Essays on Macroeconomics and Unemployment

by
William Du

A dissertation submitted to The Johns Hopkins University in conformity
with the requirements for the degree of Doctor of Philosophy

Baltimore, Maryland
May, 2025

Abstract

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem.

Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Thesis Readers

Dr. Christopher D. Carroll (Primary Advisor)
Professor
Department of Economics
Johns Hopkins University

Dr. Jonathan Wright
Professor
Department of Economics
Johns Hopkins University

Dr. Francesco Bianchi
Professor
Department of Economics
Johns Hopkins University

Dr. Michael Keane
Professor
Carey School of Business and Department of Economics
Johns Hopkins University

Dr. Vadim Elenev
Associate Professor
Carey School of Business
Johns Hopkins University

Dedicated to one or more of the various

people or pets or influences in my life.

Touching final thought.

Acknowledgements

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem.

Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Fusce mauris. Vestibulum luctus nibh at lectus. Sed bibendum, nulla a faucibus semper, leo velit ultricies tellus, ac venenatis arcu wisi vel nisl. Vestibulum diam. Aliquam pellentesque, augue quis sagittis posuere, turpis lacus congue quam, in hendrerit risus eros eget felis. Maecenas eget erat in sapien mattis porttitor. Vestibulum porttitor. Nulla facilisi. Sed a turpis eu lacus commodo facilisis. Morbi fringilla, wisi in dignissim interdum, justo lectus sagittis dui, et vehicula libero dui cursus dui. Mauris tempor ligula sed lacus. Duis cursus enim ut augue. Cras ac magna. Cras nulla. Nulla egestas. Curabitur a leo. Quisque egestas wisi eget nunc. Nam feugiat lacus vel est. Curabitur consectetuer.

Contents

List of Figures

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, 2011, 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], are worse in recessions [Davis and Wachter, 2011, 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. The thesis of this paper is that these microeconomic scars are a key determinant of the speed of macroeconomic recovery from recessions.

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

[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.

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.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 [2011], 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 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,

[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.

I then demonstrate that unemployment scarring, when disciplined by the microeconomic evidence, successfully captures 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.[6]

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. In particular, I demonstrate that if the rise in unemployment during the COVID recession had been driven primarily by permanent layoffs, GDP would not have returned to its pre-recessionary trend and income inequality (income Gini index) would have permanently risen. 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. 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

[6]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.

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 4.75 percentage points. With scarring, the decline in debt-to-GDP is only 1.23 percentage points. 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 emerging yet small body of literature on the impact of unemployment scarring on business cycle fluctuations and macroeconomic policy. This literature consists of Alves and Violante [2023] and Alves and Violante [2024], both of which explore the macroeconomic implications of unemployment scarring in the transmission of monetary policy. To the best of my knowledge, this is the first paper to quantify the macroeconomic role of unemployment scarring in explaining macroeconomic recoveries from past recessions. In particular, this paper demonstrates that unemployment scarring is a key determinant of the speed of recovery following recessions, as it introduces a novel dimension that can quantitatively capture *both* the sluggish recovery from the Great Recession and the rapid rebound following the COVID Recession. Additionally, I quantify the macroeconomic role of temporary layoffs following the pandemic, showing their critical importance in preventing both a sluggish recovery and a permanent increase in income inequality after the COVID Recession. Finally, while this literature focuses on the monetary policy implications of unemployment scarring, my analysis highlights its role in shaping 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 **??**).

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 rationale for 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, 2016, Ravn and Sterk, 2017, 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 **??**, 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

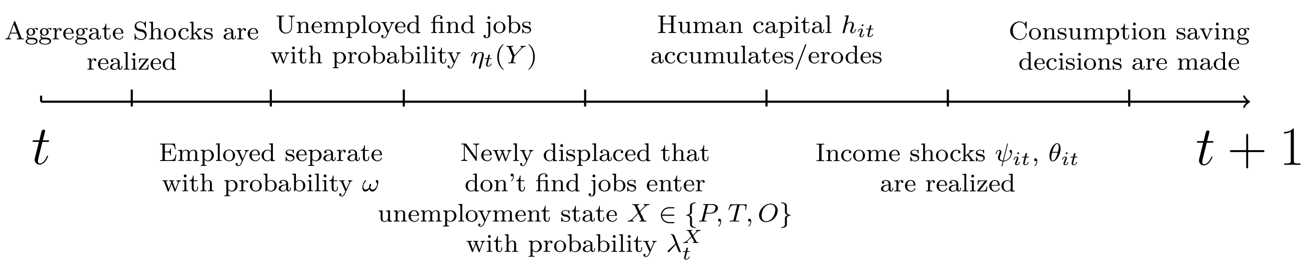


Figure 1-1. Timing of model

The Bellman problem is:

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

subject to the budget constraint

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

$$a_{it} + c_{it} = z_{it} + (1 + r^a_t)a_{it-1}$$

$$a_{it} \geq 0$$

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^a_{t+1}. m_{it} is determined by labor income, z_{it}, and the gross return on assets from the last period, $(1 + r^a_t)a_{it-1}$. 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}.

$$\mathbf{z}_{it} = p_{it}\theta_{it}\zeta_{it}h_{it}$$

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 $E \to E$, 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 $E \to U$ or $U \to U$, 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 [1982]. 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 $X_{it} \in \{\text{P, T, O}\}$ 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:

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

where ϕ_B governs the speed of adjustment.

1.2.6 Monetary Policy

The central bank follows the Taylor rule:

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

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, $\epsilon^m_t = \rho_v \epsilon^m_{t-1} + \varepsilon_t$ are innovations to the Taylor rule.

1.2.7 Equilibrium

An equilibrium in this economy is a sequence of:

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

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

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

Such that:

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

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.:

$$A_t = q_t^b B_t$$

The goods market clears: [7]

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

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

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 [2011]. The second is to simultaneously match a large aggregate

[7]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 $C_t + G_t = w_t N_t + D_t = Y_t - \kappa v_t - \frac{\varphi}{2}\left(\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t$.

