that aims to estimate the effect of transitory income shocks and stimulus payments. We particularly focus on Fagereng et al. [2021], who use Norwegian administrative panel data with sizable lottery wins to estimate the MPC out of transitory income in that year, as well as the pattern of expenditure in the following years. We build a model that is consistent with the patterns they identify. Examples of the literature that followed the Great Recession in 2008 are Parker et al. [2013] and Broda and Parker [2014]. These papers exploit the effectively random timing of the distribution of stimulus payments and identify a substantial consumption response. The results indicate an MPC that is difficult to reconcile with representative agent models.

Thus, the paper relates to the literature presenting HA models that aim to be consistent with the evidence from the micro-data. An example is Kaplan and Violante [2014], who build a model where agents save in both liquid and illiquid assets. The model yields a substantial consumption response to a stimulus payment, since MPCs are high both for constrained, low-wealth households and for households with substantial net worth that is mainly invested in the illiquid asset (the "wealthy hand-to-mouth"). Carroll et al. [2020b] present an HA model that is similar in many respects to the one we study. Their focus is on predicting the consumption response to the 2020 U.S. CARES Act that contains both an extension of unemployment benefits and a stimulus check. However, neither of these papers attempts to evaluate and rank the effectiveness of different stimulus policies, as we do.

Kaplan and Violante [2022] discuss different mechanisms used in HA models to obtain a high MPC and the tension between that and fitting the distribution of aggregate wealth. We use one of the mechanisms they consider, *ex-ante* heterogeneity in discount factors, and build a model that delivers both high average MPCs and a distribution of liquid wealth consistent with the data. The model allows for splurge consumption and thus also delivers substantial MPCs for high-liquid-wealth households. This helps the model match not only the initial MPC, but also the propensity to spend out of a windfall for several periods after it is obtained.

In our model, consumers do not adjust their labor supply in response to the stimulus policies. Our assumption is broadly consistent with the empirical findings in Ganong et al. [2022] and Chodorow-Reich and Karabarbounis [2016]. However, the literature is conflicted on this subject and Hagedorn et al. [2017] and Hagedorn et al. [2019a] find that extensions of unemployment insurance affect both search decisions and vacancy creation leading to a rise in unemployment. Kekre [2022], on the other hand, evaluates the effect of extending unemployment insurance in the period from 2008 to 2014. He finds that this extension raised aggregate demand and implied a lower unemployment rate than without the policy. However, he does not attempt to compare the stimulus effects of extending unemployment insurance with other policies.

One criterion to rank policies is the extent to which spending is "multiplied," and our paper therefore relates to the vast literature discussing the size and timing of any multiplier. Our focus is on policies implemented in the aftermath of the Great Recession, a period when monetary policy was essentially fixed at the zero lower bound (ZLB). We therefore do not consider monetary policy responses to the policies we evaluate in our primary analysis, and our work thus relates to papers such as Christiano et al. [2011] and Eggertsson [2011], who argue that fiscal multipliers are higher in such circumstances. Hagedorn et al. [2019b] present an HA model with both incomplete markets and nominal rigidities to evaluate the size of the fiscal multiplier and also find that it is higher when monetary policy is constrained. Unlike us, they focus on government spending instead of transfers and are interested in different options for financing that spending. Broer et al. [2023] also focus on fiscal multipliers for government spending and show how they differ in representative agent and HA models with different sources of nominal rigidities. Ramey and Zubairy [2018] investigate empirically whether there is support for the model-based results that fiscal multipliers are higher in certain states. While they find evidence that multipliers are higher when there is slack in the economy or the ZLB binds, the multipliers they find are still below one in most specifications. In any case, we condition on policies being implemented in a recession—when, this literature argues, multipliers are higher—but it is not crucial for our purposes whether the multipliers are greater than one or not. We are concerned with relative multipliers, and the multiplier is only one of the two criteria we use to rank policies.

The second criterion to rank policies is our measure of welfare. Thus, the paper relates to the recent literature on welfare comparisons in HA models. Both Bhandari et al. [2021] and Dávila and Schaab [2022] introduce ways of decomposing welfare effects. In the former case, these are aggregate efficiency, redistribution and insurance, while the latter further decomposes the insurance part into intra- and intertemporal components. These papers are related to ours, but we do not decompose the welfare effects. Regardless of decomposition, we want to (1) use a welfare measure as an additional way of ranking policies and (2) introduce a measure that abstracts from any incentive for a planner to redistribute in the steady state (or "normal" times).

3.1.2 Organization

The paper is organized as follows. Section 3.2 presents our baseline partial equilibrium model of households' consumption and saving problem as well as how we model a recession and the potential response in terms of three different consumption stimulus policies. Section 3.3 describes the steps we take to parameterize the model and discusses the implications for some moments that we do not target. In section 3.4 we compare the three policies implemented in a recession both in terms of their multipliers and in terms of a welfare measure that we introduce. Section 3.5 presents a general equilibrium HANK and SAM model where we compare the multipliers of the same three policies to the partial equilibrium results. Section 3.6 concludes, and, finally, the appendix shows results from a version of the model without splurge consumption and provides more details of the HANK and SAM model discussed in Section 3.5.

3.2 Model

Consumers differ by their level of education and, within education group, by subjective discount factors (calibrated to match the within-group distribution of liquid wealth). We first describe each kind of consumer's problem, given an income process with permanent and transitory shocks calibrated to their type, as well as type-specific shocks to employment. The next step describes the arrival of a recession and the policies we study as potential fiscal policy responses. The last section discusses an extension incorporating aggregate demand effects that induce feedback from aggregate consumption to income and (via the marginal propensity to consume) back to consumption, amplifying the effect of a recession when it occurs.

A consumer i has education $e(i)$ and a subjective discount factor β_i. The consumer faces a stochastic income stream, $\mathbf{y}_{i,t}$, and chooses to consume a fraction of that income when it arrives—the 'splurge', described in the introduction.[6] With what is left over, the consumer chooses to optimize consumption without regard to the fraction that was already spent. Therefore, consumption each period for consumer i can be written as

$$\mathbf{c}_{i,t} = \mathbf{c}_{sp,i,t} + \mathbf{c}_{opt,i,t}, \tag{3.1}$$

where $\mathbf{c}_{i,t}$ is total consumption, $\mathbf{c}_{sp,i,t}$ is the splurge consumption, and $\mathbf{c}_{opt,i,t}$ is the consumer's optimal choice of consumption after splurging. Splurge consumption is simply a fraction of income:

$$\mathbf{c}_{sp,i,t} = \varsigma \mathbf{y}_{i,t}, \tag{3.2}$$

while the optimized portion of consumption is chosen to maximize the perpetual-youth lifetime expected-utility-maximizing consumption, where D is the end-of-life probability:

$$\sum_{t=0}^{\infty} \beta_i^t (1-D)^t \mathbb{E}_0 u(\mathbf{c}_{opt,i,t}). \tag{3.3}$$

We use a standard CRRA (constant relative risk aversion) utility function, so $u(c) = c^{1-\gamma}/(1-\gamma)$ for $\gamma \neq 1$ and $u(c) = \log(c)$ for $\gamma = 1$, where γ is the coefficient of relative risk aversion. The optimization is subject to the budget constraint, given existing market resources $\mathbf{m}_{i,t}$ and income state, and a no-borrowing constraint:

$$\begin{aligned} \mathbf{a}_{i,t} &= \mathbf{m}_{i,t} - \mathbf{c}_{i,t}, \\ \mathbf{m}_{i,t+1} &= R\mathbf{a}_{i,t} + \mathbf{y}_{i,t+1}, \\ \mathbf{a}_{i,t} &\geq 0, \end{aligned} \tag{3.4}$$

where R is the gross interest factor for accumulated assets $\mathbf{a}_{i,t}$.

3.2.1 The income process

Consumers face a stochastic income process with permanent and transitory shocks to income, along with unemployment shocks. In normal times, consumers who become unemployed

[6] One attractive feature of the splurge assumption is that it is also consistent with evidence from Ganong and Noel [2019], that spending drops sharply following the large and predictable drop in income after the exhaustion of unemployment benefits; see Section 3.3.3.4.

receive unemployment benefits for two quarters. Permanent income evolves according to:

$$\mathbf{p}_{i,t+1} = \psi_{i,t+1}\Gamma_{e(i)}\mathbf{p}_{i,t}, \tag{3.5}$$

where $\psi_{i,t+1}$ is the shock to permanent income and $\Gamma_{e(i)}$ is the average growth rate of income for the consumer's education group $e(i)$.[7] The realized growth rate of permanent income for consumer i is thus $\hat{\Gamma}_{i,t+1} = \psi_{i,t+1}\Gamma_{e(i)}$. The shock to permanent income is normally distributed with variance σ_ψ^2.

The actual income a consumer receives will be subject to the individual's employment status as well as transitory shocks, $\xi_{i,t}$:

$$\mathbf{y}_{i,t} = \begin{cases} \xi_{i,t}\mathbf{p}_{i,t}, & \text{if employed} \\ \rho_b\mathbf{p}_{i,t}, & \text{if unemployed with benefits} \\ \rho_{nb}\mathbf{p}_{i,t}, & \text{if unemployed without benefits} \end{cases} \tag{3.6}$$

where $\xi_{i,t}$ is normally distributed with variance σ_ξ^2, and ρ_b and ρ_{nb} are the replacement rates for an unemployed consumer who is or is not eligible for unemployment benefits, respectively.

A Markov transition matrix Π generates the unemployment dynamics where the number of states is given by 2 plus the number of periods that unemployment benefits last. An employed consumer can continue being employed or move to being unemployed with benefits.[8] The first row of Π is thus given by $[1-\pi_{eu}^{e(i)}, \pi_{eu}^{e(i)}, \mathbf{0}]$, where $\pi_{eu}^{e(i)}$ indicates the probability of becoming unemployed from an employed state and $\mathbf{0}$ is a vector of zeros of the appropriate length. Note that we allow this probability to depend on the education group of consumer i and will calibrate this parameter to match the average unemployment rate for each education group. Upon becoming unemployed, all consumers face a probability π_{ue} of transitioning back into employment and a probability $1-\pi_{ue}$ of remaining unemployed with one less period of remaining benefits. After transitioning into the unemployment state where the consumer is

[7] We model the rate of growth for permanent income for each education group and keep this rate unchanged during periods of unemployment. There is evidence, e.g. in Davis and Wachter [2011b], that unemployment, especially in a recession, leads to permanent income loss. This finding could be added to the model—see Carroll et al. [2020b] for an example—but is not material to the evaluation of stimulus payments here so we have chosen to keep the model simple.

[8] That is, as long as we assume that there is at least one period of unemployment benefits.

no longer eligible for benefits, the consumer will remain in this state until becoming employed again. The probability of becoming employed is thus the same for each of the unemployment states and education groups.

3.2.2 Recessions and policies

We model the arrival of a recession, and the government policy response to it, as an unpredictable event—an MIT shock. We have four types of shocks: one representing a recession and one for each of the three different policy responses we consider. The policy responses are usually modeled as in addition to the recession, but we also consider a counterfactual in which the policy response occurs without a recession in order to understand the welfare effects of the policy.

3.2.2.0.1 Recession. At the onset of a recession, several changes occur. First, the unemployment rate for each education group doubles: Those who would have been unemployed in the absence of a recession are still unemployed, and an additional number of consumers move from employment to unemployment. Second, conditional on the recession continuing, the employment transition matrix is adjusted so that unemployment remains at the new high level and the expected length of time for an unemployment spell increases. In our baseline calibration, discussed in detail in section 3.3.3.1, we set the expected length of an unemployment spell to one and a half quarters in normal times, and this length increases to four quarters in a recession. Third, the end of the recession occurs as a Bernoulli process calibrated for an average length of recession of six quarters. Finally, at the end of a recession, the employment transition matrix switches back to its original probabilities, and, as a result, the unemployment rate trends down over time, back to its steady-state level. The details of how certain model parameters change in a recession are presented in section 3.3.3.2.

3.2.2.0.2 Policies. The policies we consider in response to a recession are inspired by the Economic Stimulus Act of 2008 and the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010. The former included means tested stimulus checks in the form of tax rebates, and the latter included both an extension of unemployment benefits and a tax cut. Based on these examples we therefore consider the following stimulus policies in our framework:

3.2.2.0.3 1. Stimulus check. In this policy response, the government sends money to every consumer that directly increases the household's market resources. The checks are means-tested depending on permanent income. A check for $1,200 is sent to every household with permanent income less than $100,000, and this amount is then linearly reduced to zero for households with a permanent income greater than $150,000. Similar policies were implemented in the U.S. in 2001, 2008, and during the pandemic.

3.2.2.0.4 2. Extended unemployment benefits. In this policy response, unemployment benefits are extended from two quarters to four quarters. That is, those who become unemployed at the start of the recession, or who were already unemployed, will receive unemployment benefits for up to four quarters (including quarters leading up to the recession). Those who become unemployed one quarter into the recession will receive up to three quarters of unemployment benefits. These extended unemployment benefits will occur regardless of whether the recession ends, and no further extensions are granted if the recession continues. This policy reflects temporary changes made to unemployment benefits in the U.S. following the great recession.

3.2.2.0.5 3. Payroll tax cut. In this policy response, employee-side payroll taxes are reduced for a period of eight quarters.[9] During this period, which continues irrespective of whether the recession continues or ends, employed consumers' income is increased by 2 percent. The income of the unemployed is unchanged by this policy. Households also believe

[9]Although payroll taxes are paid by both the employer and the employee, the payroll tax cuts in the U.S. have been applied only the employee side.

there is a 50-50 chance that the tax cut will be extended by another two years if the recession has not ended when the first tax cut expires.[10] The payroll tax cut introduced in the U.S. in 2010 was itself an extension of previously implemented cuts and had a two-year horizon.

3.2.2.0.6 Financing the policies. Some work in the HA macro literature has shown that if taxes are raised immediately to offset any fiscal stimulus, results can be very different than they would be if, as occurs in reality, recessionary policies are debt financed. However, typical fiscal rules assume that any increase in debt gets financed over a long interval. Accordingly, almost all of the effects of any particular fiscal rule will be similar for each of our policies so long as the great majority of the debt is repaid after the short recessionary period that is our main focus.

To keep our analysis as simple as possible, we do not model the debt repayment. Any of a variety of fiscal rules could be imposed for the period following our short period of interest, but we did not want to choose any particular fiscal rule in order to avoid making a choice that has little consequence for our key question. Advocates of alternative fiscal rules likely already have intuitions about how such rules' economic consequences differ, but those consequences—under our partial equilibrium analysis—will be similar for all three policies we consider. Alternative choices of fiscal rules will therefore not affect the ranking of policies that is our principal concern.[11]

3.2.3 Aggregate demand effects

Our baseline model is a partial equilibrium model that does not include any feedback from aggregate consumption to income. In an extension to the model, we add aggregate demand effects during the recession. The motivation for this specification comes from the idea that spending in an economy with substantial slack and in which the central bank is unable to

[10] The belief that the payroll tax cut may be extended makes little difference to the results.

[11] In our general equilibrium analysis in section 3.5, we apply a fiscal rule that assumes debt is slowly paid back over time.

prevent a recession will result in higher utilization rates and greater output. By contrast, government spending in an economy running at potential with an active monetary policy will not succeed in increasing output. The recent inflation experience of the U.S. provides some evidence that output responds highly non-linearly to aggregate demand. This idea is explored in a recent revival of research into non-linear Phillips curves, such as Benigno and Eggertsson [2023] and Blanco et al. [2024].

With this extension, any changes in consumption away from the steady-state consumption level feed back into labor income. Aggregate demand effects are evaluated as

$$AD(C_t) = \begin{cases} \left(\frac{C_t}{\tilde{C}}\right)^{\kappa}, & \text{if in a recession} \\ 1, & \text{otherwise,} \end{cases} \tag{3.7}$$

where $\tilde{C}$ is the level of consumption in the steady state. Idiosyncratic income in the aggregate demand extension is multiplied by $AD(C_t)$:

$$\mathbf{y}_{AD,i,t} = AD(C_t)\mathbf{y}_{i,t}. \tag{3.8}$$

The series $\mathbf{y}_{AD,i,t}$ is then used for each consumer's budget constraint.

3.3 Parameterizing the model

This section describes how we set the model's parameters. First, we estimate the extent to which consumers 'splurge' when receiving an income shock. Given the lack of empirical evidence on the marginal propensity to consume over time for the US, we instead use Norwegian data to estimate the splurge. Specifically, we calibrate our model to the Norwegian economy and match evidence from Norway on the profile of the marginal propensity to spend over time and across different wealth levels, as provided by Fagereng et al. [2021].[12]

Second, we set up the full model on U.S. data, taking the splurge factor as given from the Norwegian estimation. In the full model, agents differ according to their level of education

[12]Appendix A.1 discusses an alternative calibration method, which solely relies on US data. The main results derived in that calibration are in line with those discussed in the main text.

and their subjective discount factors. A subset of the parameters in the model are calibrated equally for all types, and some parameters are calibrated to be specific to each education group. Finally, a distribution of subjective discount factors is estimated separately for each education group to match features of each within-group liquid wealth distribution.

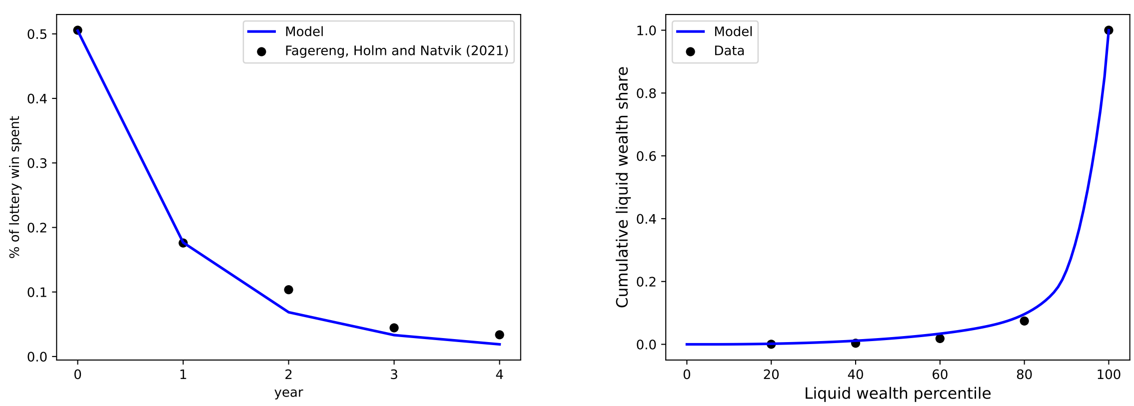
3.3.1 Estimation of the splurge factor

The splurge allows us to capture the shorter- and longer-term response of consumption to income shocks, especially for consumers with significant liquid wealth. The main aim of this paper, however, is to rank consumption stimulus policies, not to provide a microfoundation for the splurging behavior. We view the splurge factor as a model device that enables us to rank the policies in a model that is consistent with the best available micro-evidence of spending patterns over time after a transitory income shock. In appendix A.1 we provide results from our model without a splurge factor. There we show that such a model provides a worse fit to the moments in the data that we are interested in, but not dramatically so, and that our conclusions regarding the ranking of the policies are not affected. However, in our view, this version of the model requires households with unreasonably low discount factors.

The specific exercise we carry out in this section, is to show that our model can account well for the results of Fagereng et al. [2021], who study the effect of lottery winnings in Norway on consumption using millions of records from the Norwegian population registry. We calibrate our model to reflect the Norwegian economy and, using their results, estimate the splurge factor, as well as the distribution of discount factors in the population, to match two empirical moments.

First, we take from Fagereng et al. [2021] the marginal propensity to consume out of a one-period income shock. We target not only the initial (aggregate) response of consumption to the income shock, but also the subsequent effect on consumption in years one through four after the shock. We also target the initial consumption response in the cross-section, i.e. across the quartiles of the liquid wealth distribution, for which empirical estimates are also provided. The shares of lottery winnings expended at different time horizons, as found in Fagereng et al. [2021], are plotted in figure 3-1a. Table 3-I (second row) shows the initial consumption response across liquid wealth quartiles.

Second, we match the steady-state distribution of liquid wealth in the model to its empirical counterpart. Because of the lack of data on the liquid wealth distribution in Norway, we use the corresponding data from the United States, assuming that liquid wealth inequality is comparable across these countries.[13] Specifically, we impose as targets the cumulative liquid wealth shares for the entire population at the 20th, 40th, 60th, and 80th income percentiles, which, in data from the Survey of Consumer Finances (SCF) in 2004 (see section 3.3.2 for further details), equal 0.03 percent, 0.35 percent, 1.84 percent, and 7.42 percent, respectively. Hence, 92.6 percent of the total liquid wealth is held by the top income quintile. We also target the mean liquid wealth to income ratio of 6.60. The data are plotted in figure 3-1b.



(a) Share of lottery win spent

(b) Distribution of liquid wealth

Note: Panel (a) shows the fit of the model to the dynamic consumption response estimated in Fagereng et al. [2021]; see their figure A5. Panel (b) shows the fit of the model to the distribution of liquid wealth (see Section 3.3.2 for the definition) from the 2004 SCF.

Figure 3-1. Marginal propensity to consume over time and the liquid wealth distribution in the model and the data

For this estimation exercise, the remaining model parameters are calibrated to reflect

[13] Data from the Norwegian tax registry contains information on liquid assets, but not liquid debt. Only total debt is reported – which is mainly mortgage debt. Therefore, we cannot construct liquid wealth as Kaplan and Violante [2014] can for the U.S.

	MPC					
	1st WQ	2nd WQ	3rd WQ	4th WQ	Agg	K/Y
Model	0.27	0.49	0.60	0.66	0.50	6.59
Data	0.39	0.39	0.55	0.66	0.51	6.60

Table 3-I. Marginal propensities to consume across wealth quartiles and the total population as well as the wealth to income ratio, in the model and according to the data

the Norwegian economy. Specifically, we set the real interest rate to 2 percent annually and the unemployment rate to 4.4 percent, in line with Aursland et al. [2020]. The quarterly probability to survive is calibrated to $1 - 1/160$, reflecting an expected working life of 40 years. Aggregate productivity growth is set to 1 percent annually, following Kravik and Mimir [2019]. The unemployment net replacement rate is calibrated to 60 percent, following OECD [2020]. Finally, we set the real interest rate on liquid debt to 13.6 percent, following data from the Norwegian debt registry Gjeldsregistret [2022].[14]

Estimates of the standard deviations of the permanent and transitory shocks are taken from Crawley et al. [2024], who estimate an income process on administrative data for Norwegian males from 1971 to 2014. The estimated annual variances for the permanent and transitory shocks are 0.004 and 0.033, respectively.[15] As in Carroll et al. [2020a], these are converted to quarterly values by multiplying the permanent and transitory shock variances by 1/4 and 4, respectively. Thus, we obtain quarterly standard deviations of $\sigma_\psi = 0.0316$ and $\sigma_\xi = 0.363$.

Using the calibrated model, we simulated unexpected lottery winnings and calculate the share of the lottery spent in each year. Specifically, each simulated agent receives a lottery win in a random quarter of the first year of the simulation. The size of the lottery win is itself

[14]Specifically, we determine the average volume-weighted interest rate on liquid debt, which consists of consumer loans, credit and payment card debt and all other unsecured debt. We use data from December 2019. Note that although these data let us pin down aggregate quantities, they do not solve the issue referred to in footnote 3.3.1, since we cannot link them to the tax registry at the individual level. We set the borrowing limit on liquid debt to zero.