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][8]. The job finding probabilities 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,

[8] 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. 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.

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 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 [2011]. 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. [2017] 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. [2017], 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. [9]

[9] 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

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 [2017] and the vacancy cost is set to 7% of the real wage as in Christiano et al. [2016][10]. The elasticity of substitution is set to 6. The price adjustment cost parameter is set to 96.9 as in Ravn and Sterk [2017]. 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[11].

high interest rate.

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

[11]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. [2017]
Std Dev of Log Transitory Shock	σ_θ	0.2	Carroll et al. [2017]

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_{ss}^P	0.35	35% of EU from perm. layoffs
Prob. of temp. layoff in steady state	λ_{ss}^T	0.31	31% of EU from temp. layoffs
Prob. of quit/other in steady state	λ_{ss}^O	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 [2017]
Vacancy Filling Rate	ϕ	0.71	Ramey et al. [2000]
Matching Elasticity	α	0.65	Ravn and Sterk [2017]
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

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

1.4.1 Persistent earnings loss following unemployment

To evaluate the path of earnings loss following job displacement, I run a regression similar to Davis and Wachter [2011] 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[12]. With these sample restrictions, I run the following regression on simulated data.

$$log(z^b_{iy}) = c^b + \Sigma^{20}_{k\geq-6}\delta^b_k D^k_{iy} + \epsilon^b_{iy}$$

where z_{iy} is labor income, D^k_{iy} 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.

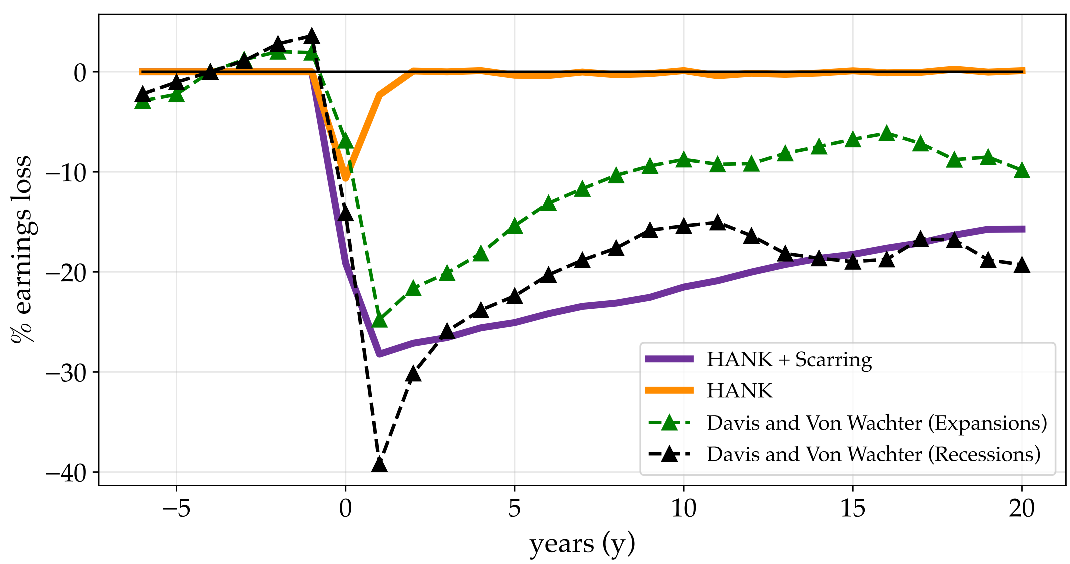


Figure 1-2. Earnings loss following job loss in $y = 0$: Model vs Data

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

[12]When aggregating to annual frequency, a worker who was unemployed for at least one quarter is denoted as displaced for that year. and is therefore not considered as employed for that year.

in the model without human capital dynamics. As in the data, these losses remain after 20 years.

1.5 Partial Equilibrium Results

1.5.1 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.

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,

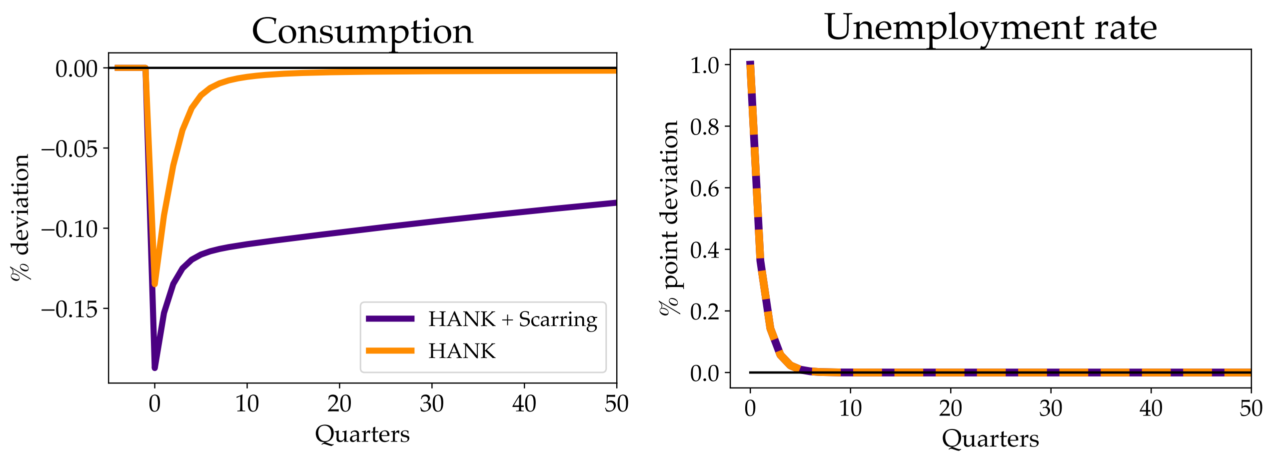


Figure 1-3. Consumption response to a transitory increase in the unemployment rate

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.

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 to consumption, output, debt, and 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

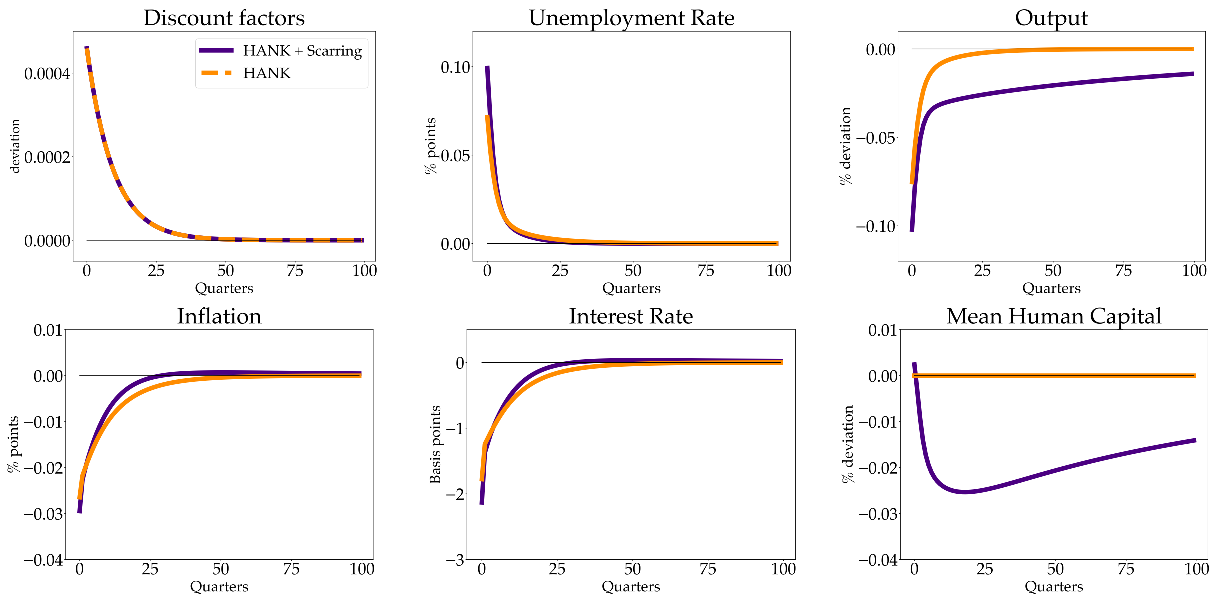


Figure 1-4. Impulse responses to a negative demand shock

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.

households. In particular, as unemployed households find reemployment at lower levels of human capital. Since the human capital of newly employed households accumulates slowly, 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.

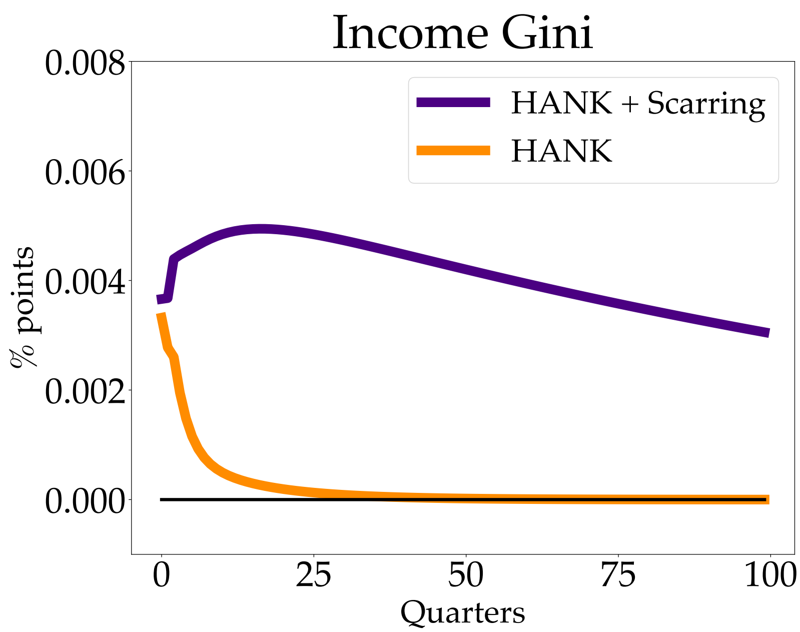


Figure 1-5. Response of income Gini index to negative demand shock.

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

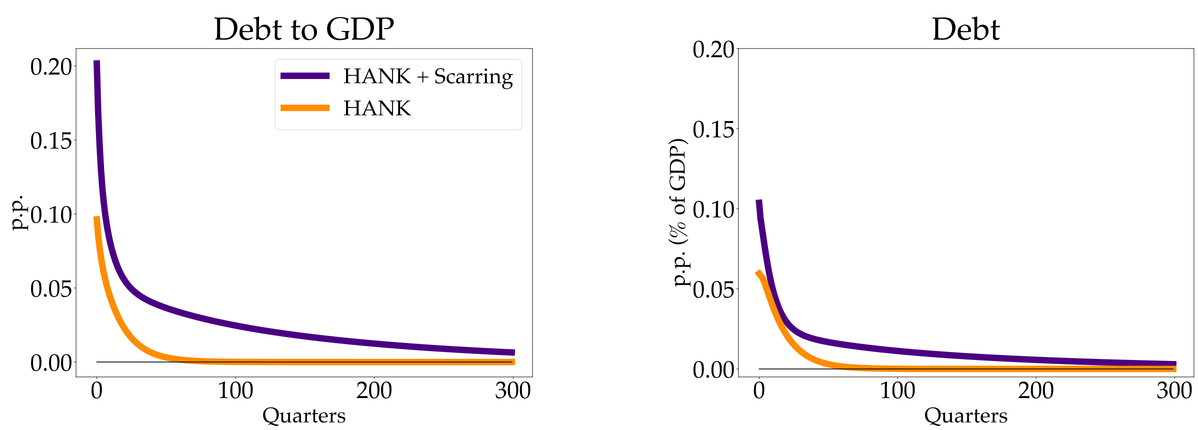


Figure 1-6. Responses of debt and debt to GDP to negative demand shock

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

1.7.1 Fiscal Multipliers

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.