[15]As shown in Crawley et al. [2024], an income process of the form that we use here is more accurately estimated using moments in levels not differences. Hence, we take the numbers from column 3 of Panel C in their table 4.

random and spans the range of lottery sizes found in Fagereng et al. [2021]. The estimation procedure minimizes the distance between the target and model moments by selecting the splurge factor and the distribution of discount factors in the population, where the latter are assumed to be uniformly distributed in the range $[\beta - \nabla, \beta + \nabla]$. We approximate the uniform distribution of discount factors with a discrete approximation and let the population consist of seven different types.

The estimation yields a splurge factor of 0.249 and a distribution of discount factors described by $\beta = 0.968$ and $\nabla = 0.0578$. Given these estimated parameters and the remaining calibrated ones, the model is able to replicate the time path of consumption in response to a lottery win from Fagereng et al. [2021] and the targeted distribution of liquid wealth very well, see Figure 3-1. Also, the targeted moments discussed in Table 3-I are captured relatively well. In particular, the model is able to account for the empirical fact, in the first column, that the MPC for high-wealth agents is substantially larger than zero.

3.3.2 Data on permanent income, liquid wealth, and education

Before we move on to the parameterization of the full model, we describe in detail the data that we use to get measures of permanent income, liquid wealth, and the division of households into educational groups in the United States. We use data on the distribution of liquid wealth from the 2004 wave of the SCF. We restrict our attention to households where the head is of working age, which we define to be in the range from 25 to 62. The SCF-variable "normal annual income" is our measure of the household's permanent income, and, to exclude outliers, we drop the observations that make up the bottom 5 percent of the distribution of this variable. The smallest value of permanent income for households in our sample is thus \$16,708.

Liquid wealth is defined as in Kaplan and Violante [2014] and consists of cash, money market, checking, savings, and call accounts; directly held mutual funds; and stocks and bonds. We subtract off liquid debt, which is the revolving debt on credit card balances. Note that the SCF does not contain information on cash holdings, so these are imputed with the procedure described in Appendix B.1 of Kaplan and Violante [2014], which also describes the credit card balances that are considered part of liquid debt. We drop any households that have negative liquid wealth.

Households are classified into three educational groups. The first group, "Dropout," applies to households where the head of household has not obtained a high school diploma; the second group, "Highschool," includes heads of households who have a high school diploma and those who, in addition, have some years of college education without obtaining a bachelor's degree; and the third group, "College," consists of heads of households who have obtained a bachelor's degree or higher. With this classification of the education groups, the Dropout group makes up 9.3 percent of the population, the Highschool group 52.7 percent, and the College group 38.0 percent.

With our sample selection criteria, we are left with a sample representing about 61.3 million U.S. households.

3.3.3 Parameters in the full model

With households classified into the three education groups using the SCF data, we proceed to set the parameters of the model as follows. First, we calibrate a set of parameters that apply to all types of households in the model. Second, we calibrate another set of parameters that are specific to each education group to capture broad differences across these groups. Finally, given the calibrated parameters we estimate discount factor distributions for each education group that allow us to match the distribution of liquid wealth in each group.

The model is a simplified model for households in that we do not take into account heterogeneity across household size or composition. The households are ex-ante heterogeneous in their subjective discount factors as well as their level of education. We classify the education level of the household based on the education of the head of the household, and we typically think of individual characteristics as applying to that person.

A period in the model is one quarter. This choice makes it realistic to consider stimulus policies that are implemented in the same period as a recession starts.

3.3.3.1 Calibrated parameters — Normal times

Table 3-II presents our calibration of the model parameters in normal times. Panel A lists parameters that are calibrated equally across all types in the model, and Panel B lists parameters in the model that are education specific. In the next subsection we present how certain model parameters change when the economy enters a recession.

Preferences, survival and interest rates. All households are assumed to have a coefficient of relative risk aversion equal to $\gamma = 2$. We also assume that all households have the same propensity to splurge out of transitory income gains and set $\varsigma = 0.249$, the value estimated in section 3.3.1. However, each education group is divided into types that differ in their subjective discount factors. The distributions of discount factors for each education group are estimated to fit the distribution of liquid wealth within that group, and this estimation is described in detail in section 3.3.3.3. Regardless of type, households face a constant survival probability each quarter. This probability is set to $1 - 1/160$, reflecting an expected working life of 40 years. The real interest rate on households' savings is set to 1 percent per quarter.

Labor market risk while employed. When consumers are born, they receive an initial level of permanent income. This initial value is drawn from a log-normal distribution that depends on the education level the household is born with. For each education group, the parameters of the distribution are determined by the mean and standard deviation of log-permanent income for households in that group where the head of the household is of age 25 in the SCF 2004. For the Dropout group, the mean initial value of quarterly permanent income is \$6,200; for the Highschool group, it is \$11,100; and for the College group, it is \$14,500. The standard deviations of the log-normal distributions for each group are, respectively, 0.32, 0.42, and 0.53.

Panel (A) Parameters that apply to all types		
Parameter	Notation	Value
Risk aversion	γ	2.0
Splurge	ς	0.249
Survival probability, quarterly	$1-D$	0.994
Risk free interest rate, quarterly (gross)	R	1.01
Standard deviation of transitory shock	σ_ξ	0.346
Standard deviation of permanent shock	σ_ψ	0.0548
Unemployment benefits replacement rate (share of PI)	ρ_b	0.7
Unemployment income w/o benefits (share of PI)	ρ_{nb}	0.5
Avg. duration of unemp. benefits in normal times (quarters)		2
Avg. duration of unemp. spell in normal times (quarters)		1.5
Probability of leaving unemployment	π_{ue}	0.667
Consumption elasticity of aggregate demand effect	κ	0.3

Panel (B) Parameters calibrated for each education group			
	Dropout	Highschool	College
Percent of population	9.3	52.7	38.0
Avg. quarterly PI of "newborn" agent ($1000)	6.2	11.1	14.5
Std. dev. of log(PI) of "newborn" agent	0.32	0.42	0.53
Avg. quarterly gross growth rate of PI (Γ_e)	1.0036	1.0045	1.0049
Unemployment rate in normal times (percent)	8.5	4.4	2.7
Probability of entering unemployment (π^e_{eu}, percent)	6.2	3.1	1.8

Note: The first three rows show numbers from the 2004 SCF. The fourth row are averages of growth rates from Carroll et al. [2020b]. The fifth row are numbers for 2004 from the Bureau of Labor Statistics, and the sixth row are calculated from these unemployment rates.

Panel (A) shows parameters calibrated the same for all types. Panel (B) shows parameters calibrated for each education group. "PI" refers to permanent income.

Table 3-II. Calibrated Model Parameters — Normal times

While households remain employed, their income is subject to both permanent and transitory idiosyncratic shocks. These shocks are distributed equally for the three education groups. The standard deviations of these shocks are taken from Carroll et al. [2020a], who set the standard deviations of the transitory and permanent shocks to $\sigma_\xi = 0.346$ and $\sigma_\psi = 0.0548$, respectively.

Permanent income also grows, on average, with a growth rate $\Gamma_{e(i)}$ that depends on the level of education. These average growth rates are based on numbers from Carroll et al. [2020b], who construct age-dependent expected permanent income growth factors using numbers from Cagetti [2003] and fit the age-dependent numbers to their life-cycle model. We construct the quarterly growth rates of permanent income in our perpetual-youth model by taking the average of the age-dependent growth rates during a household's working life. The average gross quarterly growth rates that we obtain for the three education groups are then $\Gamma_d = 1.0036$, $\Gamma_h = 1.0045$, and $\Gamma_c = 1.0049$.

Unemployment. Consumers also face the risk of becoming unemployed and will then have access to unemployment benefits for a certain period. The parameters describing the unemployment benefits in normal times are based on the work of Rothstein and Valletta [2017], who study the effects on household income of unemployment and of running out of eligibility for benefits. The unemployment benefits replacement rate is thus set to $\rho_b = 0.7$ for all households, and when benefits run out, the unemployment replacement rate without any benefits is set to $\rho_{nb} = 0.5$. These replacement rates are set as a share of the households' permanent income and are based on the initial drop in income upon entering an unemployment spell, presented in figure 3 in Rothstein and Valletta [2017].[16]

The duration of unemployment benefits in normal times is set to two quarters, so that

[16]See the lines for their UI exhaustee sample including and excluding UI income. Rothstein and Valletta [2017] also point out that "UI benefits replace about 40 percent of the lost earnings on average" (page 894). For a household with two income earners with equal income, these findings would mean that income drops to 70 percent when one earner becomes unemployed and to 50 percent when benefits run out. In this paper we ignore several of the channels studied by Rothstein and Valletta [2017] such as within household insurance and other social programs that can provide income even after UI benefits have run out.

our Markov transition matrix Π has four states. This length of time corresponds to the mean duration of unemployment benefits across U.S. states from 2004 to mid-2008 of 26 weeks, reported by Rothstein and Valletta [2017].

The probability of transitioning out of unemployment is set to match the average duration of an unemployment spell in normal times. In data from the Bureau of Labor Statistics, this average duration was 19.6 weeks or 1.5 quarters in 2004. We do not have data on education-specific duration rates, however, so we set the average duration of unemployment to 1.5 quarters for all households. This implies that the transition probability from unemployment to employment is set to $\pi_{ue} = 2/3$.

The Bureau of Labor Statistics provide data on unemployment rates for different education groups, and we match the average rate in each group in 2004 by setting an education-specific probability of transitioning from employment into unemployment. Note that this calibration strategy is consistent with the results in Mincer [1991] who finds that the main difference between education groups is in the incidence of unemployment, and not its duration.[17] More recent work by Elsby et al. [2010] includes data upto 2009 and echoes Mincer's results.

The average unemployment rate in 2004 was 8.5 percent for the Dropout group, 4.4 percent for the Highschool group, and 2.7 percent for the College group. These values imply that the probabilities of transitioning into unemployment in normal times are $\pi^d_{eu} = 6.2$ percent, $\pi^h_{eu} = 3.1$ percent, and $\pi^c_{eu} = 1.8$ percent, respectively.[18]

Finally, the strength of the aggregate demand effect in recessions is determined by the consumption elasticity of productivity. We follow Krueger et al. [2016] and set this to $\kappa = 0.3$.

[17] Mincer [1991] states that "the reduction of the incidence of unemployment [at higher education levels] is found to be far more important than the reduced duration of unemployment in creating the educational differentials in unemployment rates" (page 1).

[18] Also note that the probability of transitioning from employment to unemployment is the probability of a job separation times the conditional probability of unemployment given a job separation. Mincer [1991] reports that both of these are lower for higher education levels. For our calibration, this means that a higher job finding rate *within* the quarter of the job separation for more educated workers translates into a lower probability of transitioning from employment to unemployment during a quarter. In that sense, our calibration is consistent with short-term job-finding rates being higher for more educated workers.

3.3.3.2 Calibrated parameters — Recession

Table 3-III shows the model parameters that change when a recession hits. Panel A shows the change in two parameters that apply to all types, and Panel B shows changes in some parameters that differ across education groups. For completeness, panel C summarizes the remaining parameters describing how we model a recession and the three policies we consider as potential responses to a recession.

The two immediate changes that occur at the outset of a recession is that the unemployment rate doubles for all education groups, and the expected duration of an unemployment spell increases from 1.5 to 4 quarters. The duration of unemployment is the same across the three education groups, and this implies that the probability of leaving unemployment is set to $\pi_{ue} = 0.25$ in a recession.

The increase in the expected duration of unemployment combined with the doubling of the education-specific unemployment rates pin down new values for the probabilities of transitioning from employment to unemployment during the recession. Due to the large increase in the unemployment duration, the values that we obtain end up being slightly smaller than those transition probabilities in normal times. The probability π_{eu} in a recession is set to 5.1 percent for the Dropout group, 2.4 percent for the Highschool group, and 1.4 for the College group.

Our calibration of the transition probabilities between employment and unemployment during a recession are thus broadly in line with the results of Elsby et al. [2010]. They find that unemployment duration does not vary much between education groups and that the flow from unemployment to employment drops sharply for all groups in a recession. The flow into unemployment is more stable, but they find that it tends to increase a little bit in recessions.[19] This differs from the small decrease in the transition probabilities from employment into unemployment that our calibration strategy implies, which follows from our

[19]See the bottom row of Figure 8 in Elsby et al. [2010] for these results.

choice of targeting a doubling of the unemployment rate for each group rather than an even larger increase.

3.3.3.3 Estimating the discount factor distributions

Discount factor distributions are estimated separately for each education group to match the distribution of liquid wealth for households in that group. To do so, we let each education group consist of types that differ in their subjective discount factor, β. The discount factors within each group $e \in \{d, h, c\}$ are assumed to be uniformly distributed in the range $[\beta_e - \nabla_e, \beta_e + \nabla_e]$. The parameters β_e and ∇_e are chosen for each group separately to match the median liquid-wealth-to-permanent-income ratio and the $20th$, $40th$, $60th$, and $80th$ percentile points of the Lorenz curve for liquid wealth for that group. We approximate the uniform distribution of discount factors with a discrete approximation and let each education group consist of seven different types.

Panel A of table 3-IV shows the estimated values of (β_e, ∇_e) for each education group. The panel also shows the minimum and maximum values of the discount factors we actually use in the model when we use a discrete approximation with seven values to approximate the uniform distribution of discount factors. Panel B of table 3-IV shows that with these estimated distributions, we can exactly match the median liquid-wealth-to-permanent-income ratios for each education group. Figure 3-2 shows that with the estimated distributions, the model quite closely matches the distribution of liquid wealth within each education group as well as for the population as a whole. Thus, our model does not suffer from the "missing middle" problem, identified in Kaplan and Violante [2022], in which the middle of the wealth distribution has too little wealth.

One point we should note concerns the estimated discount factor distribution for the Highschool group. Panel A of table 3-IV reports values of $\beta_h = 0.911$ and $\nabla_h = 0.137$. With these values, the largest discount factors in our discrete approximation of the uniform distribution in the range $[\beta_h - \nabla_h, \beta_h + \nabla_h]$ would be greater than 1. More importantly, the

Panel (A) Parameters that apply to all types		
Parameter	Notation	Value
Avg. duration of unemp. spell in a recession (quarters)		4
Probability of leaving unemployment in a recession	π_{ue}	0.25

Panel (B) Parameters calibrated for each education group			
	Dropout	Highschool	College
Unemployment rate at the start of a recession (percent)	17.0	8.8	5.4
Probability of entering unemployment (π_{eu}^{e}, percent)	5.1	2.4	1.4

Panel (C) Parameters describing policy experiments	
Parameter	Value
Average length of recession	6 quarters
Size of stimulus check	\$1,200
PI threshold for reducing check size	\$100,000
PI threshold for not receiving check	\$150,000
Extended unemployment benefits	4 quarters
Length of payroll tax cut	8 quarters
Income increase from payroll tax cut	2 percent
Belief (probability) that tax cut is extended	50 percent

Panel (A) shows the parameters that apply to all types that change in a recession. Panel (B) shows the education-specific model parameters that change in a recession. Panel (C) shows numbers further describing how we model a recession and the three policies we consider. “PI” refers to permanent income.

Table 3-III. Calibrated Model Parameters — Recession

Panel (A) Estimated discount factor distributions

	Dropout	Highschool	College
(β_e, ∇_e)	(0.719, 0.318)	(0.911, 0.137)	(0.983, 0.014)
(Min, max) in approximation	(0.447, 0.991)	(0.793, 0.990*)	(0.971, 0.995)

Panel (B) Estimation targets

	Dropout	Highschool	College
Median LW/ quarterly PI (data, percent)	4.64	30.2	112.8
Median LW/ quarterly PI (model, percent)	4.64	30.2	112.8

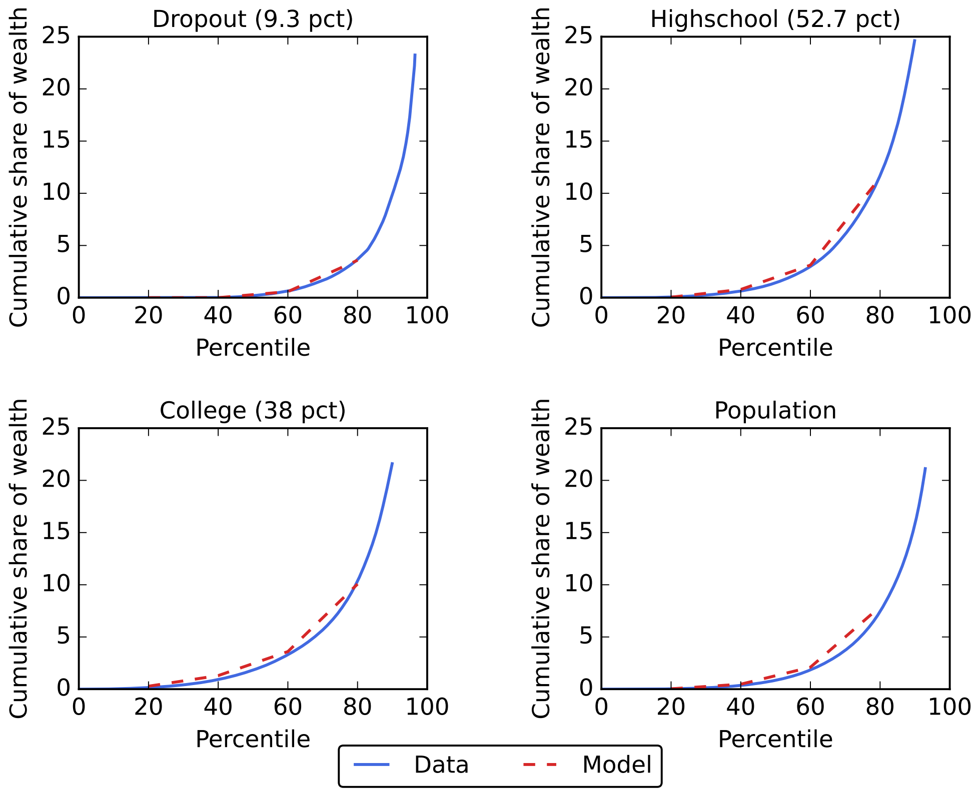
Note: Panel (A) shows the estimated parameters of the discount distributions for each education group. It also shows the minimum and maximum values we use in our discrete approximation to the uniform distribution of discount factors for each group. The $*$ indicates that the highest value in the uniform distribution of discount factor values violates the growth impatience condition (GIC) and has been replaced. Panel (B) shows the weighted median ratio of liquid wealth to permanent income from the 2004 SCF and in the model. In the annual data from the SCF, the annual PI is divided by 4 to obtain a quarterly number.

Table 3-IV. Estimated discount factor distributions and estimation targets

value would violate the Growth Impatience Condition (GIC), discussed in Carroll [2022]. (The GIC is required to prevent the ratio of total wealth to total income of any group from approaching infinity. It does this by making sure that the growth of wealth of the group is less than or equal to the growth of income.) We replace values violating the GIC with values close to the upper bound on β imposed by the GIC. In panel A of table 3-IV the largest value is marked by a $*$ to indicate that it has been replaced to avoid violating the GIC. We always impose that the GIC is satisfied in the estimation of the discount factor distributions, but for the baseline parameter values it is only binding for the Highschool group. Thus, the estimation can select a large value of ∇_h without violating the constraint.[20]

Also, note that several of the types in the Dropout group have very low discount factors and are very impatient. In this way, the model fits the feature of the data for the Dropout

[20] The constraint is imposed by calculating a discount factor β^{GIC} where the GIC holds with equality. Then the estimation can pick how close to this value the largest discount factor is by estimating x and setting the largest discount factor to $\exp(x)/(1+\exp(x))\beta^{\text{GIC}}$.



Note: The discount factor distributions are estimated separately for each education group to fit the median liquid-wealth-to-permanent-income ratio and the $20th$, $40th$, $60th$, and $80th$ percentile points of the Lorenz curve for liquid wealth for that group. The "Population" panel compares the wealth distribution that results from pooling the three groups in the model to the overall wealth distribution in the data.

Figure 3-2. Distributions of liquid wealth within each education group and for the whole population from the 2004 Survey of Consumer Finances and from the model with estimated discount factor distributions

group that the bottom quintiles do not save at all and do not accumulate any liquid wealth. Very low estimates for discount factors are in line with those obtained in the literature on payday lending.[21]

[21] See, for example, Skiba and Tobacman [2008], who estimate two-week discount rates of 21 percent, and Allcott et al. [2021], who estimate an initial period discount factor between 0.74 and 0.83 in a model where a period is eight weeks long. Both of these papers use quasi-hyperbolic preferences, so the estimates are not directly comparable with parameters in our model. Nevertheless, they support the point that very high discount rates are necessary to model the part of the population that takes out payday loans at very high interest rates.

3.3.3.4 Implications for non-targeted moments

Before we move on to compare different consumption stimulus policies in the calibrated model, we also report implications of the model for some non-targeted moments. Panel A of table 3-V shows the wealth distribution across the three education groups in the data and in the model. The model matches these shares quite closely, which may not be surprising given that we calibrate the size of each group and we manage to fit the wealth distribution within each group separately. The panel also reports the average marginal propensity to consume for the different groups. To be comparable to numbers reported in Fagereng et al. [2021], these are calculated as the average MPC in the year of a lottery win. Lottery wins occur in a random quarter of the year that differs across individuals. The MPC for an individual depends on the spending pattern after the win, and these are averaged across individuals within each education group.

Panel B of table 3-V shows similar numbers to Panel A, sorted by quartiles of the liquid wealth distribution instead of education groups. Our model yields a slightly more concentrated liquid wealth distribution than in the data. However, it does produce a fairly high MPC even for households in the highest quartile of the liquid wealth distribution. This is consistent with the results found in the Norwegian data by Fagereng et al. [2021], but also with recent results in Graham and McDowall [2024]. In an administrative dataset from a large US financial institution, they find that the spending response to an income receipt is large across the distribution of liquid asset holdings. In our model, we obtain this result due to the inclusion of the splurge factor. As shown in Appendix A.1, the model is not able to generate a high MPC for the highest wealth quartile without splurge consumption.

Finally, we consider the implications of our model for two different patterns of spending over time. The first pattern is the dynamics of spending after a lottery win from Fagereng et al.. This pattern was used in the estimation of the splurge factor in section 3.3.1, but was not targeted when estimating the discount factor distributions for each education group in

Panel (A) Non-targeted moments by education group

	Dropout	Highschool	College	Population
Percent of liquid wealth (data)	0.8	17.9	81.2	100
Percent of liquid wealth (model)	1.1	21.9	77.0	100
Avg. lottery-win-year MPC (model, incl. splurge)	0.78	0.61	0.38	0.54

Panel (B) Non-targeted moments by wealth quartile

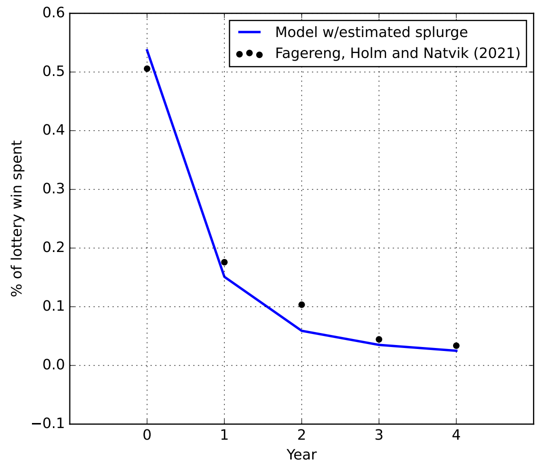
	WQ 4	WQ 3	WQ 2	WQ 1
Percent of liquid wealth (data)	0.14	1.60	8.51	89.76
Percent of liquid wealth (model)	0.09	0.96	4.55	94.40
Avg. lottery-win-year MPC (model, incl. splurge)	0.78	0.63	0.44	0.31

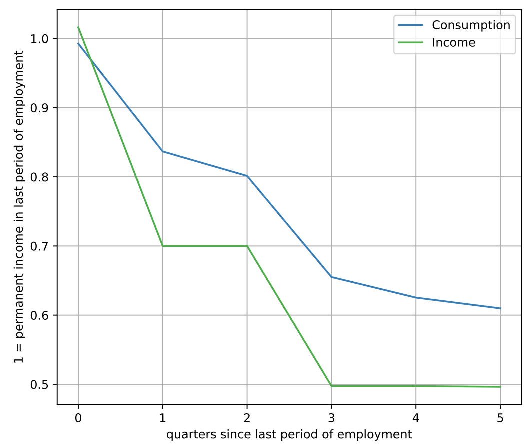
Note: Panel (A) shows percent of liquid wealth held by each education group in the 2004 SCF and in the model. It also shows the average MPCs after a lottery win for each education group. The MPCs are calculated for each individual for the year of a lottery win, taking into account that the win takes place in a random quarter of the year that differs across individuals. The MPCs are averaged across individuals within each education group. Panel (B) shows the same numbers for the population sorted into different quartiles of the liquid wealth distribution.