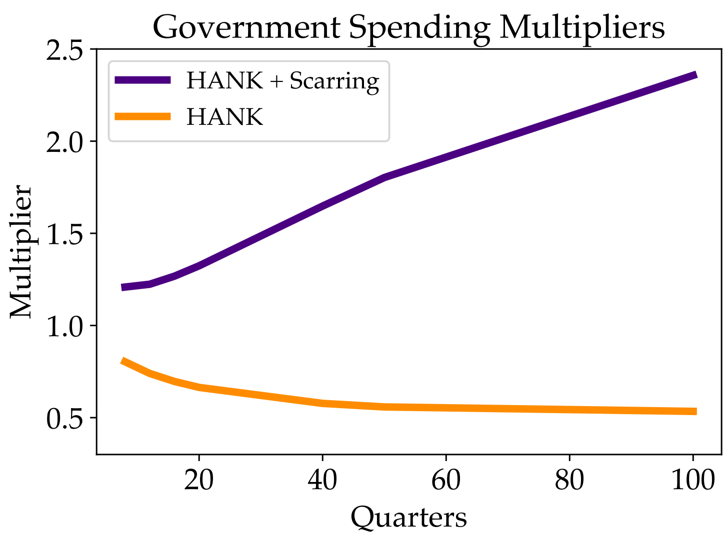


Figure 1-7. Fiscal Multipliers to a negative government spending shock.

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.

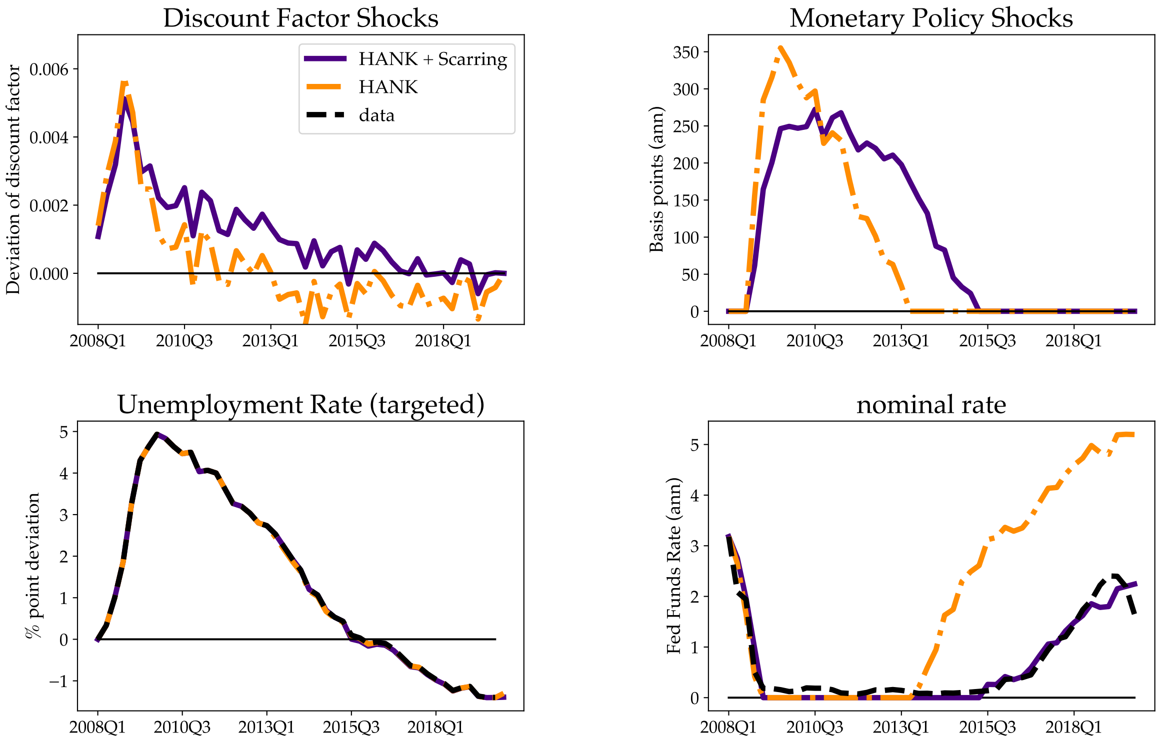


Figure 1-8. Estimated shocks to discount factor and nominal rate

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[13]. 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 persistence 0.95. As noted in Kekre [2023a], the chosen AR(1) persistence does not alter the

[13]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.

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.