Table 3-V. Model fit with respect to non-targeted moments

section 3.3.3.3. Figure 3-3a shows that the model that is estimated taking the value of the splurge as given, results in a distribution of spending over time that is very similar to the one found in the Norwegian data.

The second pattern concerns the dynamics of income and spending for households that become unemployed and remain unemployed long enough for unemployment benefits to expire. Figure 3-3b shows the pattern of income and spending for such households. Ganong and Noel [2019] report the empirical result that nondurable spending drops by 12 percent the month when benefits expire. Our quarterly model is broadly consistent with this as the drop in spending the quarter after the expiry of UI benefits is 18 percent.





(a) Share of lottery win spent **(b)** Spending upon expiry of UI benefits

Note: Panel (a) compares the dynamic consumption response in the model to the estimates in Fagereng et al. [2021]; see their Figure A5. Panel (b) shows the evolution of income and spending for households who remain unemployed long enough for UI benefits to expire; see Figure 2 in Ganong and Noel [2019].

Figure 3-3. Marginal propensity to consume over time and the spending upon expiry of UI benefits in the model

3.4 Comparing fiscal stimulus policies

In this section, we present our results where we compare three policies to provide fiscal stimulus in our calibrated model. The policies we compare are a means-tested stimulus check, an extension of unemployment benefits, and a payroll tax cut. Each policy is implemented at the start of a recession, and we compare results both with and without aggregate demand effects being active during the recession. First, we present impulse responses of aggregate income and consumption after the implementation of each policy. Then we compare the policies in terms of their cumulative multipliers and in terms of their effect on a welfare measure that we introduce. Finally, based on these comparisons, we can rank the three policies.

3.4.1 Impulse responses

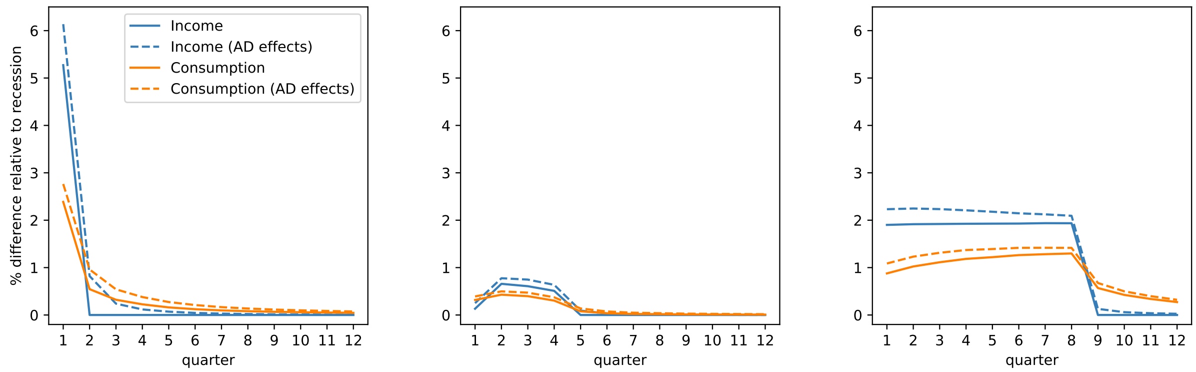
The impulse responses that we present for each stimulus policy are constructed as follows:

- A recession hits in quarter one.
- We compute the subsequent path for the economy without any policy introduced in response to the recession.
- We also compute the subsequent path for the economy with a given policy introduced at the onset of the recession in quarter one.
- The impulse responses we present are then the *difference* between these two paths for the economy and show the effect of a policy relative to a case where no policy was implemented.
- The solid lines show these impulse responses for an economy where the aggregate demand effects described in section 3.2.3 are not active, and the dashed lines show impulse responses for an economy where the aggregate demand effects are active during the recession.
- Red lines refer to aggregate labor and transfer income, and blue lines refer to consumption.

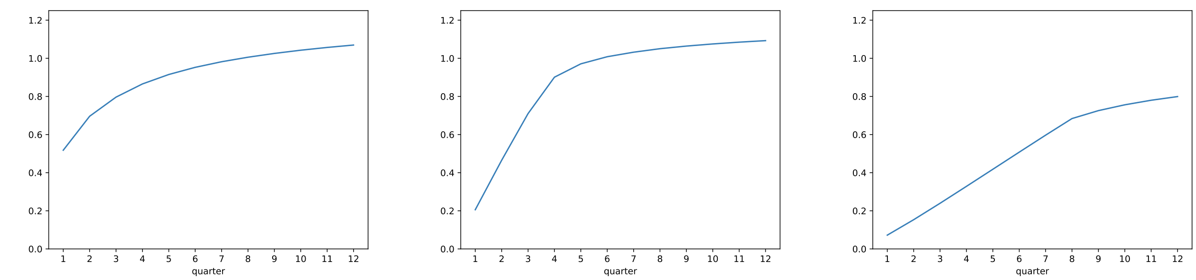
Note that all graphs show the average response of income and consumption for recessions of different length. Specifically, we simulate recessions lasting from only one quarter up to 20 quarters. We then take the sum of the results across all recession lengths weighted by the probability of this recession length occurring (given our assumption of an average recession length of six quarters).

3.4.1.1 Stimulus check

Figure 3-4a shows the impulse response of income and consumption when stimulus checks are issued in the first quarter of a recession. In the model without a multiplier, the stimulus checks account for 5 percent of the first quarter's income. In the following quarters, there are no further stimulus payments, and income remains the same as it would have been without



(a) stimulus check - IRF **(b)** UI extension - IRF **(c)** payroll tax cut - IRF



(d) stimulus check - cumulative multiplier **(e)** UI extension - cumulative multiplier **(f)** payroll tax cut - cumulative multiplier

Note: For the cumulative multiplier plots, policies are implemented during a recession with aggregate demand effects active.

Figure 3-4. Impulse responses of aggregate income and consumption to policy shocks during recessions with and without aggregate demand effects as well as cumulative multipliers as a function of the horizon for the three policies.

the stimulus check policy. Consumption is about 2.5 percent higher in the first quarter, which includes the splurge response to the stimulus check. Consumption then drops to less than 1 percent above the counterfactual, and the remainder of the stimulus check money is then spent over the next few years. In the model with aggregate demand effects, income in the first quarter is 6 percent higher than the counterfactual, as the extra spending feeds into higher incomes. Consumption in this model jumps to a higher level than without aggregate demand effects and comes down more slowly as the feedback effects from consumption to income dampen the speed with which income—and hence the splurge—return to zero. After a couple of years, when the recession is most likely over and aggregate demand effects are no longer in place, income is close to where it would be without the stimulus check policy, although consumption remains somewhat elevated.

3.4.1.2 UI extension

The impulse responses in Figure 3-4b show the response to a policy that extends unemployment benefits from 6 months to 12 months for a period of a year. In the model without aggregate demand effects, the path for income now depends on the number of consumers who receive the extended unemployment benefits. These consumers are those who have been unemployed for between 6 and 12 months. In the first quarter of the recession, the newly unemployed receive unemployment benefits regardless of whether they are extended or not. Therefore, it is in the second and third quarters, when the effects of the recession on long-term unemployment start to materialize, that the extended UI payments ramp up, amounting to an aggregate increase in quarterly income by 0.7 percent. By the fifth quarter, the policy is no longer in effect, and income from extended unemployment goes to zero. Consumption in the first quarter jumps by more than income (by 0.3 percent), prompted by both the increase in expected income and the reduced need for precautionary saving given the extended insurance. In the model without aggregate demand effects, consumption is only a little above the counterfactual by the time the policy is over. In the model with aggregate demand effects, there is an extra boost to income of about the same size in the first and second quarters. As this extra aggregate demand induced income goes to employed consumers, more of it is saved, and consumption remains elevated several quarters beyond the end of the policy.

3.4.1.3 Payroll tax cut

The final impulse response graph, Figure 3-4c, shows the impulse response for a payroll tax cut that persists for two years (eight quarters). In the model without aggregate demand effects, income rises by close to 2 percent as the take-home pay for employed consumers goes up. After the two-year period, income drops back to where it would have been without the payroll tax cut. Consumption jumps close to 1 percent in response to the tax cut. Over the period in which the tax cut is in effect, consumption rises somewhat as the stock of precautionary savings goes up. Following the drop in income, consumption drops sharply because of the splurge and then decreases over time as consumers spend out the savings they built up over the period the tax cut was in effect. In the model with aggregate demand effects, income rises by about 2.3 percent above the counterfactual and then declines steadily as the probability that the recession remains active—and hence the aggregate demand effects in place—goes down over time. Following the end of the policy, the savings stock in the model with aggregate demand effects is high, and consumption remains significantly elevated through the period shown.

3.4.2 Multipliers

In this section, we compare the fiscal multipliers across the three stimulus policies. Specifically, we employ the cumulative multiplier, which captures the ratio between the net present value (NPV) of stimulated consumption up to horizon t and the full-horizon NPV of the cost of the policy. We thus define the cumulative multiplier up to horizon t as

$$M(t) = \frac{NPV(t, \Delta C)}{NPV(\infty, \Delta G)}, \tag{3.9}$$

where ΔC is the additional aggregate consumption spending up to time t in the policy scenario relative to the baseline and ΔG is the total government expenditure caused by the policy. The NPV of a variable X_t is given by $NPV(t, X) = \sum_{s=0}^{t} \left(\prod_{i=1}^{s} \frac{1}{R_i} \right) X_s$.

The multiplier hence captures the amount of induced consumption at different horizons relative to the total (i.e. full-horizon) cost of the policies.[22]

The second row in Figure 3-4 plots the cumulative multipliers at different horizons, and table 3-VI shows the 10y-horizon multiplier for each policy. The stimulus check, which is paid out in quarter one, exhibits the largest multiplier on impact. About 50 percent of the

[22] In the case that there is no aggregate demand effect, these multipliers converge to 1 as t goes to infinity.

total policy expenditure is immediately spent by consumers. After two years, and because of the aggregate demand effects, consumption has increased cumulatively by more than the cost of the stimulus check. Over time, the policy reaches a total multiplier of 1.199. Without AD effects the policy only generates a multiplier of 0.854. The last two rows in table 3-VI show the expected share of the policy expenditures and stimulated consumption that occurs during a recession. For the stimulus check all of the policy expenditures occur in the first quarter and thus with certainty during the recession. However, since induced consumption also takes place during later periods at which time the recession may have already ended, the share of stimulated consumption during the recession is lower at 75%.

Since spending for the UI policy is spread out over four quarters (and peaks in quarters two to three), the multiplier in the first quarter is considerably lower than in the case of the stimulus check. However, the UI extension policy is targeted in the sense that it provides additional income only to those consumers who have large MPCs, because of unemployment. Also, over the medium-term UI extension expenditures are more likely to induce consumption spending during the recession compared to the check stimulus, see the last row in table 3-VI. This is because UI extension expenditures affect agents who spend the additional income relatively quickly once it reaches them. Therefore, the cumulative mulitiplier of the UI extension exceeds that of the stimulus check after about one year.

The payroll tax cut has the lowest multiplier irrespective of the considered horizon. A multiplier of close to 1 is reached only after 10 years with AD effects. These relatively small numbers reflect that policy spending lasts for a long time and is thus more likely to occur after the recession has ended. Moreover, only employed consumers, often with relatively low MPCs, benefit directly from the payroll tax cut. Therefore, the policy is poorly targeted if the goal is to provide short-term stimulus.

Table 3-VI contains an additional (middle) row with results for an economy where we only consider a "first-round" aggregate demand effect. To understand these values note that the policies initially increase the income of consumers directly, which leads to a boost

	Stimulus check	UI extension	Tax cut
10y-horizon Multiplier (no AD effect)	0.854	0.893	0.826
10y-horizon Multiplier (AD effect)	1.199	1.175	0.952
10y-horizon (1st round AD effect only)	1.125	1.119	0.926
Share of policy expenditure during recession	100.0%	79.6%	57.8 %
Share of policy cons. stimulus during recession	75.0%	79.3%	42.7 %

Note: Policies are implemented during a recession with or without the aggregate demand effect active. The row "1st round AD effect only" captures the direct consumption impact of the policies and the additional boost to consumption resulting from the aggregate demand effect acting on the direct consumption impact. It does not include higher-round aggregate demand effects materializing on aggregate demand effects acting on indirectly stimulated consumption.

Table 3-VI. Multipliers as well as the share of the policy expenditure and consumption stimulus occurring during the recession

in consumption. As a consequence, this boost triggers an aggregate demand effect which increases the income of everyone and in turn leads to an additional boost to consumption. We refer to the sum of this initial and the indirect boost to consumption as the first-round AD effect. However, the AD effect continues as the indirect boost to consumption triggers another round of income increases which further boost consumption and so on. One might argue that these higher-order rounds of the AD effect are not likely to be anticipated by consumers. Since higher-order consumption boosts only materialize if consumers anticipate them and act accordingly, the overall increase in consumption might turn out to be smaller than suggested by the full AD effect. As shown in the middle row of the table, the multipliers are smaller when excluding higher-order rounds. Nevertheless, the ranking of the policies remains unchanged.

3.4.3 Welfare

In this section, we look at the welfare implications of each stimulus policy. To do so, we need a way to aggregate welfare in our model with individual utility functions. In our model, some households consume much less than other households, and a social planner with equal weights on each household could significantly increase welfare through redistribution across households even in normal times. We are interested in the benefit of carrying out fiscal policies in a recession, so we do not want our results to reflect the benefits of redistribution inherent in our model in normal times.

Our welfare measure weights the felicity of a household at time t by the inverse of the marginal utility of the same household in a counterfactual simulation in which neither the recession occurred nor the fiscal policy was implemented, discounted by the real interest rate.[23] This weighting scheme means that in normal times the marginal benefit or cost to a social planner of moving a dollar of consumption from one household at one time period to another household at the same or a different time period is zero. Hence, in normal times, any re-distributive policy has zero marginal benefit. However, in a recession when the average marginal utility is higher than in normal times, there can be welfare benefits to government borrowing to allow households to consume more during the recession.

As with all social welfare measures, ours is not without ethical issues. We have chosen our welfare measure over one with equal weights because an equal-weights measure would be increasing with the size of any redistributive policy.[24] However, similar to Negishi weights, our welfare measure gives greater weight to households that are well off.[25] Furthermore, our welfare measure distinguishes between households that would have suffered unemployment in normal times and households that are made unemployed as a result of the recession—–giving the latter a higher weight in the social welfare function.

[23]Discounting at the real interest rate accounts for the fact that a redistributive policy over time will require borrowing or lending at the real interest rate. The preference discount factors of households would appear in both the numerator and the denominator—the utility and marginal utility—and therefore cancel and do not play a role in our welfare measure.

[24]Using a version of an equal-weights measure results in an even greater welfare benefit to extended unemployment insurance—see the previously distributed draft of this paper, Carroll et al. [2023]. However, because the size of the extended unemployment benefits policy is much larger in a recession compared to normal times, while the size of the other two policies does not change significantly in a recession, this equal-weights measure almost mechanically favored the extended unemployment benefits policy.

[25]Negishi weights have been used in the climate literature as a way to separate the welfare benefits of climate mitigation policies from broader questions about global income redistribution. Our problem of separating the welfare benefits of recession mitigation policies from income redistribution in normal times is similar, but complicated by our incomplete markets setup. With complete markets, under which there is no potential benefit to redistributing consumption across time for any individual household, our measure is identical to Negishi weights.

Let $\mathbf{c}_{it,normal}$ be the consumption—inclusive of the splurge—of household i at time t in the baseline simulation with no recession and no fiscal policy. The (undiscounted) marginal utility of an extra unit of consumption for this household in this time period is $u'(\mathbf{c}_{it,normal})$.

Let $\mathbf{c}_{it,policy,Rec,AD}$ be the consumption of the same household under the fiscal policy, *policy*, possibly a recession, $Rec \in \{0,1\}$, and in an economy with or without aggregate demand effects, $AD \in \{0,1\}$.[26]

We also denote the net present value of the government expenditures of the policy as $NPV(policy, Rec, AD)$. With this notation, we can now define the welfare bang for the buck of a policy as:

$$\mathcal{W}(\text{policy}, Rec, AD) = \frac{1}{NPV(\text{policy}, Rec, AD)} \sum_{i=1}^{N} \sum_{t=0}^{\infty} \frac{1}{R^t} \frac{u(\mathbf{c}_{it,policy,Rec,AD}) - u(\mathbf{c}_{it,none,Rec,AD})}{u'(\mathbf{c}_{it,normal})}, \tag{3.10}$$

In normal times, this welfare measure will be exactly equal to one for any small-scale fiscal expansion. To see this, note that the numerator, $u(\mathbf{c}_{it,policy,0,0}) - u(\mathbf{c}_{it,none,0,0})$, is equal to the change in consumption multiplied by the marginal utility in normal times. As the total change in consumption is equal to the net present value of the policy, which we divide by, the total welfare measure is equal to one. Note that for large increases in consumption, this measure may be less than one because the utility function is concave.

	Stimulus check	UI extension	Tax cut
$\mathcal{W}(\text{policy}, Rec = 0, AD = 0)$	0.96	0.85	0.99
$\mathcal{W}(\text{policy}, Rec = 1, AD = 0)$	0.99	1.82	0.98
$\mathcal{W}(\text{policy}, Rec = 1, AD = 1)$	1.34	2.11	1.10

Table 3-VII. Welfare measures, calculated for policies implemented both out of and in a recession with and without aggregate demand effects

Table 3-VII shows the welfare measure for each policy as defined by equation (3.10). The

[26] In the simulations, household i experiences the same permanent and transitory shock sequence, but in the recession simulation some households experience unemployment during periods in which the same household is employed in the baseline simulation.

top row of the table shows the welfare measure for implementing each policy in normal times. For marginal policies, this is equal to one by definition. Indeed, the value for both the stimulus check and the tax cut policy is very close to one. However, the welfare measure for the extended unemployment policy in normal times is noticeably less than one. This is because, although this policy is smaller in absolute size than the other policies, its consumption effects are concentrated on a small number of households that remain unemployed long enough to receive the extended benefits. For these households, the effect on consumption is large enough such that the non linearity of the consumption function leads to smaller welfare benefit than the marginal utility of consumption would otherwise imply.

The second row of table 3-VII shows the welfare benefit of each policy in a recession without any aggregate demand effects. Again, the stimulus check and tax cut policies have measures that are close to one—pulling forward consumption has little welfare benefit for the average household because the average marginal utility of consumption is only a little higher than in normal times. By contrast, the policy sees benefits of 1.8 dollars for every dollar spent on extended UI benefits during a recession. This is because many of the households who are unemployed for many quarters in the recession would have never been unemployed, or quickly reemployed, in normal times and hence their marginal utility of consumption is much higher in the recession than in normal times.

The third row of the table shows the welfare measure for each policy in a recession in the version of the model with aggregate demand effects during the recession. The payroll tax cut now has a noticeable benefit, as some of the tax cut gets spent during the recession, resulting in higher incomes for all consumers. However, the tax cut is received over a period of two years, and much of the relief may be after the recession—and hence the aggregate demand effect—is over. Furthermore, because the payroll tax cut goes only to employed consumers who have relatively lower MPCs, the spending out of this stimulus will be further delayed, possibly beyond the period of the recession. By contrast, the stimulus check is received in the first period of the recession and goes to both employed and unemployed consumers. The earlier arrival and higher MPCs of the stimulus check recipients mean more of the stimulus is spent during the recession, leading to greater aggregate demand effects, higher income, and higher welfare. The extended UI arrives, on average, slightly later than the stimulus check. However, the recipients, who have been unemployed for at least six months, spend the extra benefits relatively quickly, resulting in significant aggregate demand effects during the recession. In contrast to the payroll tax cut, extended UI has the benefit of automatically reducing if the recession ends early, making fewer consumers eligible for the benefit.

3.4.4 Comparing the policies

The results presented in sections 3.4.2 and 3.4.3 indicate that the extension of unemployment benefits is the clear "bang for the buck" winner. The extended UI payments are well targeted to consumers with high MPCs and high marginal utility, giving rise to large multipliers and welfare improvements. The stimulus checks come in slightly higher when measured by their short-term multiplier effect but are a distant second when measured by their welfare effects. The stimulus checks have large initial multipliers because the money gets to consumers at the beginning of the recession and therefore induce aggregate demand effects more quickly. However, the checks are not well targeted to high-MPC consumers, so even though the funds arrive early in the recession, they are spent out more slowly than the extended unemployment benefits.[27] Furthermore, the average recipient of a stimulus check has a much lower marginal utility than consumers receiving unemployment benefits, so the welfare benefits of this policy are substantially muted relative to UI extensions.

The payroll tax cut policy does poorly by both measures: It has a low overall multiplier and negligible welfare benefits. The reasons are that the funds are slow to arrive, so the subsequent spending often occurs after the end of the recession, and that the payments are particularly badly targeted—they go only to employed consumers.

[27]Theoretically, stimulus checks could be targeted to the highest-MPC households which, for small-sized policies, would mean households with an MPC of one. However, data limitations and other practicalities make means-testing stimulus checks by income the extent of targeting in practice.

While it is clear from the analysis that the extended unemployment benefits should be the first tool to use, a disadvantage of them is that they are limited in their size. If a larger fiscal stimulus is deemed appropriate, then stimulus checks provide an alternative option that will stimulate spending during the recession even if the welfare benefits are substantially lower than the UI extension.

3.4.5 Results in a model without the splurge

We introduce the splurge in our model with the aim of matching empirical evidence on the dynamics of spending in response to transitory income shocks. The splurge acts as a stand-in for competing theories for why agents may spend more out of those shocks than suggested by a simple model in which forward-looking agents solely maximize utility. However, it is natural to consider to what extent the splurge is in fact necessary to match the empirical patterns and the implications for our results ranking the different policies. To assess this we reestimate the model without the splurge and recompute all our results regarding the relative effectiveness of the policies in this version of the model.

The details of this exercise are in Appendix A.1. There we discuss how the estimation of the Norwegian model in section 3.3.1 is affected if we do not include splurge consumption, and the estimation of the discount factor distributions for each education group in the US economy without taking the splurge as given. The general result is that the we can match the liquid wealth distributions that we target also in models that do not include a splurge. The models do so by estimating wider distributions of discount factors than we found in section 3.3.1 and 3.3.3.3.

Without the splurge the models do struggle to exactly match the dynamics of spending after a temporary income shock, however. In particular, for the estimation of the Norwegian model, we can compare the model's implications for MPCs for different wealth quartiles to empirical estimates. Without the splurge, the model leads to an MPC for the top wealth quartile that is far lower than in the data. In the US model this MPC is also quite low compared to the model with splurge consumption, but for the US we do not have an empirical estimate to compare to.

To evaluate the impact of splurge consumption on our ranking of the policies, we simulate the three fiscal policies in the reestimated model without the splurge. There are only minor shifts in the multipliers of the policies, but the lower average MPCs reduces multipliers for the check and tax cut policy relative to the model with the splurge. In contrast, the UI extension becomes slighlty more effective in stimulating consumption as the wider distribution of discount factors implies a larger share of the population that hits the borrowing constraint upon expiry of UI benefits. Hence, the extension of UI benefits affects agents more strongly in the model without the splurge.

More importantly for the main conclusion of our paper, table 3-VIII compares the welfare implications of the policies in the two models. Generally, the welfare metric varies only marginally across the models. When aggregate demand effects are active, we see slightly larger differences in the welfare evaluation, with the check policy losing ground against the UI extension. This is because the welfare impact of the check in the model with the splurge is contingent on the checks being spent quickly due to a high average MPC and thus generating strong aggregate demand effects while the recession is still ongoing. In the absence of the splurge only liquidity-constrained agents spend the check money quickly, such that recession-induced aggregate demand effects are smaller.

	Stimulus check	UI extension	Tax cut
$\mathcal{W}(\text{policy}, Rec = 0, AD = 0)$	0.97(0.96)	0.84(0.85)	0.99(0.99)
$\mathcal{W}(\text{policy}, Rec = 1, AD = 0)$	1.00(0.99)	1.80(1.82)	0.97(0.98)
$\mathcal{W}(\text{policy}, Rec = 1, AD = 1)$	1.27(1.34)	2.12(2.11)	1.09(1.10)

Note: The values outside of the brackets capture the multipliers in the model without the splurge, while those inside the brackets are mulitipliers with the splurge.

Table 3-VIII. Welfare measure, calculated for policies implemented both out of and in a recession with and without aggregate demand effects.

Overall, we can conclude that the ranking of the policies remains unaffected by the splurge.

The splurge is thus helpful in matching available empirical evidence, but does not affect the assessment of the effectiveness of the considered policies.

3.5 Robustness in a HANK and SAM Model

The main results of this paper are presented in a partial equilibrium setup with aggregate demand effects that do not arise from general equilibrium effects. We think there are many advantages to studying the welfare and multiplier effects in this setting without embedding the model in general equilibrium. First, general equilibrium models often struggle to adequately capture the feedback mechanisms between consumption and income, particularly the asymmetric nature of these relationships during recessionary versus expansionary periods. Additionally, a complete general equilibrium treatment would necessitate the analysis of numerous complex channels including investment dynamics, firm ownership structures and dividend distribution policies, inventory management, and international trade flows—elements that, while important in their own right, would potentially obscure the core mechanisms we aim to investigate.

Despite the advantages of our partial equilibrium approach, here we complement our analysis with a general equilibrium HANK and SAM model, as standard as possible, that is able to capture supply-side effects that are absent from the partial equilibrium model. In particular, fiscal policies can generate labor market responses that our partial equilibrium analysis does not address. These supply-side channels can affect both the welfare implications and the fiscal multipliers of different policy interventions. Furthermore, standard to the HANK and SAM literature, the general equilibrium model generates a self-reinforcing precautionary saving channel that amplifies business cycles. During a recession, heightened unemployment risk prompts households to increase savings and reduce consumption which in turn weakens both aggregate and labor demand. The resulting decline in labor demand further raises unemployment risk, reinforcing precautionary savings.

We embed the consumption choices of our households—with heterogeneity over education type and discount factors—in a New Keynesian model with search and matching frictions that closely follows Du [2024], which, in turn, is in spirit of the seminal work of Ravn and Sterk [2017a, 2021]. Aside from the household block of the model, the framework is standard and follows from the HANK and SAM literature. The model features nominal price rigidities à la Rotemberg, a monetary authority that sets the nominal interest rate following a standard Taylor rule that responds to inflation, and a fiscal authority that taxes labor income and borrows debt from households to fund unemployment insurance and interest on past debt. As in Gornemann et al. [2021], Bardoczy [2024], and Graves [Forthcoming], households randomly search for jobs and match with a labor agency that sells labor to intermediate good producers. Complete details of the model are provided in appendix A.5.

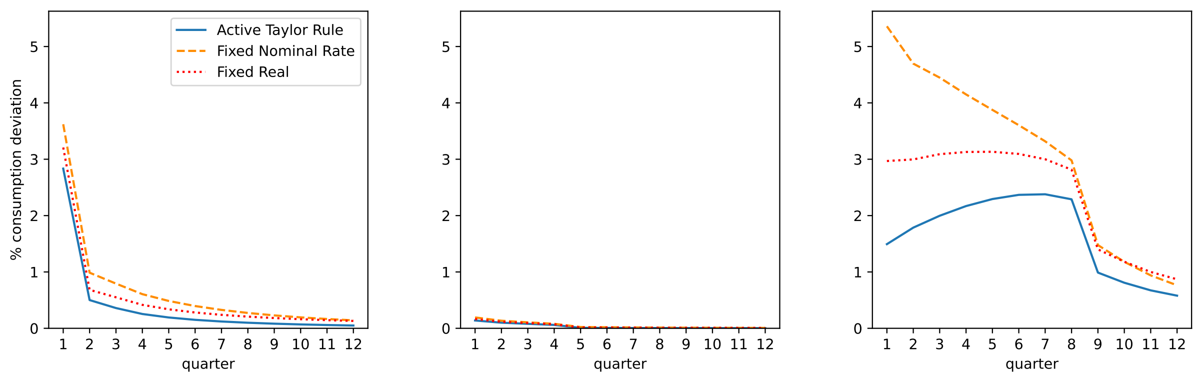
The general equilibrium structure generates fiscal multipliers through an intertemporal Keynesian cross mechanism, which becomes particularly pronounced when monetary policy is passive. Moreover, the search and matching framework allows the employment rate to respond to policy interventions, allowing us to capture both demand and supply effects of fiscal policies.

Our approach in this section relies on linearizing the macro dynamics of the model and employs the Sequence Space Jacobian methods developed by Auclert et al. [2021b]. This linearization imposes certain constraints on our analysis. Notably, we cannot evaluate the effects of different policies starting from a deep recessionary state, as we do in our main results.[28] This limitation prevents us from conducting welfare comparisons between recessionary periods and the steady state. Additionally, the Keynesian cross mechanism embedded in the model exhibits uniform behavior regardless of the degree of economic slack—a feature that stands in contrast to the state-dependent multipliers we apply in our partial equilibrium analysis.[29]

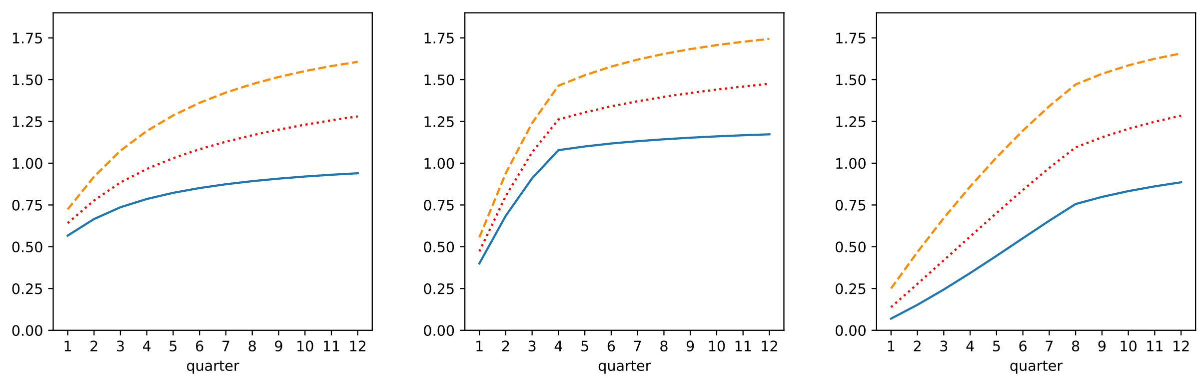
[28] One approach to overcome this limitation, which could be used in future work, is described in Boppart et al. [2018].

[29] We note two additional technical limitations of our general equilibrium implementation. First, stimulus

The consumption response in this general equilibrium model to each of the three policies is shown in the top row of Figure 3-5. For each of the three fiscal policies, we have shown the consumption response under three different monetary policy rules: 1) an active Taylor rule with a coefficient of 1.5 on inflation; 2) a fixed nominal rate (simulating an effective lower bound); and 3) a fixed real rate (closest in spirit to our partial equilibrium analysis).



(a) stimulus check - IRF **(b)** UI extension - IRF **(c)** payroll tax cut - IRF



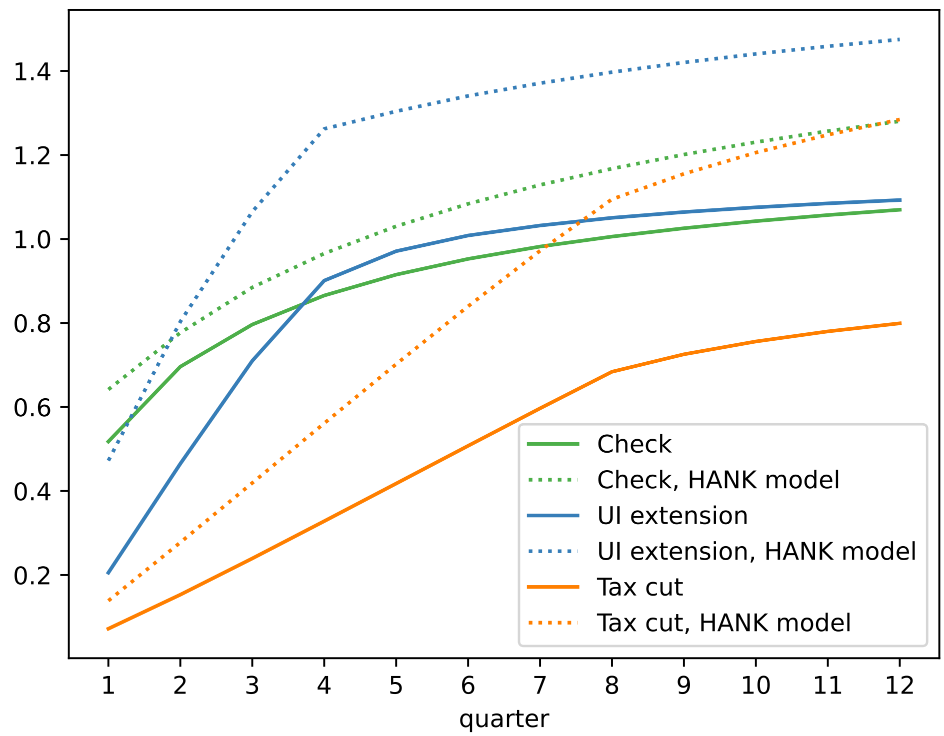
(d) stimulus check - cumulative multiplier **(e)** UI extension - cumulative multiplier **(f)** payroll tax cut - cumulative multiplier

Figure 3-5. Impulse responses of aggregate consumption to policy shocks as well as cumulative multipliers as a function of the horizon for the three policies.

Overall, the IRFs from this model are similar to those from the partial equilibrium analysis, especially under the fixed real-rate rule. Note that the magnitude of the consumption response to the UI extension is lower than in our main analysis—a consequence of lower long-term

payments in the model are specified as proportional to permanent income, rather than as means-tested fixed dollar amounts as implemented in practice and in our partial equilibrium framework. Second, splurge behavior only occurs out of equilibrium.

unemployment in this HANK exercise of deviating from the steady state.[30] Furthermore, although we are unable to repeat our welfare analysis under a recession in this model, the distributional effects of the policies are similar. Most importantly, the mechanism leading to far greater welfare benefits for the UI extension, namely that the newly unemployed have high marginal utility, are robust to the supply-side effects of a general equilibrium HANK and SAM model.



Note: In the partial equilibrium model, policies are implemented during a recession with aggregate demand effect active.

Figure 3-6. Consumption multiplier as a function of the horizon for the three policies in the partial equilibrium vs the HANK model

The bottom row of Figure 3-5 shows the corresponding cumulative multipliers for each

[30] By contrast, our main analysis considers deviations from a recessionary scenario. Note that the dynamics of the UI extension IRF are also somewhat faster acting. This is because, under the recession that we study in the partial equilibrium analysis, the large mass of newly-unemployed households do not start receiving extended UI for six months.

policy and monetary policy rule. Figure 3-6 compares these consumption multipliers over different horizons under a fixed real rate rule to those in our baseline partial equilibrium model. The multipliers are bigger in the HANK and SAM model. Nevertheless, in both models, the relative ranking of the consumption multipliers over time horizons are similar, with the effect of the tax cut substantially smaller than the stimulus check or UI extension policies, despite the inclusion of supply-side effects in this HANK model. However, in contrast to the partial equilibrium model, towards the end of the period shown the tax cut consumption multiplier is near that of the stimulus check. This is because the aggregate demand effects in our partial equilibrium model do not continue beyond the recession, dampening the benefits of the tax cut policy—in which much of the extra spending occurs after the recession is over—relative to the stimulus check and extended UI policies.

As discussed in the literature review, Broer et al. [2025] also compute fiscal multipliers for commonly implemented stimulus policies in a HANK and SAM framework. A key distinction is that our model exhibits more spending out of income shocks in the quarters following the quarter of the shock. As shown in Auclert et al. [2018], accounting for the path of iMPCs beyond the first quarter significantly amplifies cumulative fiscal multipliers. By capturing this persistence—consistent with microeconomic evidence—our model produces larger multipliers for the untargeted stimulus check than those in Broer et al. [2025].

3.6 Conclusion

For many years leading up to the Great Recession, a widely held view among macroeconomists was that countercyclical policy should be left to central banks, because fiscal policy responses were unpredictable in their timing, their content, and their effects. Nevertheless, even during this period, fiscal policy responses to recessions were repeatedly tried, perhaps because the macroeconomists' advice to fiscal policymakers — "don't just do something; stand there"— is not politically tenable.

This paper demonstrates that macroeconomic modeling has finally advanced to the point where we can make reasonably credible assessments of the effects of alternative policies of the kinds that have been tried. The key developments have been both the advent of national registry datasets that can measure crucial microeconomic phenomena and the creation of tools of heterogeneous agent macroeconomic modeling that can match those micro facts and glean their macroeconomic implications.

We examine three fiscal policy experiments that have actually been implemented in the past: an extension of UI benefits, a stimulus check, and a tax cut on labor income. Our model suggests that the extension of UI benefits is a clear "bang for the buck" winner. While the stimulus check arrives faster and generates multiplier effects more quickly, it is less well targeted to high-MPC households than an extension of UI benefits. By contrast, the welfare gains of extended UI benefits are significantly greater than those of a stimulus check. The chief drawback of the UI extension is that its size is limited by the fact that a relatively small share of the population is affected by it. In contrast, stimulus checks are easily scalable while exhibiting only slightly less recession-period stimulus (in a typical recession). However, since some of the stimulus checks flow to well-off consumers, such checks do worse than UI extensions when we evaluate welfare consequences. Finally, the payroll tax cut is the least effective in terms of both the multiplier and welfare effect, since it targets only employed consumers and, for a typical recession, more of its payouts are likely to occur after the recessionary period (when multipliers may exist) has ended.

The tools we are using could be reasonably easily modified to evaluate a number of other policies. For example, in the COVID-driven recession, not only was the duration of UI benefits extended, but those benefits were also supplemented by substantial payments to all UI recipients. We did not calibrate the model to match this particular policy, but the framework could easily accommodate such an analysis.

Appendix I

A Appendix I: The Macroeconomic Consequences of Unemployment Scarring

A.1 Simulating The 1980s, 1990-91, and 2000s Recessions

In this section, I explore whether scarring can explain the recoveries of all other recessions since the 1980s. For each recession, I assume the steady state of the model is the quarter in which the given recession begins and recalibrate ζ^X to match the proportion of the increase in the unemployment rate due to permanent layoffs, temporary layoffs, and quits/others that is estimated in Gertler et al. [2022] and from the decomposition of unemployment flows constructed by Fujita and Moscarini [2017]. In addition, I fix the real wage by setting $\phi_w = 1$. I then repeat the estimation procedure for simulating the Great Recession without estimating monetary policy shocks for parsimony. In addition, for each recession, the data are detrended from the end of the previous recession up until beginning of the next recession.[1]

A.1.1 The 80s Recession

The model suggests that scarring played a limited role in explaining the recovery of consumption and output from the recessions in the 80s. Figure I-1 plots the responses of the unemployment rate, hourly labor compensation, consumption and GDP against the data. The responses represent deviations from 1980Q1, the beginning of the first recession of the 80s. From the figure, the model with scarring has difficulty accounting for the response of consumption but can account for the long run behavior of output. The path of hourly labor compensation provides a good fit to the data until 1985. The model has difficulty accounting for the path of hourly labor compensation after 1985 because it cannot capture the compositional changes of hourly labor compensation due to the absence of working hours as well as not having the job separation rate depend on human capital.

[1] Pushing back the beginning of the detrending interval to be 20 years before the beginning of the recession makes little difference to the results.

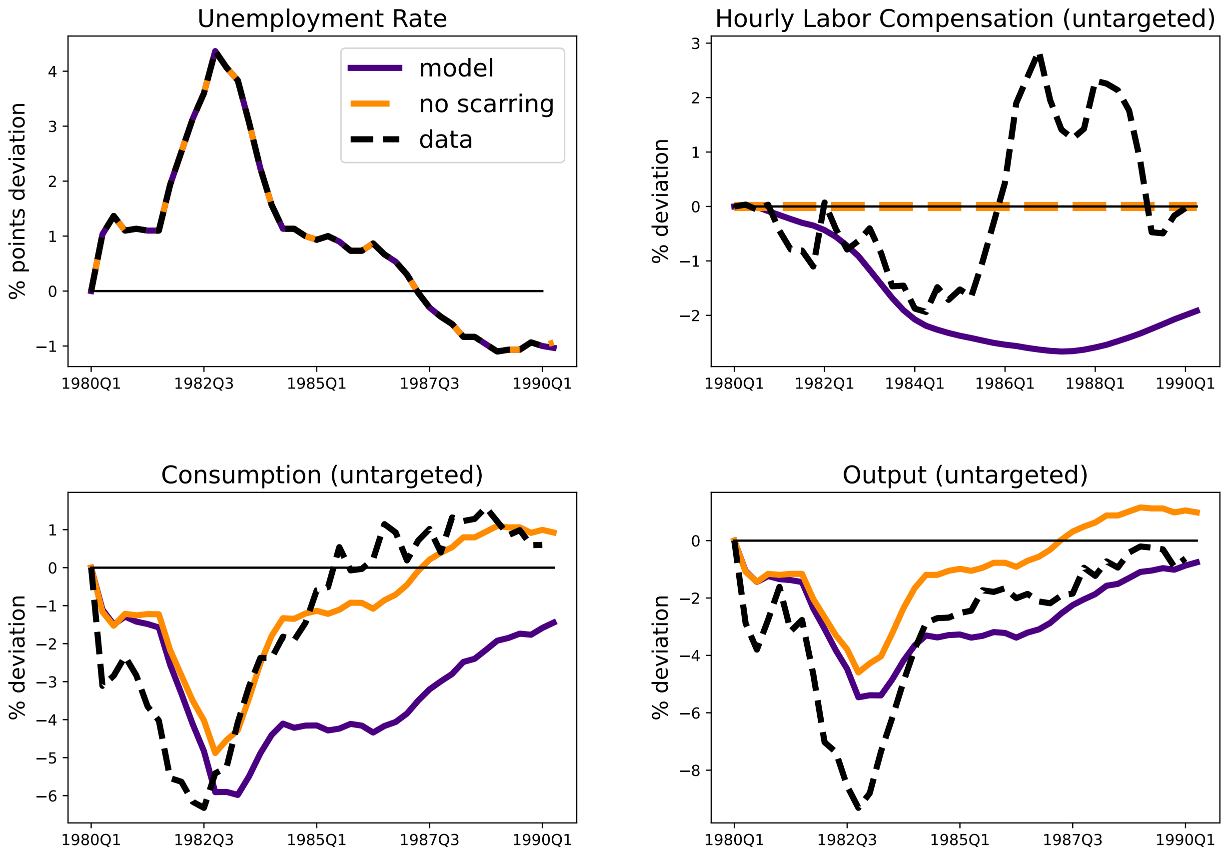


Figure I-1. Model vs data: 1980s

A.1.2 The 1990-1991 Recession

According to the model, scarring plays an important role in explaining the recovery from the 1990s recession. Figure I-2 plots the responses for the 1990-1991 recession against the data. The responses represent deviations from 1990Q3. With scarring, the model matches the responses of consumption and GDP well as well as matching the overall trend in hourly labor compensation. The response of hourly labor compensation likely rises in the beginning due lower wage workers being fired first. As mentioned previously, the model does not capture this fact.

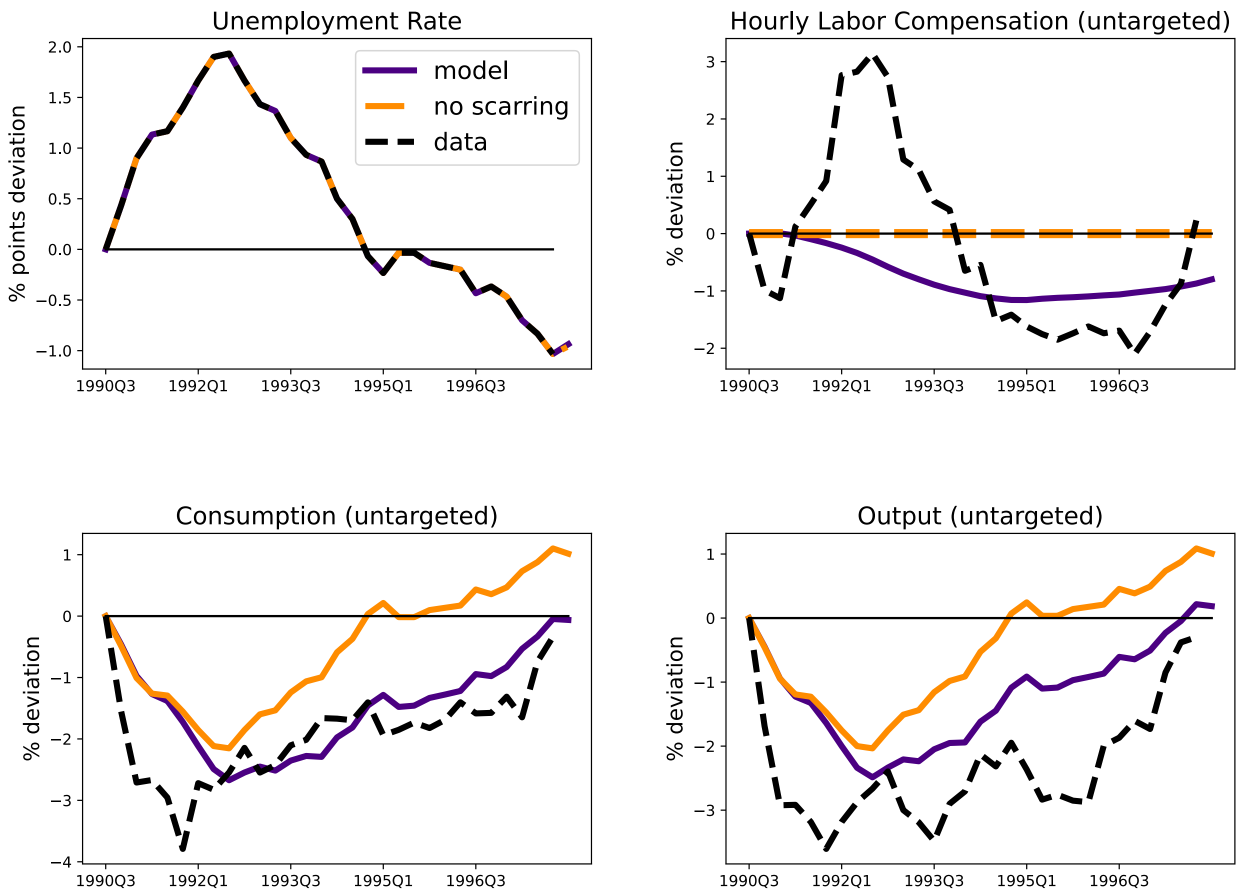


Figure I-2. Model vs data: 1990-1991 recession

A.1.3 The 2001 Recession

Similar to the 1990-1991 recession, scarring can help explain the recovery from the 2001 recession. Figure I-3 plots the responses for the 2001 recession against the data. The responses represent deviations from 2001Q2. With scarring, the model can help explain the long run behavior of consumption and GDP. The model also captures the trend in hourly labor compensation seen in the data.