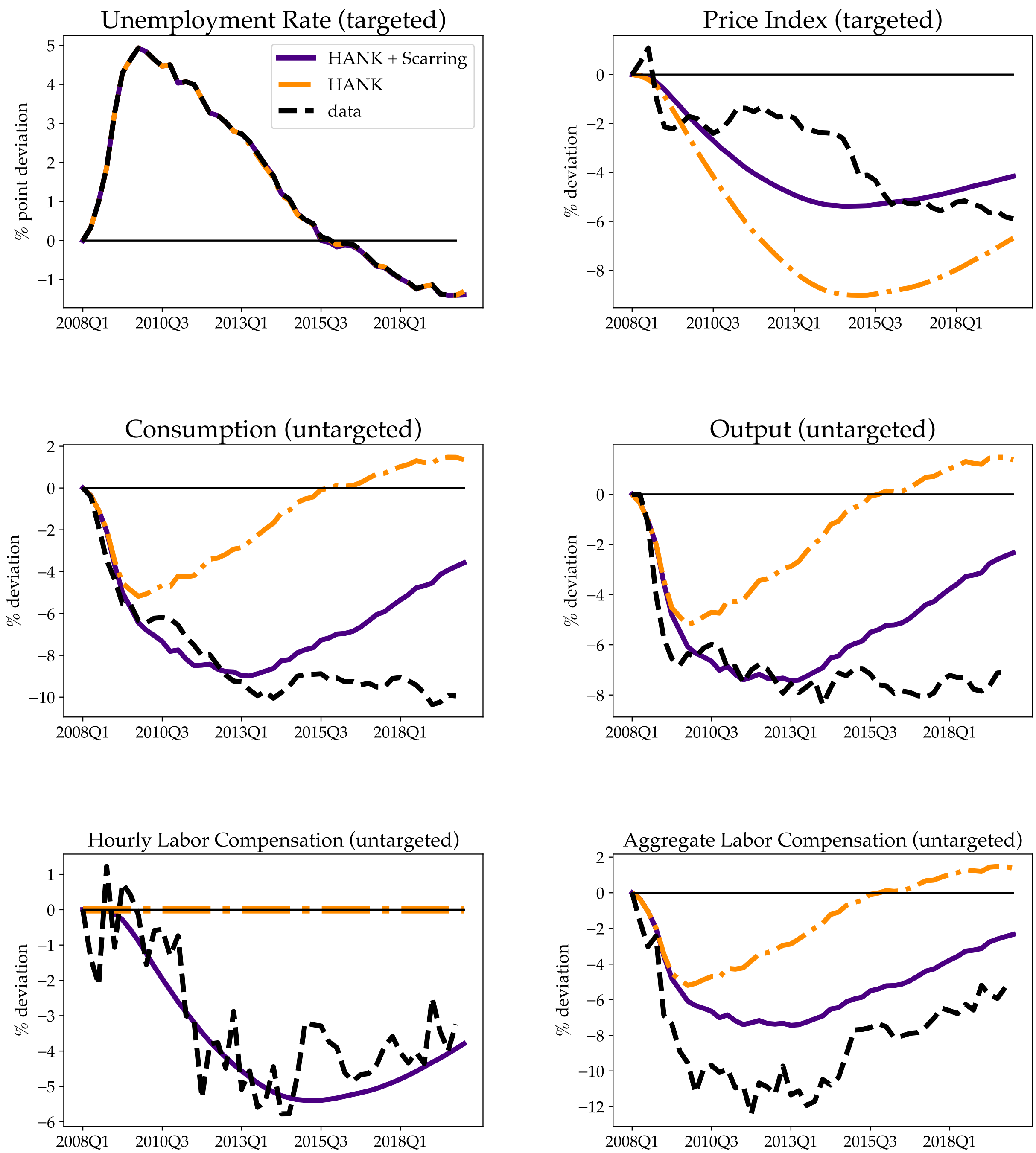


Figure 1-9. Great Recession: Model vs Data (detrended)

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.