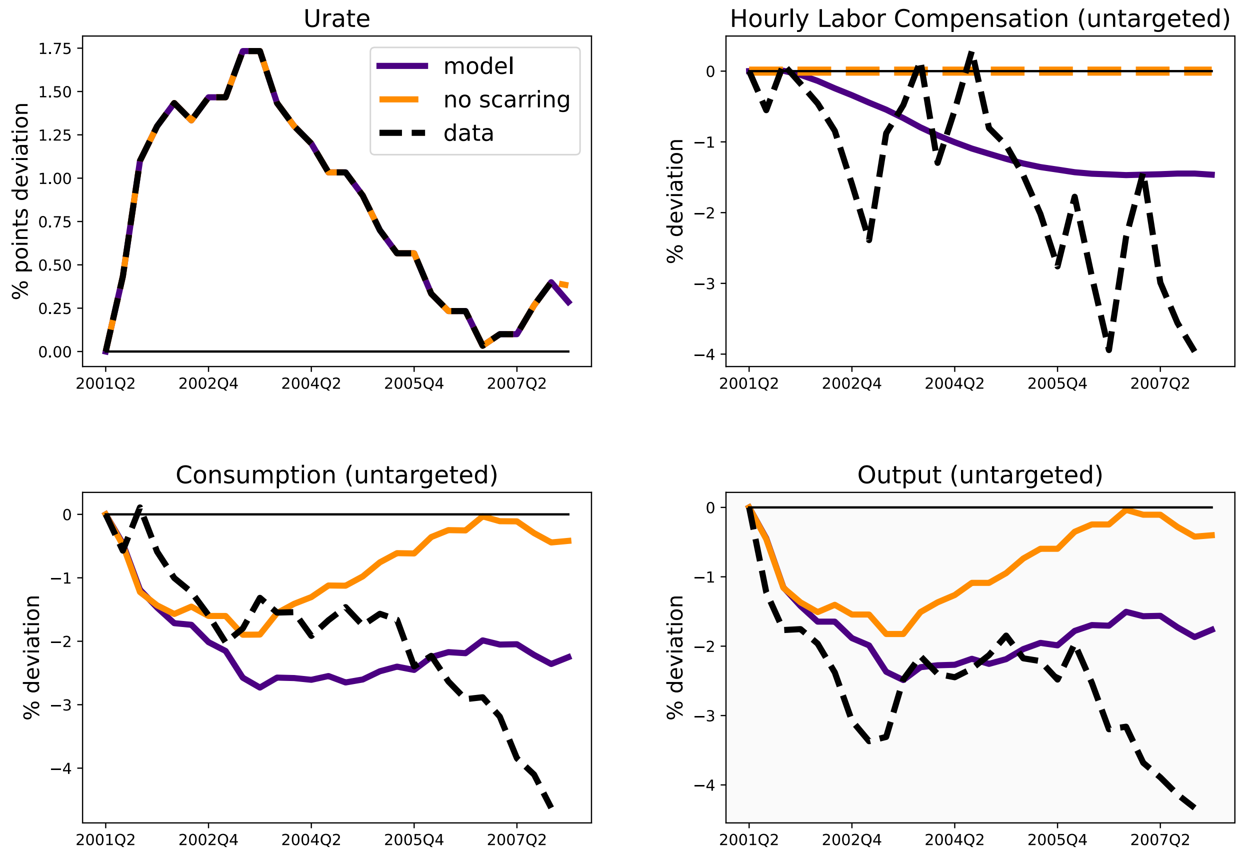


Figure I-3. Model vs data: 2000s

A.2 Unemployment Risk as an Amplifier of Business Cycles

Precautionary saving in response to heightened unemployment risk is larger in the presence of scarring. This greater intensity in precautionary behavior leads unemployment risk to be a larger amplifier of business cycles. Figure I-4 (baseline calibration) and figure I-5 (fixed real wage) plot the response of consumption to the negative demand shock from section 6.1 with and without perceived unemployment risk under the baseline model and the model with no scarring. The plots demonstrate that unemployment risk is a larger amplifier of business cycles, especially under a fixed real wage. Increased precautionary saving in response to heightened unemployment risk dampens consumption, reduces labor demand, and therefore further raises the unemployment rate. This sequence of events is self reinforcing as the increase in the unemployment rate further increases precautionary saving. When households perceive that unemployment can lead to scars, this channel is substantially larger,

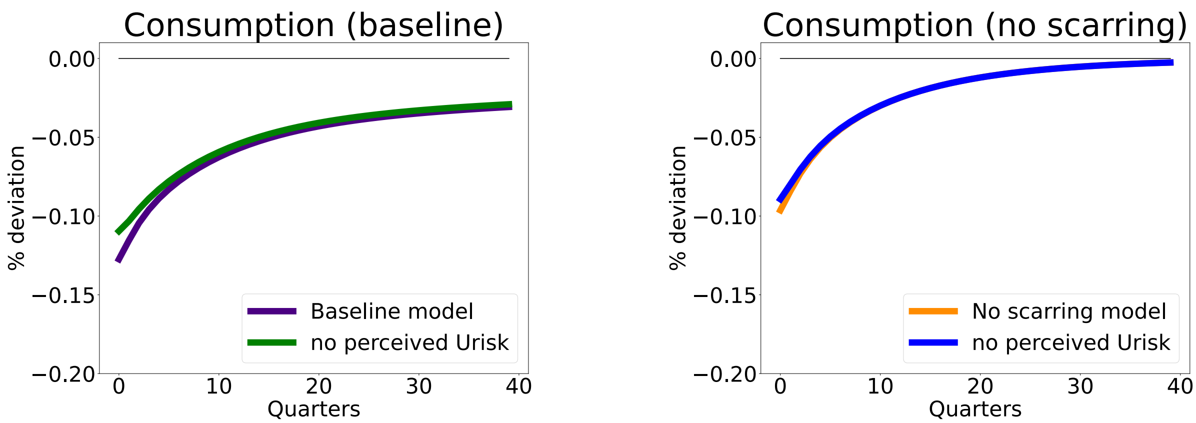


Figure I-4. Responses of Consumption to demand shock with and without perceived unemployment risk.

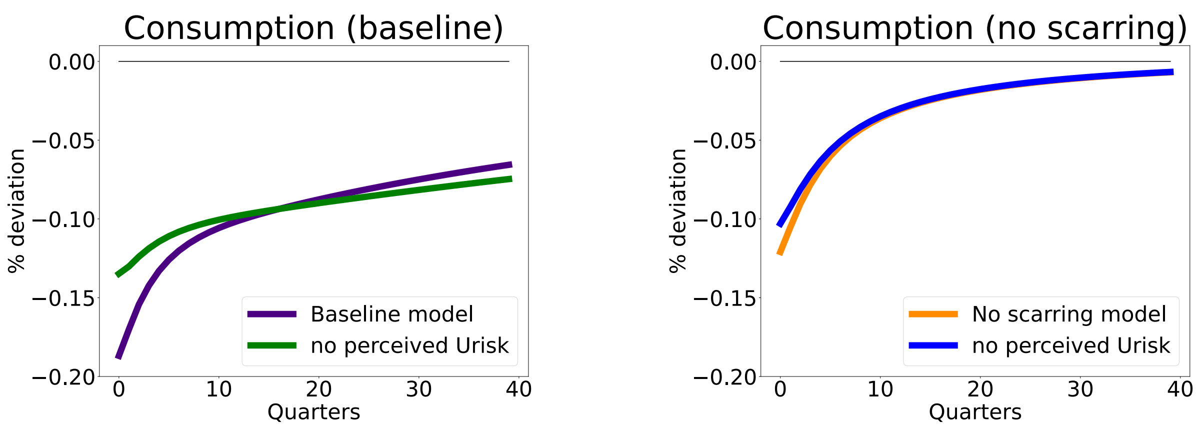


Figure I-5. Responses of Consumption to demand shock under a fixed real wage with and without perceived unemployment risk.

Note: The response of consumption in the baseline model is less persistent than its counterpart without scarring because the response of precautionary saving is front loaded in a model with perfect foresight. To be specific, in response to the negative demand shock, the decumulation of precautionary savings after $t = 0$ is larger in the model with scarring because their buffer stocks were substantially large to begin with. This decumulation is large enough to to reduce the persistence of consumption.

A.3 Using other shocks to simulate the Great Recession

This section demonstrates that the choice of shock chosen to match the unemployment rate during the Great Recession in figure 1-8 does not matter. I consider a price markup shock and a shock to the variance of permanent income. For each type of shock, I estimate innovations to the respective variable to match the unemployment rate. Figure I-6 plots the responses of consumption and output when either shock process is estimated to match the unemployment rate during the Great Recession.

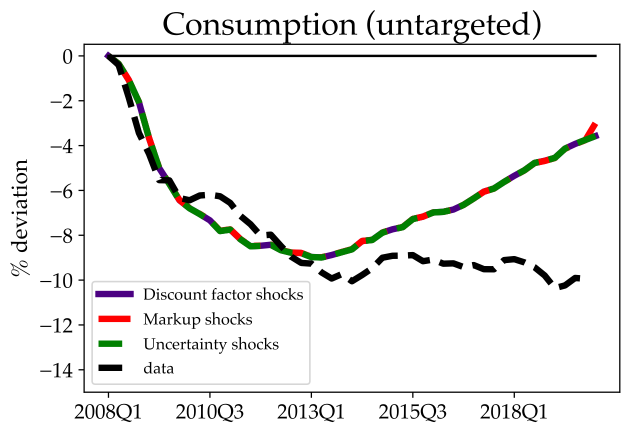


Figure I-6. Simulation of Great Recession Using different shocks.

B Labor Productivity during the Great Recession: Model vs Data

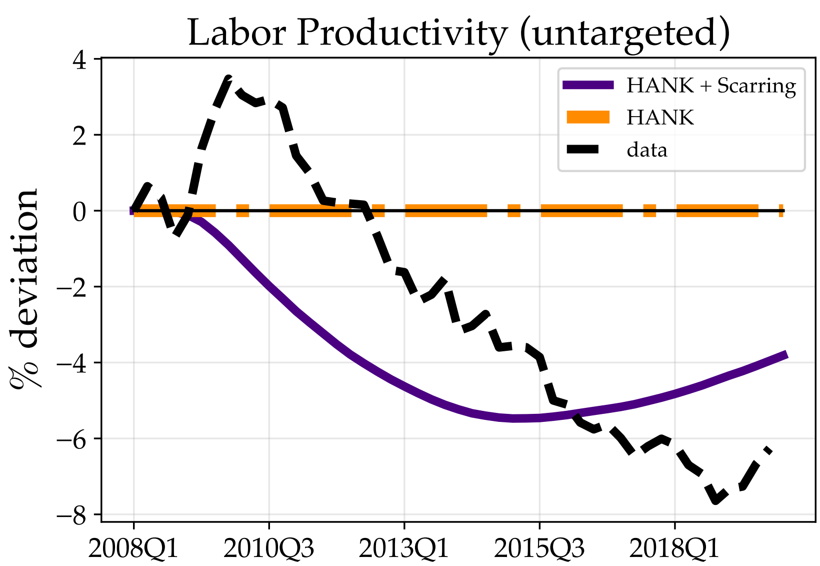


Figure I-7. Labor Productivity: Model vs Data

B.1 Monetary Policy and Unemployment Scarring

This section demonstrates that monetary policy exerts persistent effects on output, aggregate labor productivity, and income inequality when unemployment scarring is present. Figure I-8 plots the impulse responses to a 25 basis point shock to the Taylor rule. The results reveal that monetary policy triggers enduring responses in output, mean human capital, and the Gini index for income. For this analysis, I modify the Taylor rule to include inertia:

$$i_t = r^* + \phi_{ev} i_{t-1} + (1 - \phi_{ev})(\phi_\pi \pi_t + \phi_Y (Y_t - Y_{ss})) + \epsilon_t^m$$

where the inertial parameter ϕ_{ev} is calibrated to 0.8. The persistent impulse responses to a monetary tightening align with the findings of Jorda et al. [2023], who show that monetary contractions produce lasting declines in output without a prolonged increase in the unemployment rate. The key mechanism is that unemployment scarring results in a permanent decline in workers' human capital. Consequently, this scarring effect does not cause an extended rise in unemployment but instead transmits to output through a persistent reduction in aggregate labor productivity. As a result, unemployment scarring offers an alternative rationale for the empirical results in Jorda et al. [2023].

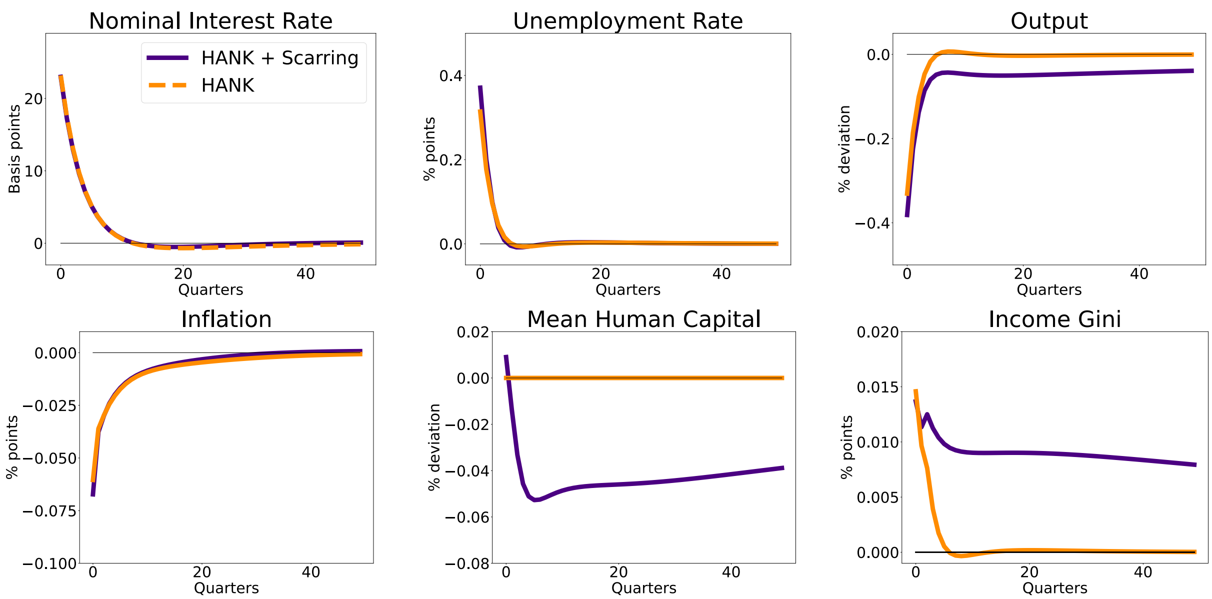


Figure I-8. Impulse responses to a monetary policy shock

Note: The exercise above plots the impulse responses to a 25 basis point shock to the Taylor rule. I assume that the Taylor rule now is $i_t = r^* + \phi_{ev} i_{t-1} + (1 - \phi_{ev})(\phi_\pi \pi_t + \phi_Y (Y_t - Y_{ss})) + \epsilon_t^m$ where I set $\phi_{ev} = 0.8$ as in Bardóczy [2020]

B.2 Self Defeating Fiscal Consolidation

The idea of self defeating fiscal consolidation in the presence of hysteresis was proposed by Fatás and Summers [2018] in a simple toy model. This section shows that fiscal consolidation is indeed substantially less effective at reducing the debt-to-GDP ratio when hysteresis is calibrated to microeconomic evidence on unemployment scarring. I consider a decrease in government spending shock that is 1% of GDP with a quarterly persistence of the shock is 0.933. Figure I-9 plots responses of relevant variables to this shock. With unemployment scarring, debt to GDP falls substantially less in response to a decrease in government spending and in the long run increases. The initial jump in debt to GDP is due to the model featuring realistic aggregate MPCs. In the long run, debt to GDP rises because of persistent losses in tax revenues. For debt to GDP, scarring drives both persistent losses in output as well as the increased pressure on debt to rise. The bottom right panel plots the response of the Gini index to the negative government spending shock and shows that fiscal consolidation almost permanently raises income inequality. In particular, a one percentage point decrease in government spending increases the income Gini index by 0.05 percentage points.

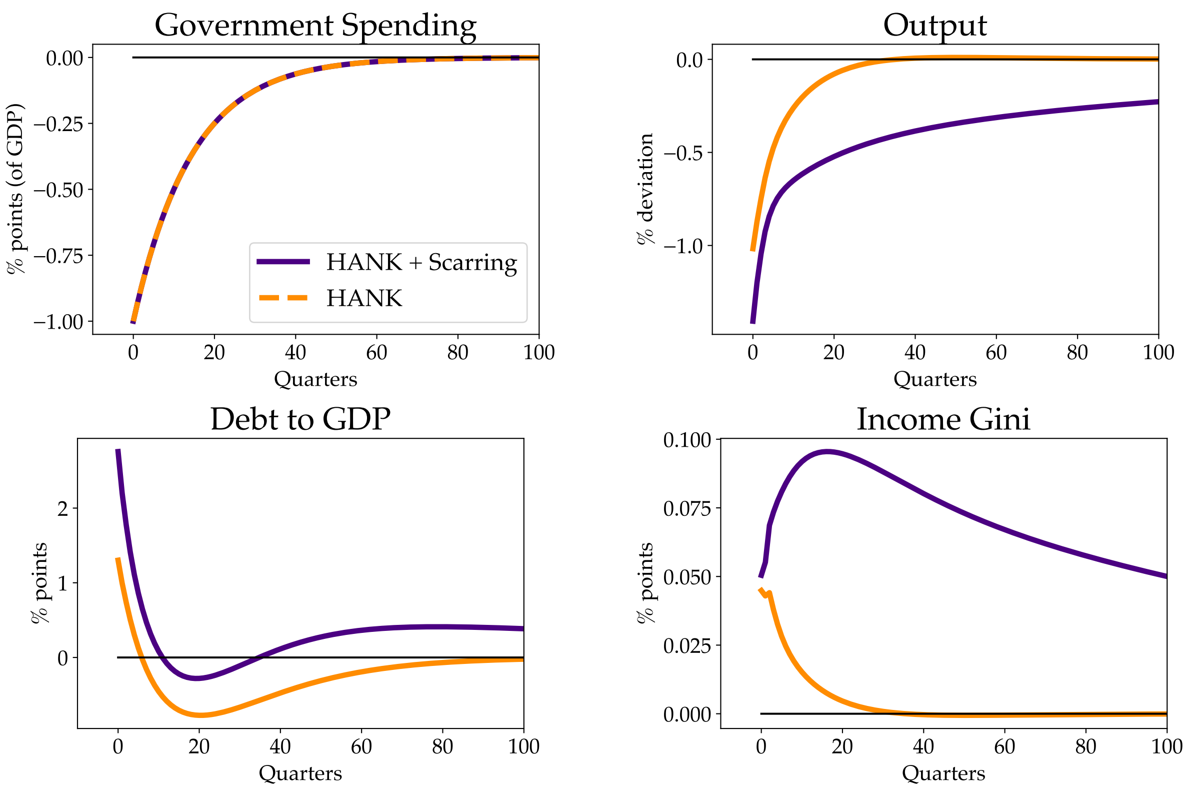
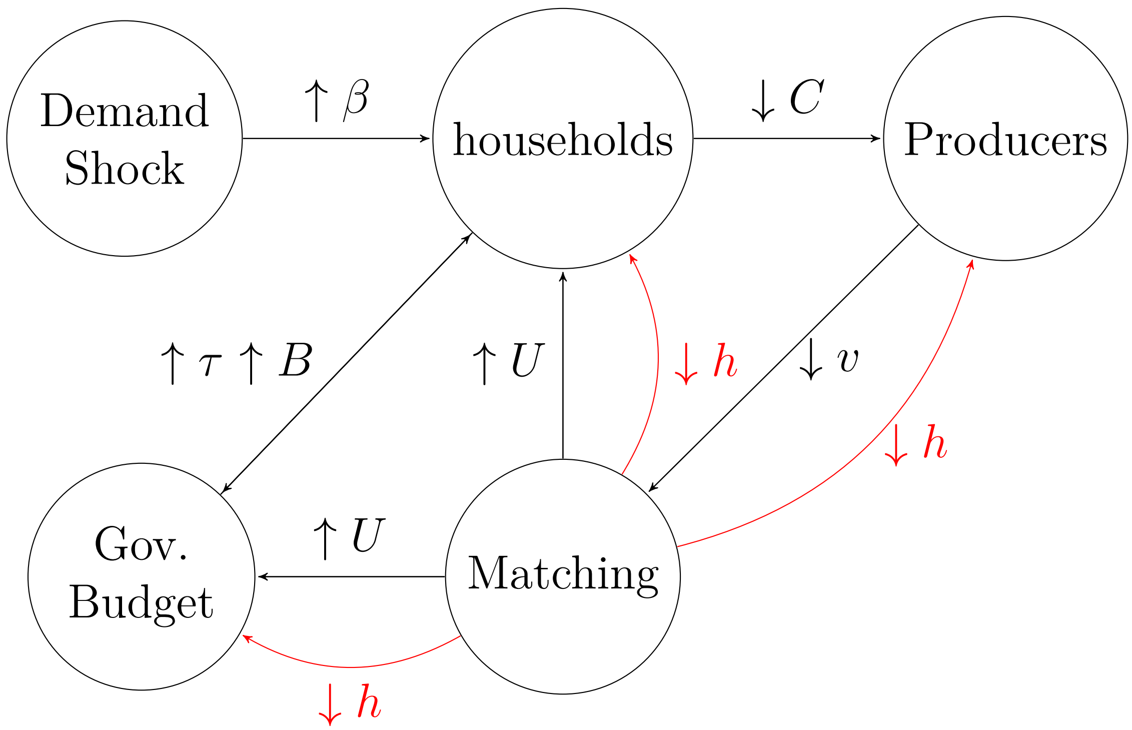


Figure I-9. Responses to a negative government spending shock

Note: This exercise plots the impulse responses to a one percentage point decrease in government spending G_t with AR(1) persistence 0.9.