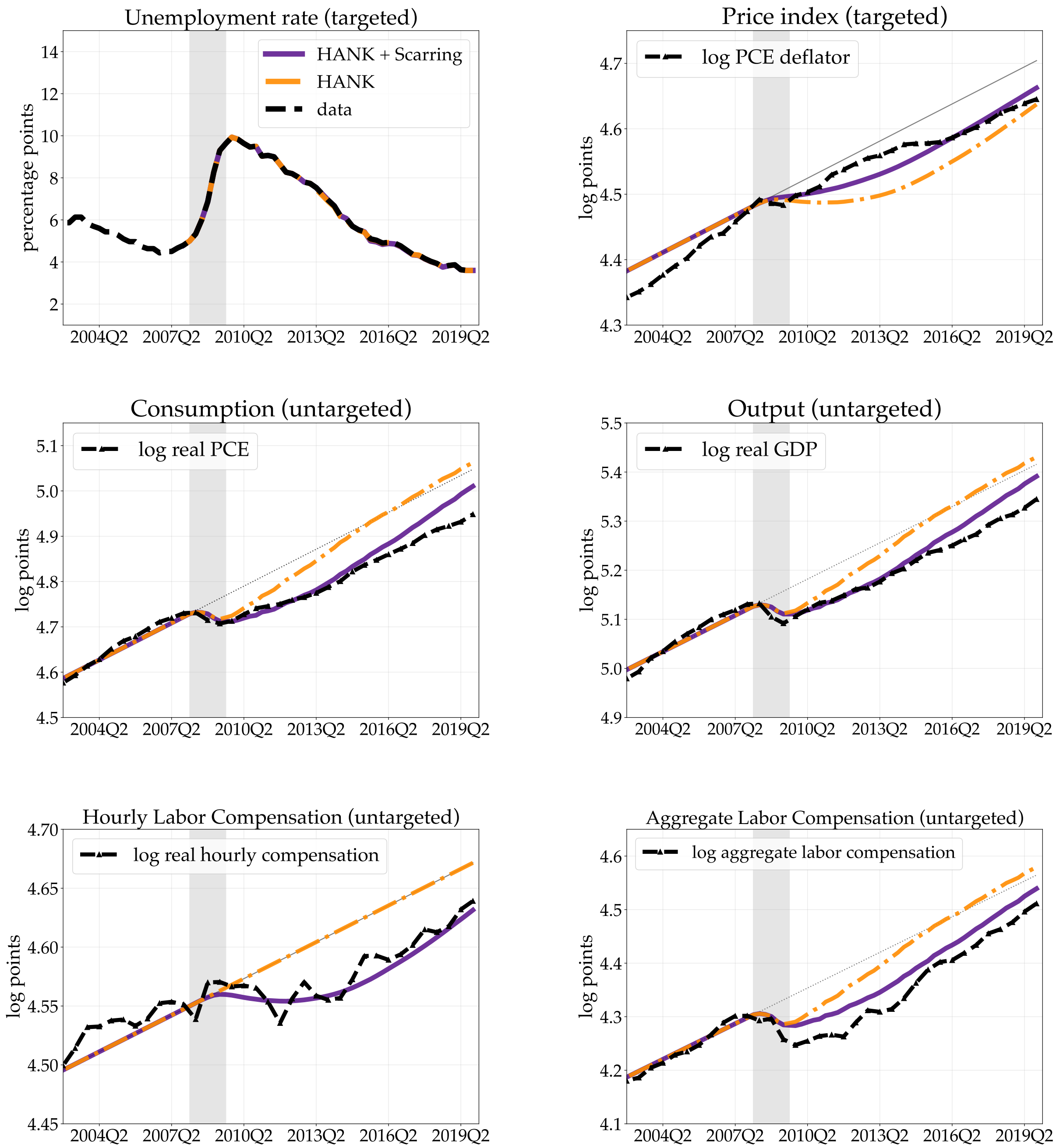


Figure 1-10. Great Recession: Model vs Data (with trend)

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.

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

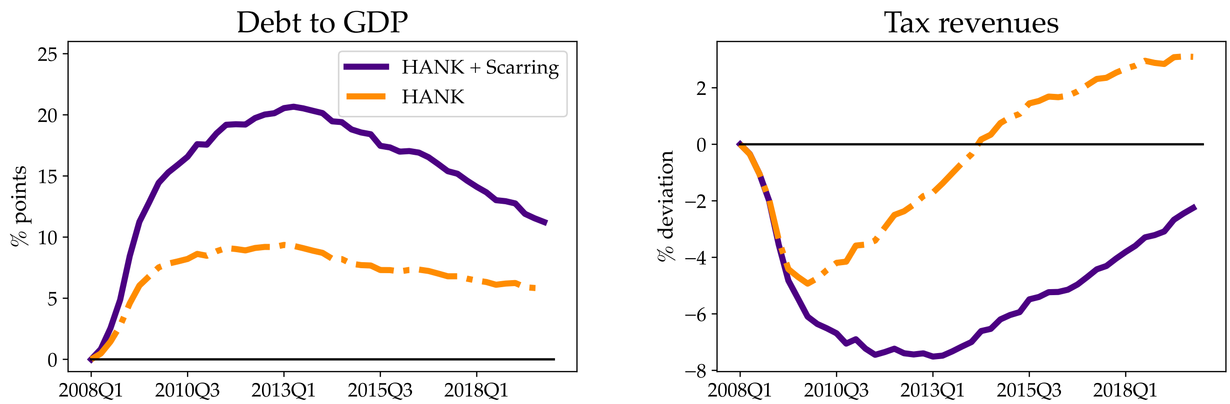


Figure 1-11. The response of debt to GDP and tax revenues

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.

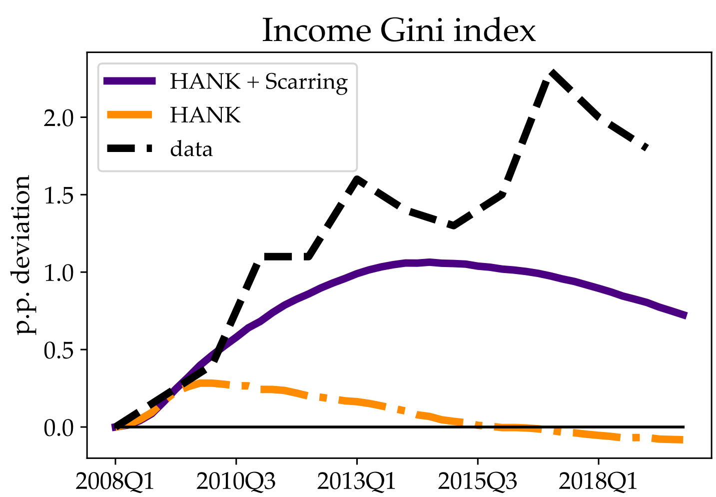


Figure 1-12. Gini Coefficient: Model vs Data

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 $P_{TLPL} = 0$.[14] 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