B.3 Overview of the Model

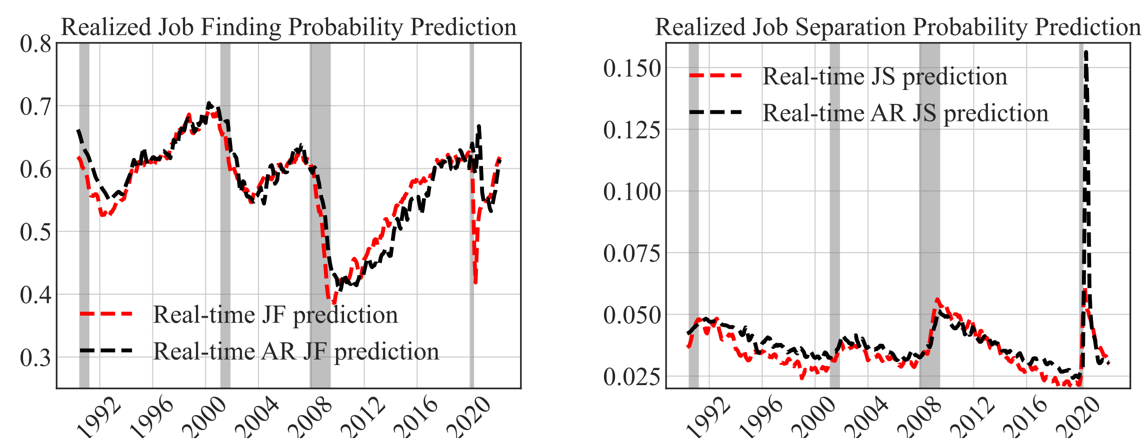


Appendix II

A Appendix II: Perceived Unemployment Risks over Business Cycles

A.1 Additional results with real-time forecasting of job risks

Figure II-1 compares the real-time machine-efficient forecasts of job risks based on the Lasso with one from an AR(1) model using only the 3-month lag of the realized job flow rate. The two closely move with each other. The mean square errors (MSE) from the two are almost equal for both job finding and separation. This indicates that near-term job risks are highly predictable, especially in normal times. The major exceptions were during the Covid era.



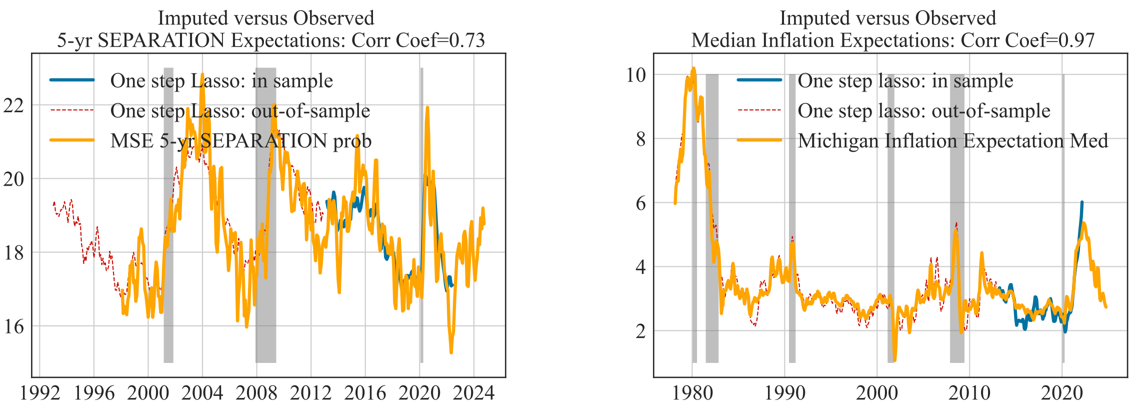
Note: Multi-variate Lasso real-time forecasts versus one from AR(1) model.

Figure II-1. Real-time Machine-efficient Risks from Lasso and AR(1)

A.2 Additional results with imputation of perceived job risks

A.2.1 Cross-validation of the imputing methodology

We evaluate the performance of imputing methods used to backcast SCE job beliefs by examining if the imputed beliefs based on the 2013-2022 in-sample can successfully generate belief backcasts that match the observed expectations in MSC. In particular, Figure II-2 plots the imputed beliefs for two series of expectations on median inflation expectations and 5-year-ahead job separation expectations in MSC based on 2013-2022 in-sample. They have an impressively large degree of comovement with the observed data. We are particularly careful to exclude any indices in MSC that are directly correlated to the target expectation series. They provide a strong external validation of our belief imputation methods.



Note: the figure plots the imputed beliefs from SCE regarding the percent chance the nationwide unemployment rate will be higher in the next year relative to the unemployment expectation index in MSC.

Figure II-2. Imputed Beliefs versus Observed Expectations in MSC

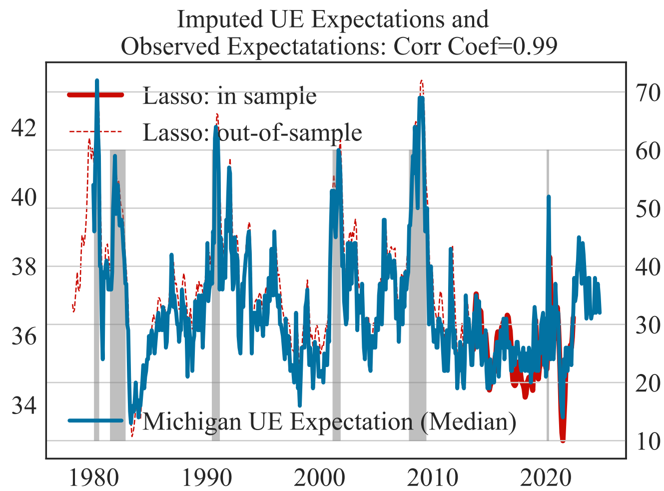
As a further validation of the imputation methodology across surveys, Figure II-3 plots the imputed expectations in SCE regarding the median percent probability of nationwide unemployment rate to be higher, against the series of Michigan index regarding the direction of unemployment rate, which was observed for a much longer period. Again, in our in-sample Lasso imputation, we particularly exclude all Michigan indices regarding unemployment expectations to make it a fair test of the validity of our imputation methods. Because the SCE unemployment expectations are expressed as a percent probability while the MSC index is measured as the share of respondents expecting higher unemployment rates minus those expecting lower, we can not directly compare the imputation errors out-of-sample. We nevertheless show that the correlation between imputed expectations and the observed index in MSC is as high as 0.99. This suggests that our imputation method is able to do a great job of backcasting beliefs.

A.2.2 Hyper-parameter tuning of the Lasso model using cross-validation

Figure II-4 plots the model score, i.e. out-of-sample average MSE from k-fold samples, under various values of α.

A.2.3 Inclusion of the pandemic era

Figure II-5 compares the imputed job risk belief relied upon pre-2020 sample as the in-sample of Lasso model with one relied on an extended sample covering the Covid era (2020-2022). The gap between the two series reveals a possible structural break in the relationship between job perceptions and other household expectations and macroeconomic conditions. However, such a different choice of in-sample period of the belief imputation does not significantly alter the patterns of the imputed out-of-sample job beliefs. The major exception was the job separation perceptions in the early 1980s.



Note: the figure plots the imputed beliefs from SCE regarding the percent chance the nationwide unemployment rate will be higher in the next year relative to the unemployment expectation index in MSC.

Figure II-3. Imputed SCE versus Observed UE Expectations in MSC

A.2.4 Selected covariates of perceived risks

Figure II-6 report the 10 most important variables selected from the Lasso model of imputation of perceived job risks, ranked by the absolute value of their estimated coefficients associated with the normalized value of each variable.

A.2.5 Imputed beliefs by education group

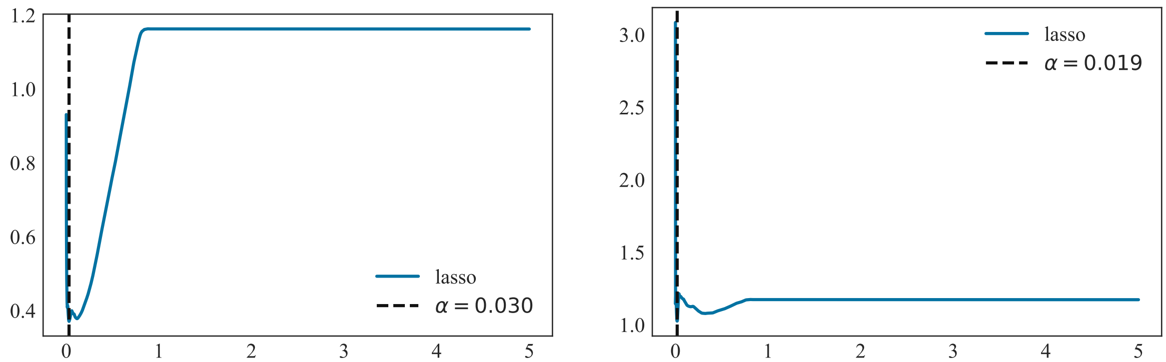
Figure II-8 plots the in-sample fitted and out-of-sample imputed perceptions of the job finding and separations rates for low, middle, and high education groups, versus the realized rates for each group.

A.3 Additional results with forecast errors

The upper panel in Figure II-9 plots the FEs using two alternative series as realizations of job findings. During the majority of times in the sample, FEs lie in the negative domains, suggesting that on average, household beliefs underpredicted the realization of job-findings. This is consistent with the observation in Figure II-7 that the imputed beliefs are below the realization most of the time. The periods with notable exceptions were the 1981-1982 recession and the Great Recession.

The lower panel plots the size of (absolute values) of the FEs. The size of FEs seemed to dramatically drop during recessions, compared to normal times. Some research has found that information-rigidity is counter-cyclical.[1]

[1] See Coibion and Gorodnichenko [2015] for the evidence with inflation expectations.



Note: mean square error scores under different penalization parameter α of the Lasso model.

Figure II-4. Model Selection using Cross-Validation

A.4 Additional evidence for the belief distortions over business cycles

Instead of calculating peak-to-trough values of job risks as in Figure 2-9, Figure II-10 plots the average job finding/separation rates in normal times versus recessions and their average ratios, which show largely similar business cycle patterns of realized transition rates, risk forecasts and perceived job risks.

A.5 Heterogeneous Agent model with Unemployment

The model is partial equilibrium and only consists of households. In particular, there is a continuum of workers of mass 1 indexed by i who face both idiosyncratic shocks to labor productivity, and stochastic transitions between employment states. A worker is either employed or unemployed. Their employment state is indexed by n_{it}. Employed households ($n_{it} = 1$) separate from employment with probability JS_t. Unemployed workers find a job with probability, JF_t. Workers receive unemployment insurance.

The Bellman problem is:

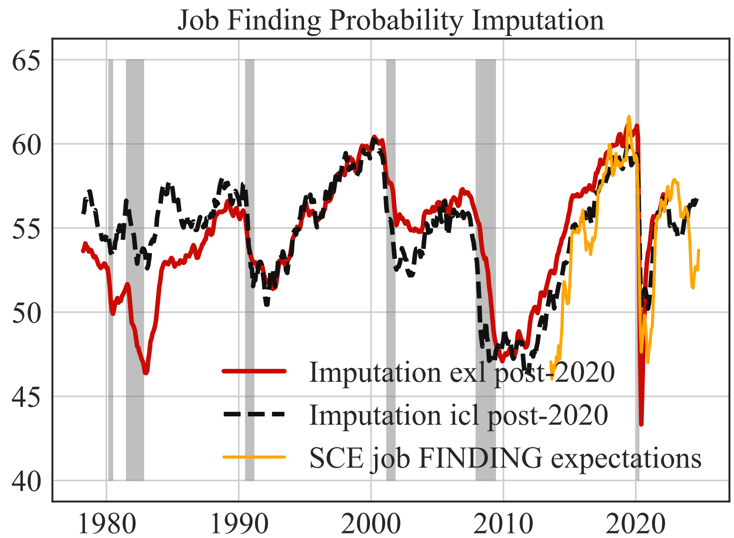
$$v_t\left(\mathbf{m}_{it}, e_{it}, n_{it}\right) = \max_{\{\mathbf{c}_{it}, \mathbf{a}_{it}\}} \left\{ U\left(\mathbf{c}_{it}\right)\right) + \beta \mathrm{E}_{\mathrm{t}}\left[v_{t+1}\left(\mathbf{m}_{t+1}, e_{it+1}, n_{it+1}\right)\right] \}$$

subject to the budget constraint

$$\begin{aligned} \mathbf{a}_{it} &= \mathbf{m}_{it} - \mathbf{c}_{it} \\ \mathbf{a}_{it} + \mathbf{c}_{it} &= \mathbf{z}_{it} + (1 + r_t)\mathbf{a}_{it-1} \\ \mathbf{a}_{it} &\geq 0 \end{aligned}$$

where $\mathbf{m}_{it}$ denotes market resources to be expended on consumption or saved into a risk free asset, $\mathbf{a}_{it}$. $\mathbf{c}_{it}$ is the level of consumption and the return to the asset at time t is r_t. $\mathbf{m}_{it}$ is determined by labor income, $\mathbf{z}_{it}$, and the gross return on assets from the last period, $(1 + r_t)\mathbf{a}_{it-1}$. β is the discount factor.

Worker i's at time t labor income is composed of their labor productivity e_{it} and of their un(employment) income ζ_{it}. In particular, labor income, $\mathbf{z}_{i,t}$, follows



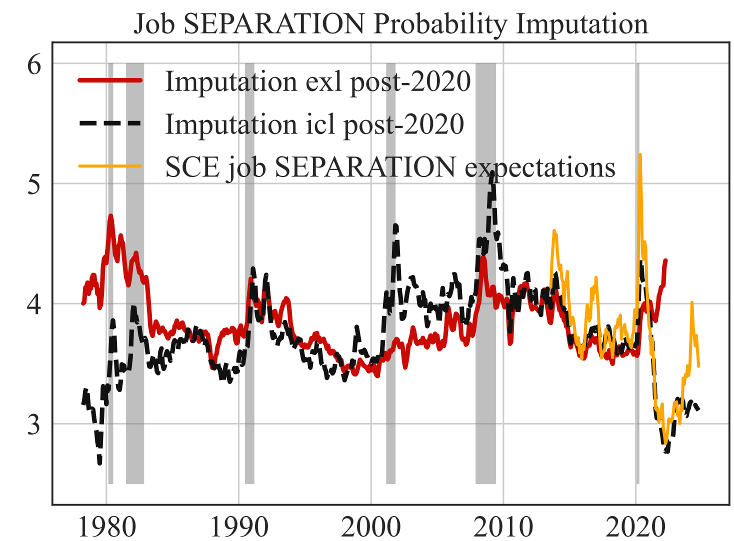
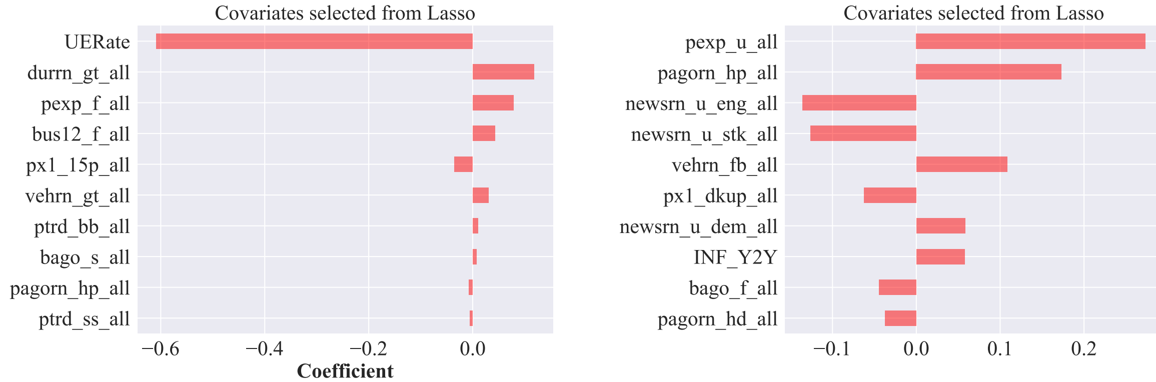


Figure II-5. Imputing Beliefs Including or Excluding Covid Era



Note: selected variables ranked by the absolute value of their estimated coefficients in the Lasso imputation model for perceived job finding (left) and separation (right). The in-sample is between 2013-2020. UERate: real-time unemployment rate. Durrn_gt_all: good time to buy durables. Pexp_f_all: expecting better personal finance one year from now. Bus12_f_all: better nationwide business conditions a year from now. Px1_15p_all: expected inflation above 15 percent. Vehrn_gt_all: good time to buy vehicles. ptrd_bb_all: better off financially a year ago and better off a year from now. bago_s_all: same business conditions compared to a year ago. Pagorn_hp_all: worse financial situation than a year ago due to higher prices. Ptrd_ss_all: same personal finance compared to a year ago and will be the same a year from now. Pexp_u_all: worse personal finance one year from now. Newsrn_u_eng_all: heard unfavorable news about the energy crisis. Newsrn_u_stk_all: heard about unfavorable news regarding the stock market. Vehrn_fb_all: a bad time to buy vehicles due to uncertain future. Px1_dkup_all: do not know about future inflation. Newsrn_u_dem_all: heard unfavorable news about lower consumer demand. INF_Y2Y: real-time annual realized inflation rate. Bago_f_all: better business conditions compared to a year ago. Pagorn_hd_all: worse personal finance due to higher debt.

Figure II-6. Selected variables of Lasso model of perceived job risks

$$
\begin{aligned}
\mathbf{z}_{i,t} &= e_{i,t}\zeta_{it} \\
\log e_{i,t} &= \rho_e \log e_{i,t-1} + \eta_{i,t}, \quad \eta_{i,t} \sim \mathcal{N}(0, \sigma_e^2)
\end{aligned}
$$

We assume labor productivity, e_{it}, follows an AR(1) process with persistence ρ_e and a standard deviation σ_e.

(Un)Employment income, $\zeta_{i,t}$ depends on the employment status $n_{i,t}$ between employment and unemployment.

$$
\zeta_{it} = \begin{cases} \theta_{it}, & \text{if employed} : n_{i,t} = e \\ \\ \theta_{it}\gamma, & \text{if unemployed} : n_{i,t} = u \end{cases}
$$

where θ_{it} is iid mean one lognormal with standard deviation σ_θ. γ is the replacement ratio of an unemployment insurance.

Transitions between employment states follows a markov process. In particular, the e-to-u and u-to-e probabilities are, respectively, the following.

$$
\begin{aligned}
p(n_{i,t+1} = e | n_{i,t} = u) &= JF_t \\
p(n_{i,t+1} = u | n_{i,t} = e) &= JS_t
\end{aligned}
$$

Description	Parameter	Value	Source/Target
CRRA	CRRA	2	Standard
Real Interest Rate	r	$1.05^{\frac{1}{12}} - 1$	5% annualized real rate
UI replacement rate	γ	0.5	50% replacement rate
Persistence of idiosyncratic income process	ρ_e	0.997	Kekre [2023b]
Std Dev of idiosyncratic income process	σ_e	0.057	Kekre [2023b]
Std Dev of Log Transitory Shock	σ_θ	0.244	Kekre [2023b]
Steady state Job Finding Rate	JF	0.25	CPS
Steady state Job Separation Rate	JS	0.017	CPS
Discount Factor	β	0.988	Quarterly MPC = 0.21

Table II-I. Household Calibration

where JF_t is the probability of finding a job and a JS_t is the job separation probability. We calibrate these probabilities using the observed transition rates between employment and unemployment estimated from the Current Population Survey.

Worker beliefs are dictated by the same Markov process as above however the values of probabilities finding and separating from a job may differ. In particular, denote variables with a tilde as worker beliefs on those variable

$$p(n_{i,t+1} \tilde{=} e | n_{i,t} = u) = \tilde{JF_t}$$
$$p(n_{i,t+1} \tilde{=} u | n_{i,t} = e) = \tilde{JS_t}$$

We calibrate these perceived probabilities with our measure of perceived risk or our measure of objective risk.

The calibration of the model is described in table III-IV.

A.6 Details of the model experiments

A.6.1 Baseline model at the monthly frequency

The model experiments in Figure 2-13 are based on directly estimated shocks to JF/JS, $\widetilde{JF}/\widetilde{JS}$ and JF^*/JS^*. To obtain such shocks, we estimate, respectively, a quarterly AR(1) model of each one of these sequences in the sample period up to the 2020 Q1. The predicted residuals are the estimated shocks to realized rates, beliefs, and rational job risk, which are plotted in Figure II-11.

Figure II-12 complements Figure 2-15 by showing the education-specific consumption aggregation fluctuations due to job separation and finding risks, separately.

Description	Parameter	Value	Source/Target
CRRA	CRRA	2	Standard
Real Interest Rate	r	$1.03^{.25}-1$	3% annualized real rate
Probability of Death	D	0.00625	Carroll et al. [2017a]
UI replacement rate	γ	0.5	50% income drop at unemployment
Std Dev of Log Permanent Shock	σ_ψ	0.06	Carroll et al. [2017a]
Std Dev of Log Transitory Shock	σ_θ	0.2	Carroll et al. [2017a]
Steady state Job Finding Rate	JF	0.58	CPS
Steady state Job Separation Rate	JS	0.070	steady state unemployment rate=0.05
Discount Factor	β	0.976	Quarterly MPC = 0.16

Table II-II. Household Calibration

A.6.2 Alternative model experiment at quarterly frequency

In this section, we report results from the baseline model experiments with a quarterly version of the model with several modifications.

Labor income is composed of permanent income p_{it} and (un)employment income ζ_{it}.

$$\mathbf{z}_{it} = \mathbf{p}_{it}\zeta_{it}$$

Permanent income is subject to shocks, $\mathbf{p}_{it+1}$ where ψ_{it} is iid mean one lognormal with standard deviation σ_ψ .

$$\mathbf{p}_{it+1} = \mathbf{p}_{it}\psi_{it+1}$$

(Un)Employment income, $\zeta_{i,t}$ depends on the employment status $n_{i,t}$ between employment and unemployment.

$$\zeta_{it} = \begin{cases} \theta_{it}, \text{ if employed} : n_{i,t} = e \\ \\ \gamma, \text{ if unemployed} : n_{i,t} = u \end{cases}$$

where θ_{it} is iid mean one lognormal with standard deviation σ_θ. γ is the replacement ratio of an unemployment insurance, which is set to be 0.5. Our benchmark model does not consider the expiration of unemployment insurance as in Kekre [2023b].[2]

The employment status $n_{i,t}$ transitions between two states following a 2-state Markov process. Its transition probabilities are jointly determined by job-finding $JF_{i,t}$ and job separation $JS_{i,t}$ rates. The e-to-u and u-to-e probabilities are, respectively, the following.

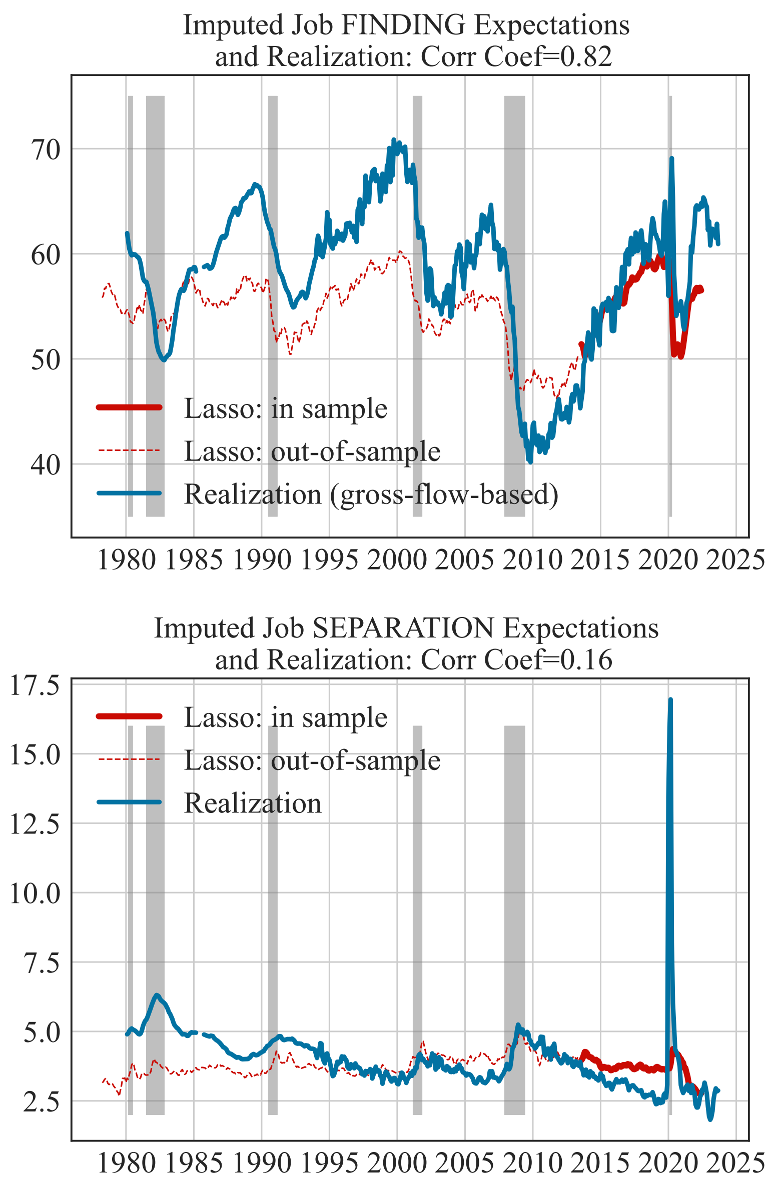
$$p(n_{i,t+1} = e|n_{i,t} = u) = JF_t$$
$$p(n_{i,t+1} = u|n_{i,t} = e) = JS_t(1 - JF_t)$$

[2] Kekre [2023b] estimates the income ratios during unemployment relative to pre-displacement with and without unemployment insurance to be 0.76 and 0.55, respectively.

Description	Parameter	Value	Source/Target
CRRA	CRRA	2	Standard
Real Interest Rate	r	$1.03^{.25} - 1$	3% annualized real rate
Probability of Death	D	0.00625	Carroll et al. [2017a]
UI replacement rate	γ	0.5	50% income drop at unemployment
Std Dev of Log Permanent Shock	σ_ψ	0.06	Carroll et al. [2017a]
Std Dev of Log Transitory Shock	σ_θ	0.2	Carroll et al. [2017a]
Steady state Job Finding Rate	JF	0.58	CPS
Steady state Job Separation Rate	JS	0.070	steady state unemployment rate=0.05
Discount Factor	β	0.976	Quarterly MPC = 0.16

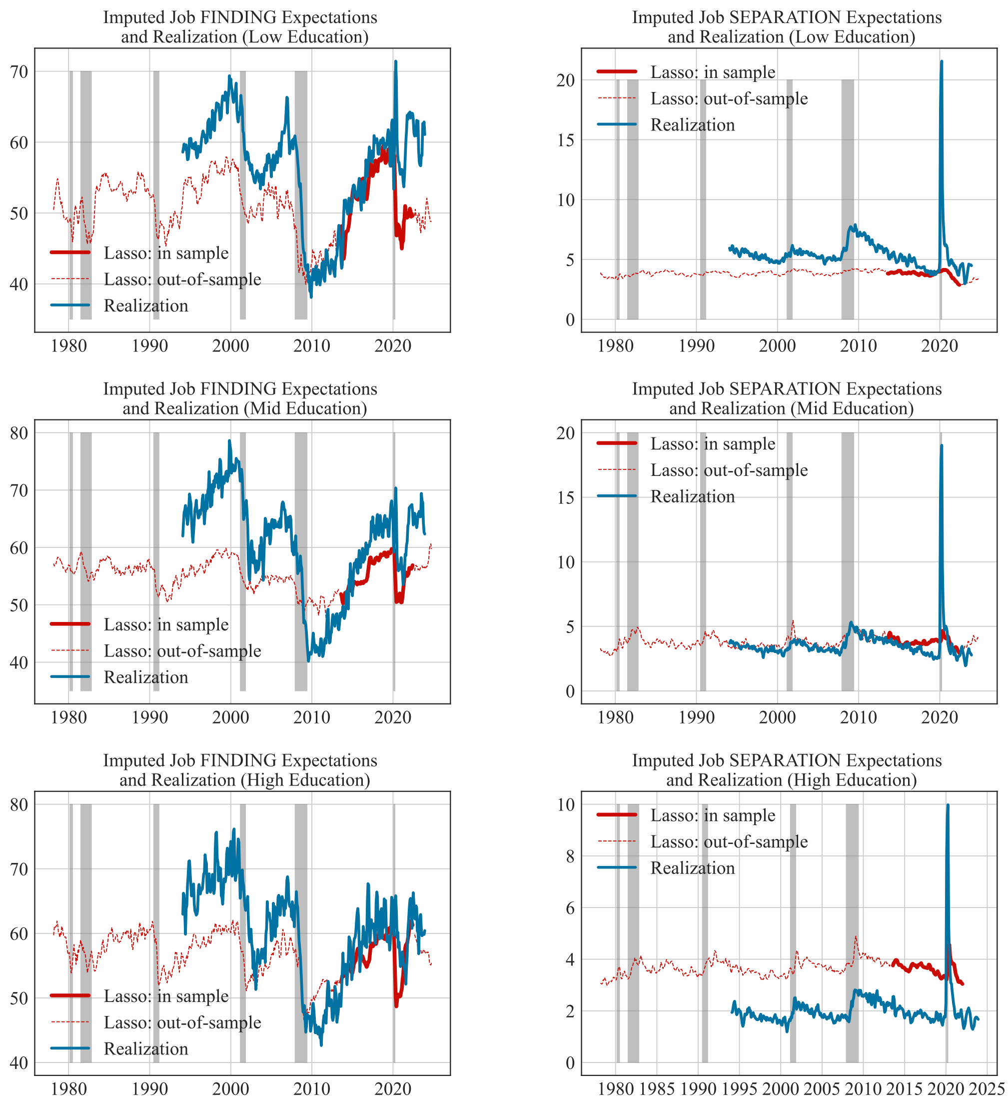
Table II-III. Household Calibration in Model at Quarterly Frequency

The calibration of the quarterly version of the model is described in the table below:



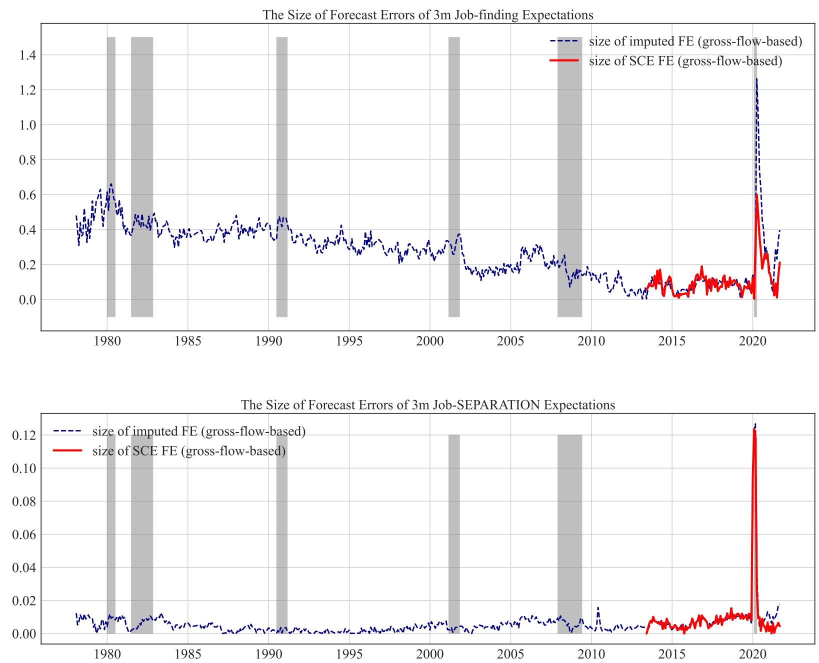
Note: imputed perceived risks in the sample (2013-2022) and out-of-sample (1980-2013) compared to realized job flow rates.

Figure II-7. Imputed job finding rate and realizations



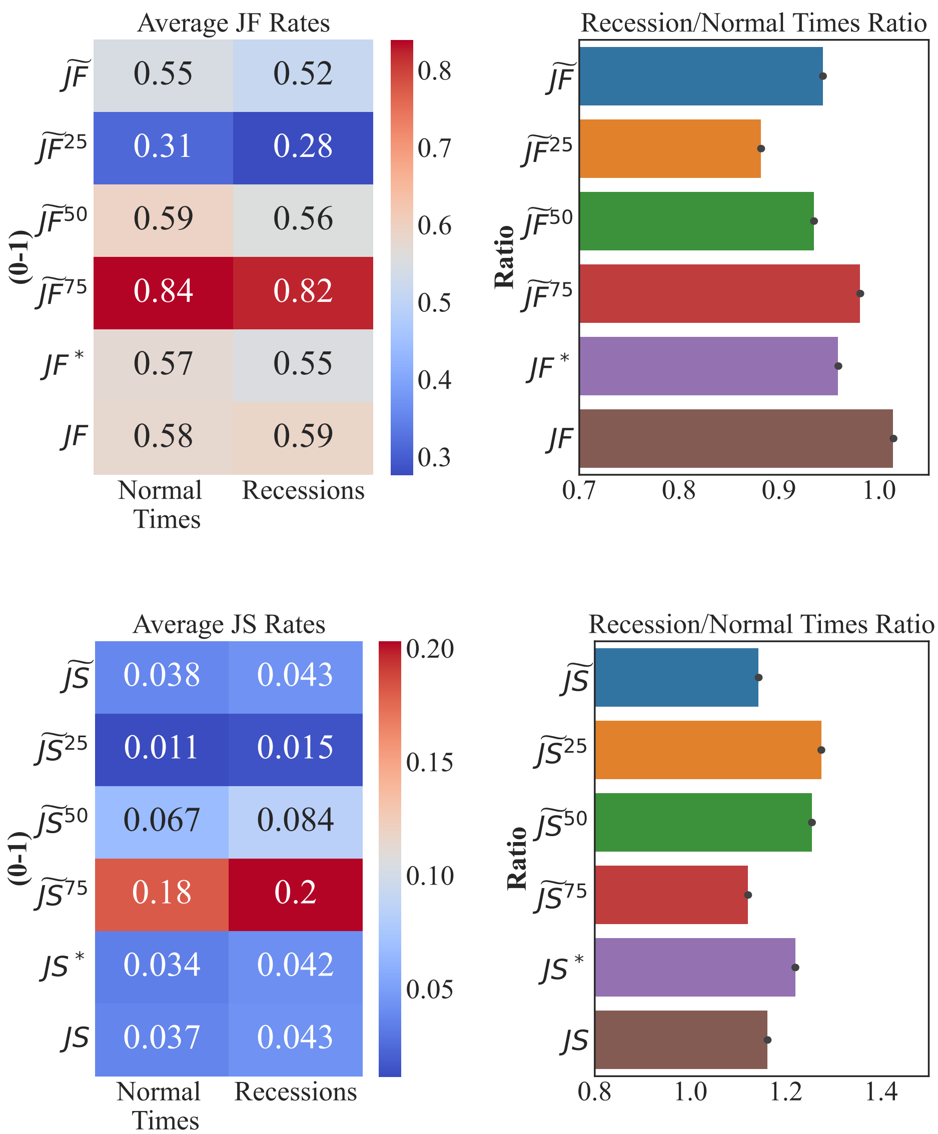
Note: these figures plot the imputed perceived job separation and finding rates by low, middle and high educations, respectively, using the same methodology and the education-specific expectations in MSC.

Figure II-8. Imputed beliefs by education



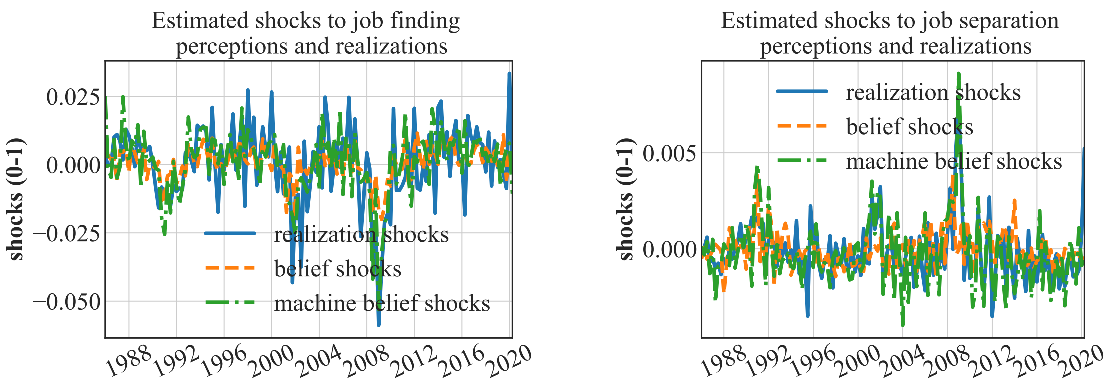
Note: the absolute value of forecast errors of job finding and separation rates, defined as the difference both imputed/or observed perceived risk and the realized job transition rates.

Figure II-9. Forecast errors of job-finding and separation expectations



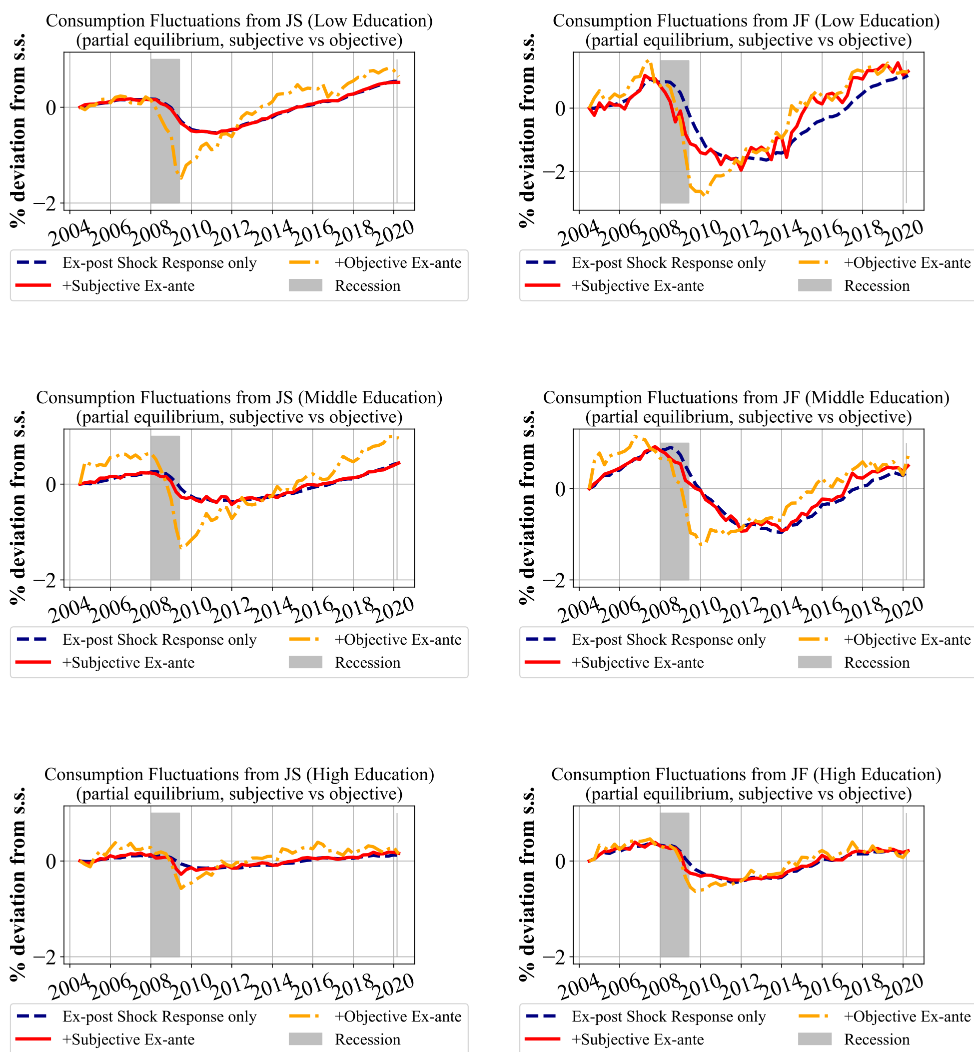
Note: The left tables report the average perceived job risks, perceived job risks at different quantiles, real-time job risks, and realized job transition rates in normal times and NBER-labeled recessions. The right figures plot the ratio of these rates between recessions and normal times. The sample period is 1990-2024.

Figure II-10. Business Cycle Patterns of Risks and Perceptions: Normal Times versus Recessions



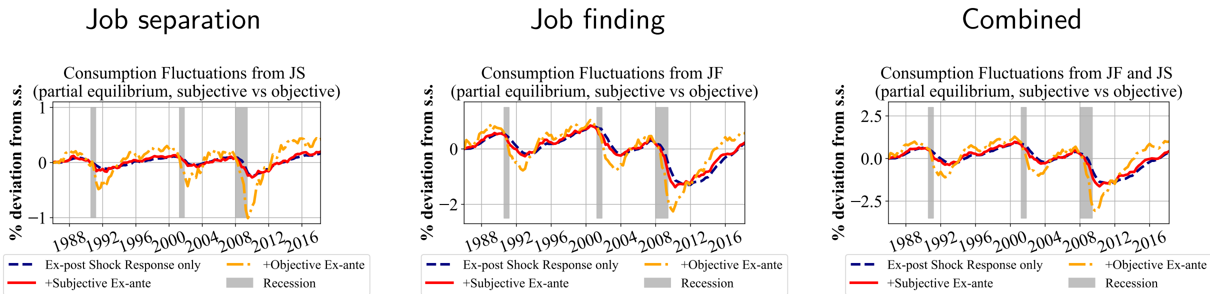
Note: The figure plots the estimated shocks used for the experiments in Figure 2-13, based on an estimation of a quarterly AR(1) model on demeaned $JS_t\&JF_t$, $\widetilde{JS}_t\&\widetilde{JF}_t$, and $JS^*_t\&JF^*_t$. The sample period is between 1987 and 2020.

Figure II-11. Shocks to realized job transitions, perceptions and rational forecasts



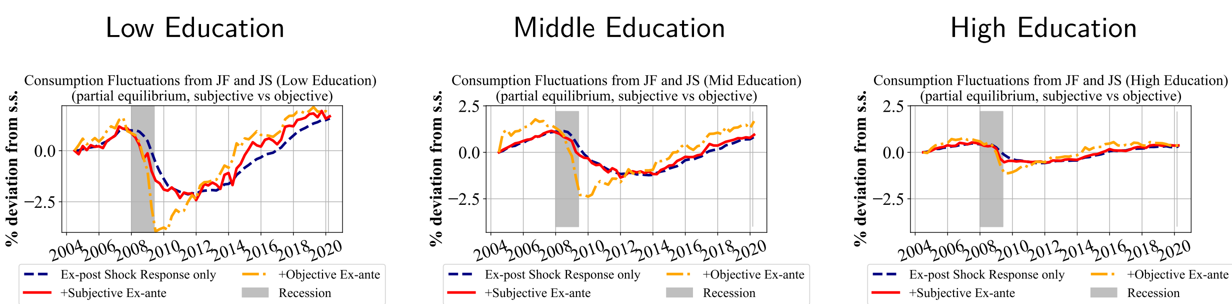
Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates.

Figure II-12. Consumption Fluctuations due to JS and JF Risks: by Education



Note: The figure compares the partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. The results are from a quarterly variation of the baseline model set at the monthly frequency.

Figure II-13. Quarterly Consumption Fluctuations due to Unemployment Risks



Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. The results are from the quarterly version of the baseline model with modified assumptions.

Figure II-14. Quarterly Consumption Fluctuations due to Unemployment Risks: by Education

Appendix III

A Appendix III: Welfare and Spending Effects of Consumption Stimulus Policies

A.1 Results in a model without the splurge

In this appendix, we consider the implications for our results of removing splurge consumption from the model. First, we discuss that model's ability to match the empirical targets that we used to estimate the splurge in section 3.3.1. Second, we repeat the estimation of discount factor distributions in the US model in section 3.3.3.3, and discuss the implications for both targeted and untargeted moments. Finally, we use the reestimated model to asses the relevance of the splurge for the effectiveness of the three policies.

A.2 Matching the iMPCs without the splurge

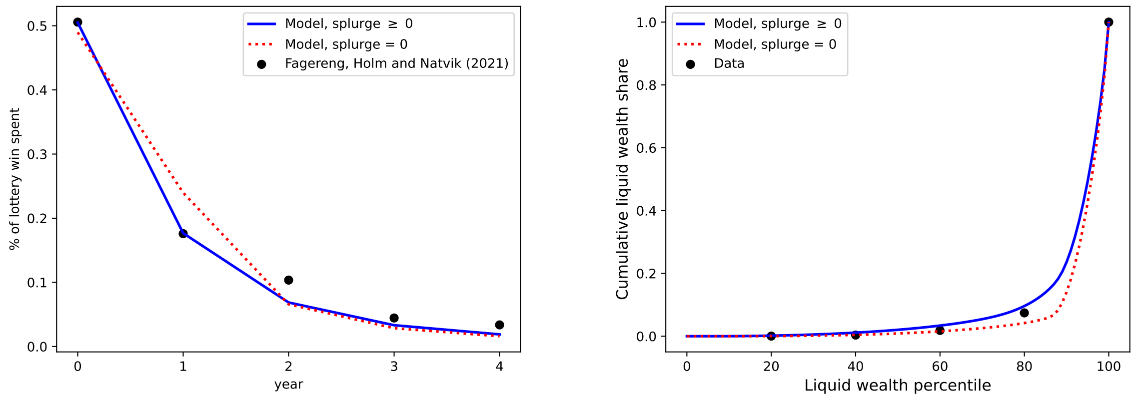
For the purpose of evaluating the results in the model without the splurge we do not require the reestimation of our Norwegian model, as the purpose of the latter is the estimation of the splurge. Nevertheless, we test how well the model can match the dynamics of spending after a temporary income shock as reported by Fagereng et al. [2021] when the splurge is zero. Figure III-1 illustrates the fit without the splurge and compares it to our baseline estimation.

While the splurge helps in matching the empirical evidence on the iMPC, the model without the splurge also performs relatively well. This is because the model without the splurge is able to generate a high initial marginal propensity to consume through a wider distribution of discount factors ($\beta = 0.921$ and $\nabla = 0.116$) relative to the model with a splurge ($\beta = 0.968$ and $\nabla = 0.0578$). This ensures that sufficiently many agents are at the borrowing constraint and thus sensitive to transitory income shocks.[1]

However, the model is not quite able to match the difference in spending between the initial year of the lottery win and the year after. The model without the splurge exhibits a higher spending propensity in the year after the shock occurs as borrowing-constrained agents spend the additional income quicker. The model without the splurge also provides a worse fit of the distribution of liquid wealth. Relative to the baseline model, and to the data, the model without a splurge generates a more unequal wealth distribution.

The reason for these two effects, becomes apparent when considering the cross-sectional implications of the models with and without the splurge across different wealth quartiles. While the model with the splurge can account for the empirically-observed initial MPCs among the wealthiest, the model without the splurge exhibits much lower MPCs among that group, see Table III-I. The wealthiest group will thus be very patient and have low MPCs, which can explain why the wealth distribution becomes more unequal and doesn't quite

[1]The model without the splurge implies there is a group of highly impatient households who have discount rates close to 0.8. While this is possible, such a discount rate implies these households care very little about their consumption even just a few years in the future.