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

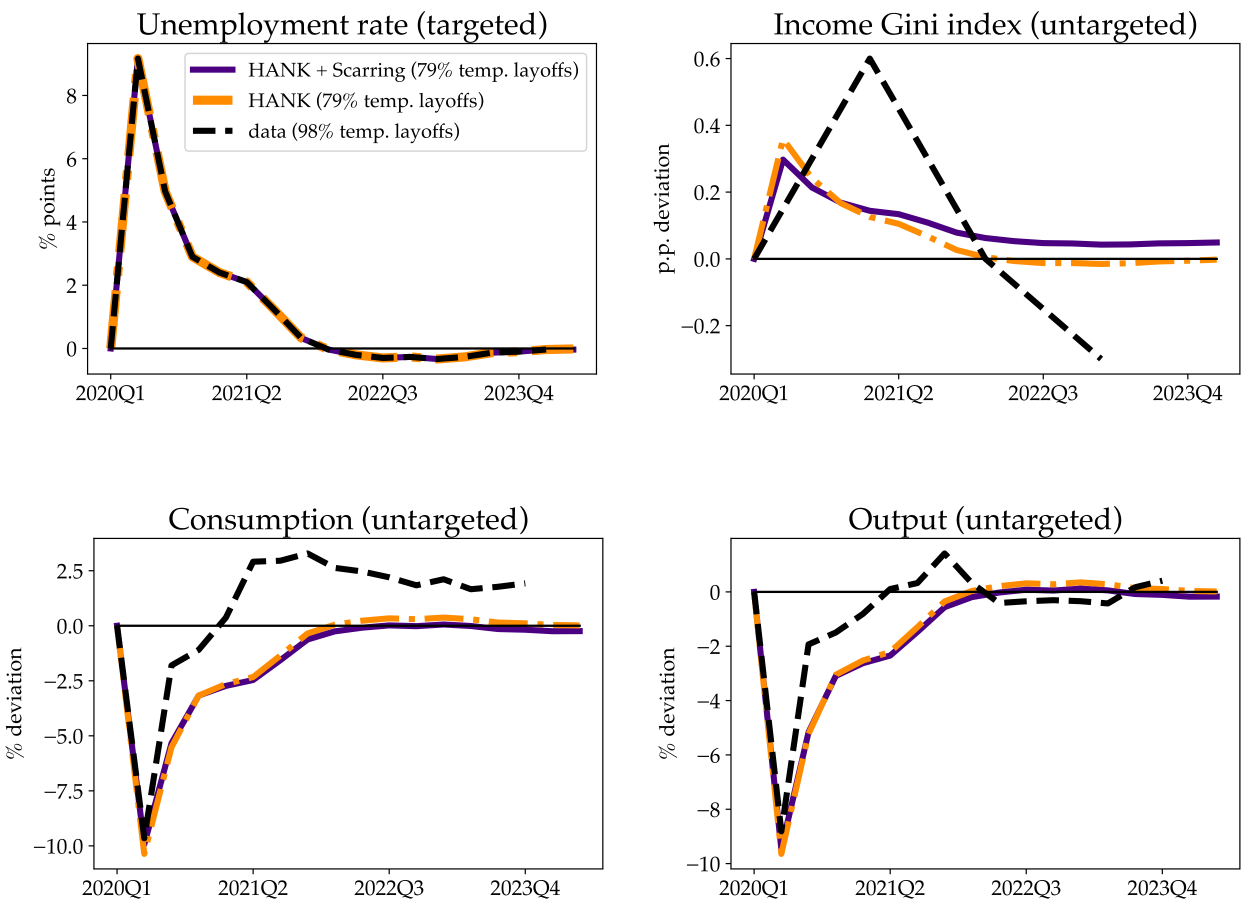


Figure 1-13. Model vs data: The COVID Recession

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.[15]

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.

[15] 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.

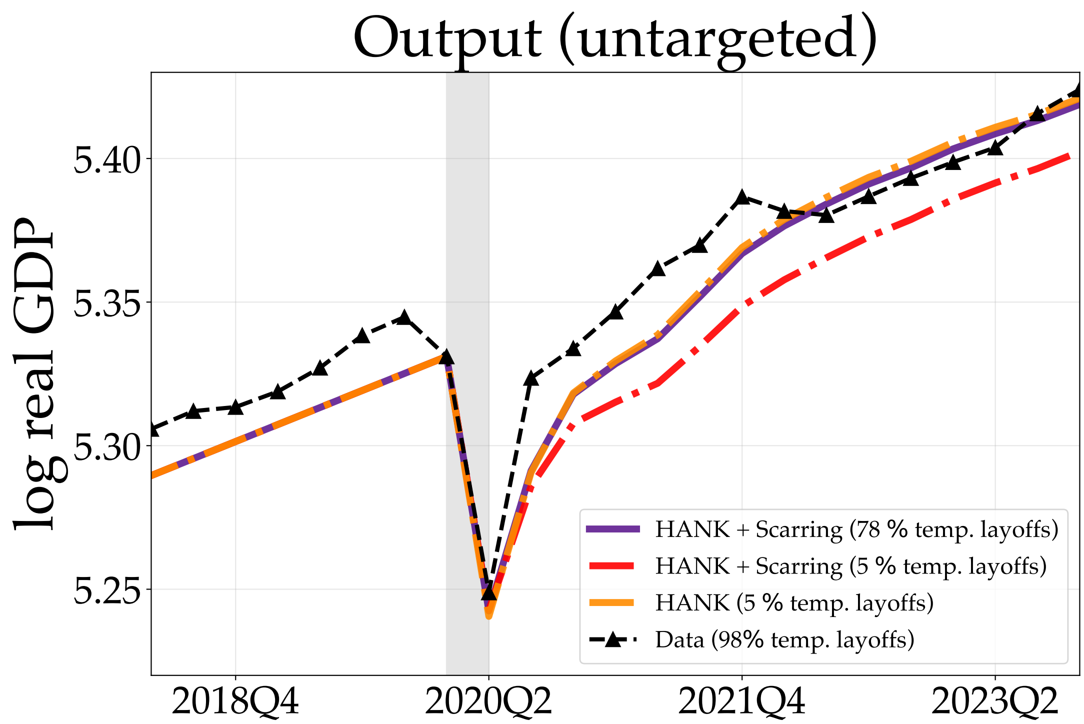


Figure 1-14. Counterfactual for GDP: What if the rise in unemployment during the pandemic was due to permanent layoffs?

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.[16] In this

[16] Bertheau et al. [2023]