(a) Share of lottery win spent

(b) Distribution of liquid wealth

Note: Panel (a) shows the fit of the model to the dynamic consumption response estimated in Fagereng et al. [2021]; see their figure A5. Panel (b) shows the fit of the model to the distribution of liquid wealth (see Section 3.3.2 for the definition) from the 2004 SCF.

Figure III-1. Marginal propensity to consume over time and the liquid wealth distribution in the model with and without the splurge as well as in the data

	MPC					
	1st WQ	2nd WQ	3rd WQ	4th WQ	Agg	K/Y
Splurge ≥ 0	0.27	0.49	0.60	0.66	0.50	6.59
Splurge $= 0$	0.13	0.52	0.62	0.68	0.49	6.58
Data	0.39	0.39	0.55	0.66	0.51	6.60

Table III-I. Marginal propensities to consume across wealth quartiles and the total population as well as the wealth to income ratio, in the model with and without the splurge and according to the data

fit the targeted distribution in the data in the version of the model without the splurge.

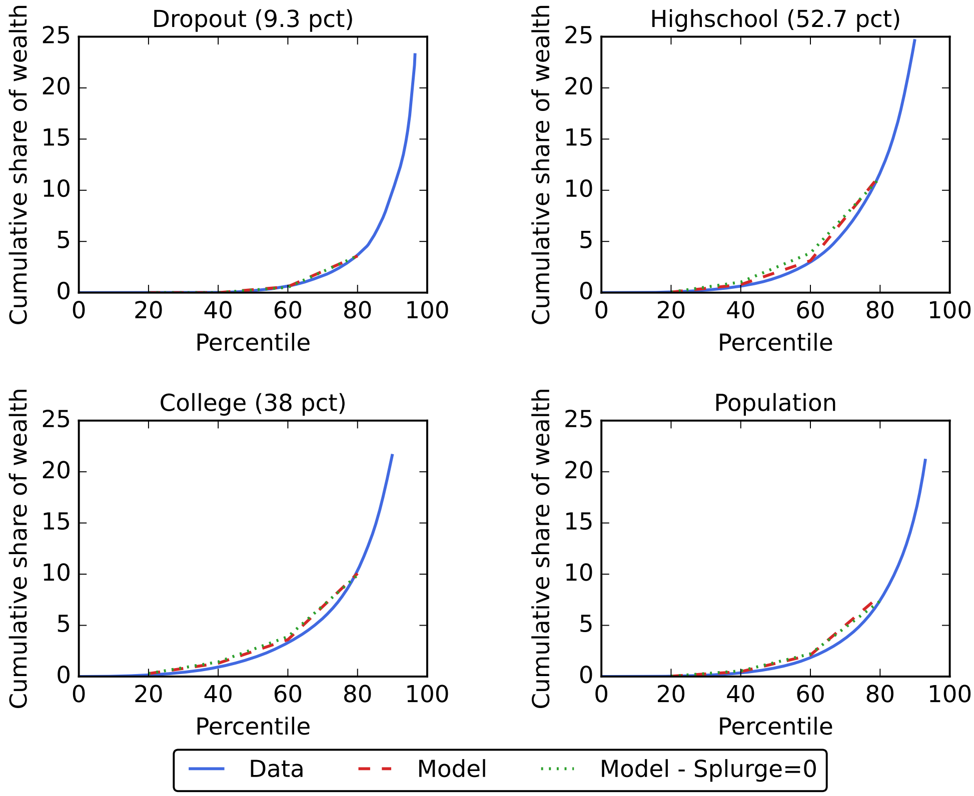
Overall, the model fit with the data deteriorates roughly by a factor of two measured by the Euclidean norm of the targeting error.[2]

A.3 Estimating discount factor distributions without the splurge

Figure III-2 shows that the model without splurge consumption can also match the wealth distributions in the three education groups very well. We therefore turn to the implications of this version of the model for the untargeted moments discussed in section 3.3.3.4.

The main difference between the models with and without splurge consumption is that without splurge consumption the MPCs drop for each education group and wealth quartile. The difference is largest for the College group and for the highest wealth quartile (obviously with substantial overlap between these two

[2]Specifically, the Euclidean norm of the targeting error increases from 0.04 to 0.08 for the time-profile of the marginal propensity to consume when the splurge is removed, from 0.16 to 0.29 for the marginal propensity to consume across wealth quartiles and from 0.027 to 0.032 for the Lorentz curve.



Note: The discount factor distributions are estimated separately for each education group to fit the median liquid-wealth-to-permanent-income ratio and the $20th$, $40th$, $60th$, and $80th$ percentile points of the Lorenz curve for liquid wealth for that group. The "Population" panel compares the wealth distribution that results from pooling the three groups in the model to the overall wealth distribution in the data. The model is reestimated when the splurge is set to 0.

Figure III-2. Distributions of liquid wealth within each education group and for the whole population from the 2004 Survey of Consumer Finances and from the model estimated with and without splurge consumption

groups). This is shown in the two panels in Table III-II. The rest of the table shows that the distribution of wealth is not substantially different in the model estimated without splurge consumption.

Finally, we again consider the implications of our model for the dynamics of spending over time and for the dynamics of spending for households that remain unemployed long enough for unemployment benefits to expire. Figure III-3 repeats Figure 3-3 with results from the model without splurge consumption added. The implication is that the model without a splurge leads to a slightly too low MPC in the year of a lottery win and a slightly higher MPC in the year after.

The drop in spending when unemployment benefits expire is virtually the same in the model without splurge consumption (17 percent versus 18 percent in the baseline). While the consumption dynamics across the models with and without a splurge are fairly similar, the underlying drivers of the consumption drop upon expiry of unemployment benefits are different. In the model with the splurge, the drop in income translates directly into lower consumption via the splurge itself. In the model without the splurge it is the sharp rise in agents hitting the borrowing constraint which accounts for the consumption drop after UI benefits expire. This is shown in the solid and dashed red lines in Figure III-3b, and is due to the wider distribution of

Panel (A) Non-targeted moments by education group

	Dropout	Highschool	College	Population
Percent of liquid wealth (data)	0.8	17.9	81.2	100
Percent of liquid wealth (model, baseline)	1.2	20.1	78.7	100
Percent of liquid wealth (model, Splurge=0)	1.6	18.7	79.7	100
Avg. lottery-win-year MPC (model, incl. splurge)	0.78	0.63	0.44	0.54
Avg. lottery-win-year MPC (model, splurge=0)	0.70	0.53	0.23	0.43

Panel (B) Non-targeted moments by wealth quartile

	WQ 4	WQ 3	WQ 2	WQ 1
Percent of liquid wealth (data)	0.14	1.60	8.51	89.76
Percent of liquid wealth (model, baseline)	0.09	0.96	4.55	94.40
Percent of liquid wealth (model, Splurge=0)	0.10	1.07	4.24	94.60
Avg. lottery-win-year MPC (model, incl. splurge)	0.78	0.63	0.44	0.31
Avg. lottery-win-year MPC (model, splurge=0)	0.69	0.53	0.36	0.14

Note: Panel (A) shows percent of liquid wealth held by each education group in the 2004 SCF and in the model. It also shows the average MPCs after a lottery win for each education group. The MPCs are calculated for each individual for the year of a lottery win, taking into account that the win takes place in a random quarter of the year that differs across individuals. The MPCs are averaged across individuals within each education group. Panel (B) shows the same numbers for the population sorted into different quartiles of the liquid wealth distribution.

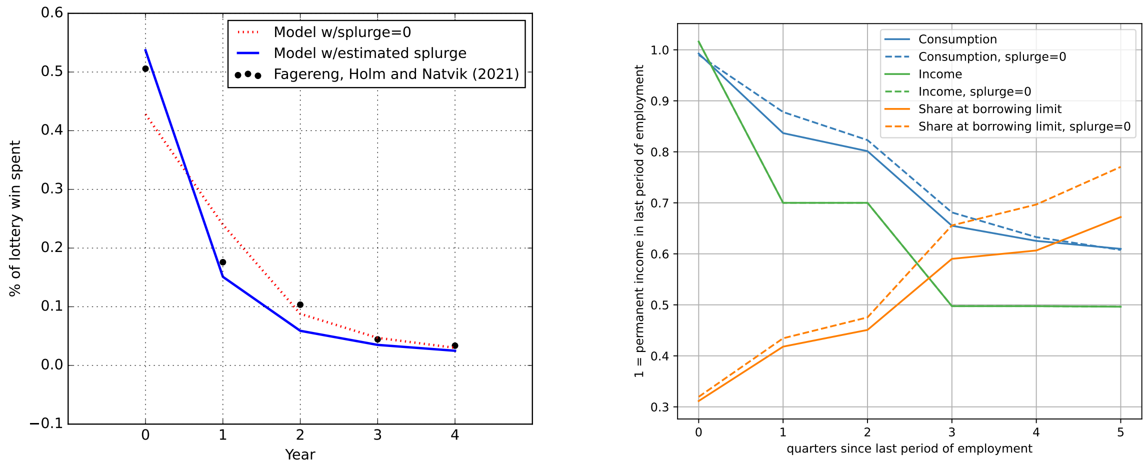
Table III-II. Model fit with respect to non-targeted moments

discount factors that is needed to match the wealth distributions in the model without the splurge. This leads to a greater number of agents being close the borrowing constraint.

A.4 Multipliers in the absence of the splurge

In this section we simulate the three fiscal policies from the main text in the estimated model without the splurge. The shape of the impulse response functions only marginally change relative to the model with the splurge. Hence, we focus on the quantitative changes as summarized by the cumulative multipliers in Figure **??**. The figure shows the multipliers when AD effects are switched on for the model with and without the splurge. Table III-III shows the 10y-horizon multiplier across the two models.

The absence of the splurge entails a calibration with a lower average MPC in the population. Hence, the check and tax cut exhibit lower multipliers when there is no splurge. For the UI extension we observe the opposite pattern, as the multiplier is larger in the model without the splurge. This due to the consumption dynamics around the expiry of UI benefits described in the previous section. In the model without the splurge more agents hit the borrowing constraint upon the expiry of benefits. Providing those agents with an



(a) Share of lottery win spent

(b) Spending upon expiry of UI benefits

Note: Panel (a) compares the dynamic consumption response in the model to the estimates in Fagereng et al. [2021]; see their Figure A5. Panel (b) shows the evolution of income and spending for households who remain unemployed long enough for UI benefits to expire; see Figure 2 in Ganong and Noel [2019].

Figure III-3. Marginal propensity to consume over time and the spending upon expiry of UI benefits in the model

Figure III-4. Cumulative multiplier as a function of the horizon for the three policies with and without the splurge. Note: Policies are implemented during a recession with AD effect active.

extension of UI benefits thus turns out to be slightly more powerful.

The policy ranking in terms of the multiplier shifts slighlty. In the model with the splurge, the check policy delivers multiplier effects much more rapidly than the UI extension. In the model without splurge consumption, the UI extension appears superior to the check, both at shorter and longer horizons. Both models agree on the tax cut being the least effective policy.

A.5 Details of the HANK and SAM Model

A.5.1 Households

The household block follows closely to the main text with a few exceptions. First, the splurge only occurs out of equilibrium—that is, the steady state of the model is calculated without the splurge behavior. Second, the level of permanent income of all newborns is equal to one. Furthermore, all households face the same employment to unemployment and unemployment to employment probabilities. The probabilities are calibrated to the transition probabilities of high school graduates from the main text. Lastly, following the notation of Auclert et al. [2020], r_t^a will denote the economy wide ex-ante real interest rate.

A.5.2 Goods Market

A continuum of monopolistically competitive intermediate goods producers, indexed by $j \in [0, 1]$, produces intermediate goods Y_{jt}, which are sold to a final goods producer at price P_{jt}. Each period, these producers

	Stimulus check	UI extension	Tax cut
10y-horizon Multiplier (no AD effect)	0.870(0.854)	0.910(0.893)	0.839(0.826)
10y-horizon Multiplier (AD effect)	1.143(1.199)	1.221(1.175)	0.947(0.952)

Note: The values outside of the brackets capture the multipliers in the model without the splurge, while those inside the brackets are the corresponding mulitipliers with the splurge.

Table III-III. Multipliers, calculated for policies implemented in a recession with and without aggregate demand effects.

fully consume their profits.

A.5.3 Final Goods Producer

A perfectly competitive final goods producer purchases intermediate goods Y_{jt} from intermediate good producer j at price P_{jt} and produces the final good Y_t using a CES production function:

$$Y_t = \left(\int_0^1 Y_{jt}^{\frac{\epsilon_p - 1}{\epsilon_p}}\, dj\right)^{\frac{\epsilon_p}{\epsilon_p - 1}},$$

where ϵ_p is the elasticity of substitution.

Given P_{jt}, the price of intermediate good j, the final goods producer maximizes profits by solving:

$$\max_{Y_{jt}} P_t \left(\int_0^1 Y_{jt}^{\frac{\epsilon_p - 1}{\epsilon_p}}\, dj\right)^{\frac{\epsilon_p}{\epsilon_p - 1}} - \int_0^1 P_{jt} Y_{jt},\ dj.$$

The first order condition leads to demand for good j given by

$$Y_{jt} = \left(\frac{P_{jt}}{P_t}\right)^{-\epsilon_p} Y_t,$$

and the price index

$$P_t = \left(\int_0^1 P_{jt}^{1-\epsilon_p}\, dj\right)^{\frac{1}{1-\epsilon_p}}.$$

A.5.4 Intermediate Goods Producers

Intermediate goods producers produce according to a production function linear in labor L_t:

$$Y_{jt} = Z L_{jt},$$

where Z is total factor productivity.

Each intermediate goods producer hires labor L_t from a labor agency at cost h_t. Given this labor cost, each producer sets P_{jt} to maximize profits while facing price stickiness à la Rotemberg [1982a]. In HANK models with sticky prices, profits tend to be countercyclical, and when households have high MPCs, this can generate countercyclical consumption responses to dividends. To simplify, we assume that intermediate goods producers fully consume their profits rather than distributing them to households, thereby abstracting from consumption responses to firm profits. Each producer maximizes profits by solving:

$$J_t\left(P_{jt}\right) = \max_{\{P_{jt}\}} \left\{ \frac{P_{jt} Y_{jt}}{P_t} - h_t L_{jt} - \frac{\varphi}{2}\left(\frac{P_{jt} - P_{jt-1}}{P_{jt-1}}\right)^2 Y_t + J_{t+1}\left(P_{jt+1}\right) \right\},$$

where φ determines the cost of adjusting the price and, hence, the degree of price stickiness.

The problem can be rewritten as the standard New Keynesian maximization problem:

$$\max_{\{P_{jt}\}} \mathrm{E}_t \left[\sum_{s=0}^{\infty} M_{t,t+s} \left(\left(\frac{P_{jt+s}}{P_{t+s}} - MC_{t+s} \right) Y_{jt+s} - \frac{\varphi}{2} \left(\frac{P_{jt+s}}{P_{jt+s-1}} - 1 \right)^2 Y_{t+s} \right) \right],$$

where $MC_t = \frac{h_t}{Z}$.

Given that all firms face the same adjustment costs, there exists a symmetric equilibrium where all firms choose the same price with $P_{jt} = P_t$ and $Y_{jt} = Y_t$.

The resulting Phillips Curve is

$$\epsilon_p MC_t = \epsilon_p - 1 + \varphi(\Pi_t - 1)\Pi_t - M_{t,t+1}\varphi(\Pi_{t+1} - 1)\Pi_{t+1}\frac{Y_{t+1}}{Y_t}$$

where $\Pi_t = \frac{P_t}{P_{t+1}}$.

A.5.5 Labor market

A risk-neutral labor agency supplies labor N_t to intermediate goods producers at cost h_t by hiring households at wage w_t. To hire workers, the agency posts vacancies v_t, which are filled with probability ϕ_t. Household job search is random. Following Bardoczy [2024], we assume the labor agency cannot observe individual household productivity. Instead, it only observes the average productivity of all employed workers, which is normalized to one.

Labor agency. The labor agency determines how many vacancies to post and how much labor to sell by solving the following problem:

$$J_t(N_{t-1}) = \max_{N_t, v_t} \left\{ (h_t - w_t)N_t - \kappa v_t + \mathrm{E}_t \left[\frac{J_{t+1}(N_t)}{1 + r_t^a} \right] \right\},$$

subject to

$$N_t = (1 - \omega)N_{t-1} + \phi_t v_t.$$

The parameters κ and ω are, respectively, the cost of posting a vacancy, and the job separation rate.

The resulting job creation curve is:

$$\frac{\kappa}{\phi_t} = (h_t - w_t) + (1 - \omega)\mathrm{E}_t \left[\frac{\kappa}{(1 + r_t^a)\phi_{t+1}} \right].$$

Matching. The matching process between households and the labor agency follows a Cobb-Douglas matching function:

$$m_t = \chi e_t^{\alpha} v_t^{1-\alpha},$$

where m_t is the mass of matches, e_t is the mass of job searchers, α is the matching function elasticity, and χ is a matching efficiency parameter.

The vacancy filling probability ϕ_t and the job finding probability η_t evolve as follows:

$$\eta_t = \chi \Theta_{it}^{1-\alpha}$$

$$\phi_t = \chi \Theta_t^{-\alpha}$$

where $\Theta_t = \frac{v_t}{e_t}$ is labor market tightness.

Wage Determination. Following Gornemann et al. [2021] and Blanchard and Gali [2010], we assume the real wage evolves according to the following rule:

$$log\left(\frac{w_t}{w_{ss}}\right) = \phi_w log\left(\frac{w_{t-1}}{w_{ss}}\right) + (1 - \phi_w) log\left(\frac{N_t}{N_{ss}}\right),$$

where ϕ_w dictates the extent of real wage rigidity.

A.5.6 Fiscal Policy

The government issues long term bonds B_t at price q_t^b in period t that pays δ^s in period $t+s+1$ for $s \in \{0, 1, 2, \ldots\}$.

The bond price satisfies the no arbitrage condition:

$$q_t^b = \frac{1 + \delta \mathrm{E}_t[q_{t+1}^b]}{1 + r_t^a}.$$

The government funds its expenditures through debt and taxes, subject to the following budget constraint:

$$(1 + \delta q_t^b) B_{t-1} + G_t + S_t = \tau_t w_t N_t + q_t^b B_t,$$

where S_t are payments for unemployment insurance and other transfers.

For all stimulus policies, except tax cuts, we follow Auclert et al. [2020] and allow the tax rate to adjust in order to stabilize the debt-to-GDP ratio:

$$\tau_t - \tau_{ss} = \phi_B q_{ss}^b \frac{B_{t-1} - B_{ss}}{Y_{ss}}$$

where ϕ_B governs the speed of adjustment.

For the tax cuts, we assume government expenditures adjust following:

$$G_t - G_{ss} = \phi_G q_{ss}^b \frac{B_{t-1} - B_{ss}}{Y_{ss}}$$

where ϕ_G governs the speed of adjustment of government spending in response to debt.

A.5.7 Monetary Policy

The central bank follows a standard Taylor rule that responds solely to inflation:

$$i_t = r^* + \phi_\pi \pi_t,$$

where ϕ_π is the coefficient on inflation. Inflation is given by $\pi_t = P_t / P_{t-1} - 1$, and r^* is the steady state interest rate.

A.5.8 Equilibrium

An equilibrium in this economy is a sequence of:

- Policy Functions $(c_{it}(m))_{t=0}^{\infty}$ normalized by permanent income.
- Prices $\left(r_{t+1}^a, i_t, q_t^b, w_t, h_t, \pi_t, \tau_t\right)_{t=0}^{\infty}$.
- Aggregates $(C_t, Y_t, N_t, \Theta_t, B_t, A_t)_{t=0}^{\infty}$.

Such that:

- $(c_{it}(m))_{t=0}^{\infty}$ solves the household's maximization problem given $(w_t, \eta_t, r_t^a, \tau_t)_{t=0}^{\infty}$.
- The final goods producer and intermediate goods producers both maximize their respective objective functions.
- The nominal interest rate is determined by the central bank's Taylor rule.
- The tax rate is set according to the fiscal rule, ensuring that the government budget constraint is satisfied.

Description	Parameter	Value	Source/Target
Elasticity of Substitution	ϵ_p	6	Standard
Price Adjustment Costs	φ	96.9	Ravn and Sterk [2017a, 2021]
Vacancy Cost	κ	0.056	$\frac{\kappa}{w\phi} = 0.071$
Job Separation Rate	ω	0.092	Match $\pi(eu)$ for Highschool group
Matching Elasticity	α	0.65	Ravn and Sterk [2017a, 2021]
Job Finding Probability	η_{ss}	0.67	$\pi(ue)$ in section 3.3.3.1
Vacancy Filling Rate	ϕ_{ss}	0.71	den Haan et al. (2000)
Real Wage Rigidity parameter	ϕ_w	0.837	Gornemann et al. (2021)
Government Spending	G	0.38	Gov. budget constraint
Decay rate of Gov. Coupons	δ	0.95	5 Year Maturity of Debt
Response of Tax Rate to Debt	ϕ_B	0.015	Auclert et al. (2020)
Taylor Rule Inflation Coefficient	ϕ_π	1.5	Standard

Table III-IV. Calibration

- The value of assets is equal to the value of government bonds:

$$A_t = q_t^b B_t.$$

- The goods market clears[3]:

$$C_t = w_t N_t + G_t,$$

  where $C_t \equiv \int_0^1 \mathbf{c}_{it}\, di$.

- The labor demand of intermediate goods producers equals labor supply of labor agency:

$$L_t = N_t.$$

A.6 Calibration of Non-Household Blocks

The elasticity of substitution is set to 6, and the price adjustment cost parameter is set to 96.9 as in Ravn and Sterk [2017a, 2021]. The vacancy cost is set to 7% of the real wage as in Christiano et al. [2016].[4] The matching elasticity is 0.65 following Ravn and Sterk [2017a, 2021]. The job separation rate is set to 0.092. As

[3]Note if profits were not held by firms then the goods market condition would be $C_t + G_t = Y_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$. In particular, since firm profits are $D_t = Y_t - w_t N_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$, then the goods market condition would become $C_t + G_t = w_t N_t + D_t = Y_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$.

[4]The range of plausible values lie between 4% and 14% Silva and Toledo [2009b]

in section 3.3.3.1, we set the job finding probability in the steady state for the unemployed η_{ss} to 0.67. Along with the job separation rate, this gives a probability of transitioning from employment to unemployment within a quarter of 3.1 percent which is the value we use for the Highschool group in section 3.3.3.1. The quarterly vacancy filling rate is 0.71 as in den Haan et al. [2000] (and together with our other choices, this pins down the matching efficiency χ). The degree of wage rigidity ϕ_w is set to 0.837 following Gornemann et al. [2021]. The tax rate is set to 0.3 and government spending is set to clear the government budget constraint. The parameters that dictate the speed of fiscal adjustment, ϕ_B and ϕ_G, are set to 0.015, the lower bound of the estimates in Auclert et al. [2020].[5] Furthermore, the decay rate of government coupons is set to $\delta = 0.95$ to match a maturity of 5 years.[6] Finally, the Taylor rule coefficient on inflation is set to the standard value of $\phi_\pi = 1.5$.

[5]The speed of adjustment parameter is set to the lower bound to ensure that the policies evaluated in the HANK and SAM model are almost entirely deficit financed.

[6]The duration of bonds in the model is $\frac{(1+r)^4}{(1+r)^4-\delta}$

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