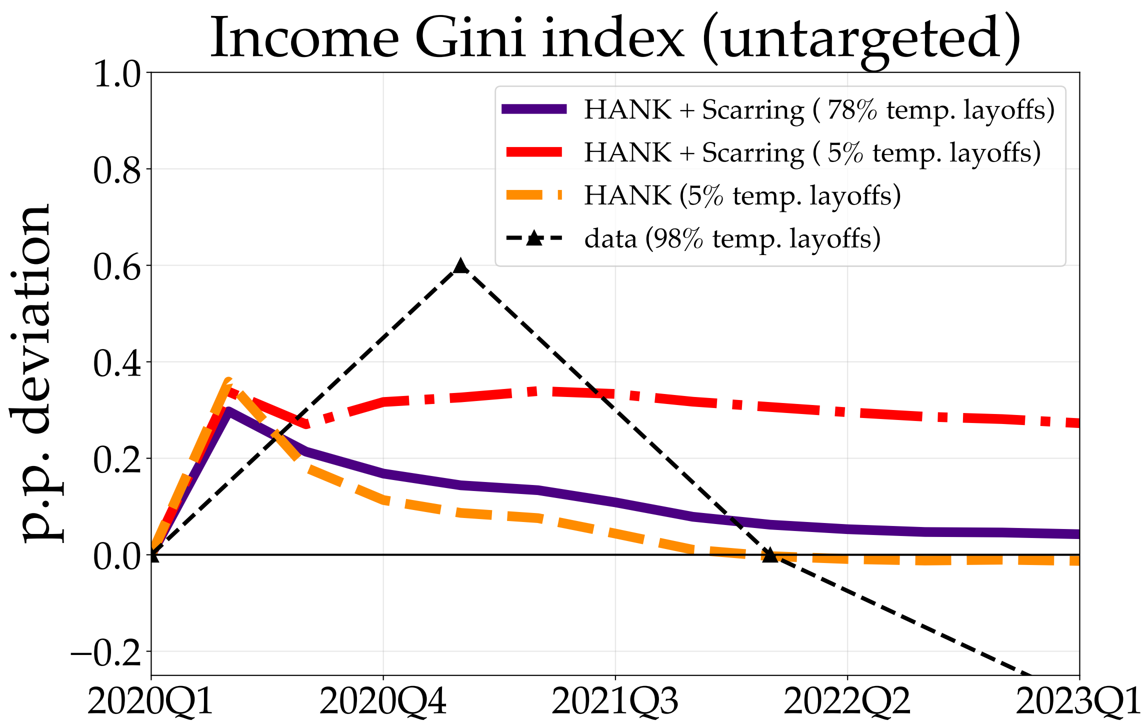


Figure 1-15. Counterfactual for Gini index: What if the rise in unemployment during the pandemic was due to permanent layoffs?

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 1.23 percentage points. In the absence of human capital losses from scarring, the green dashed line demonstrates that debt to GDP would have fallen by 4.75 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.

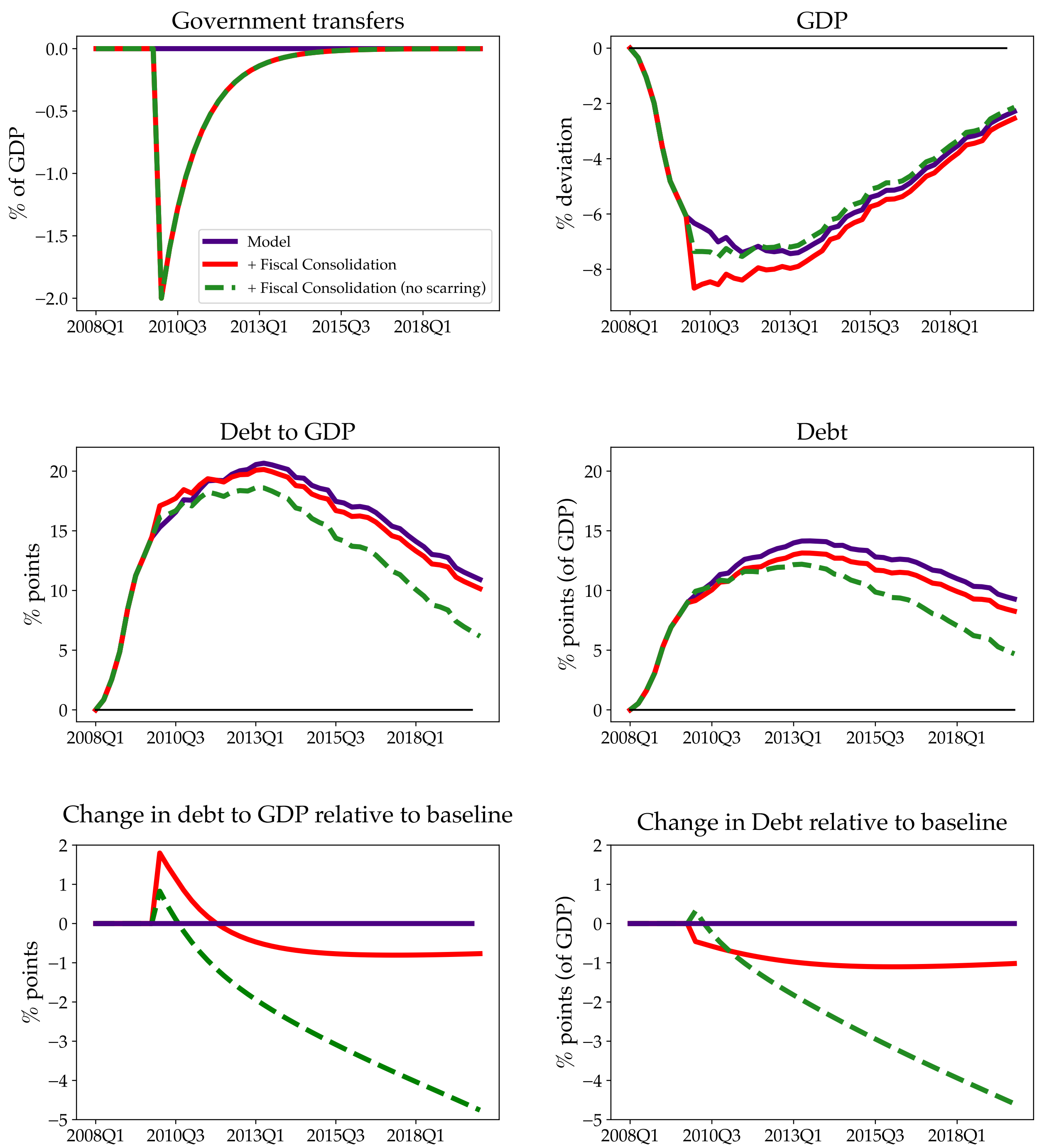


Figure 1-16. Counterfactual: Fiscal Consolidation in the US

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.

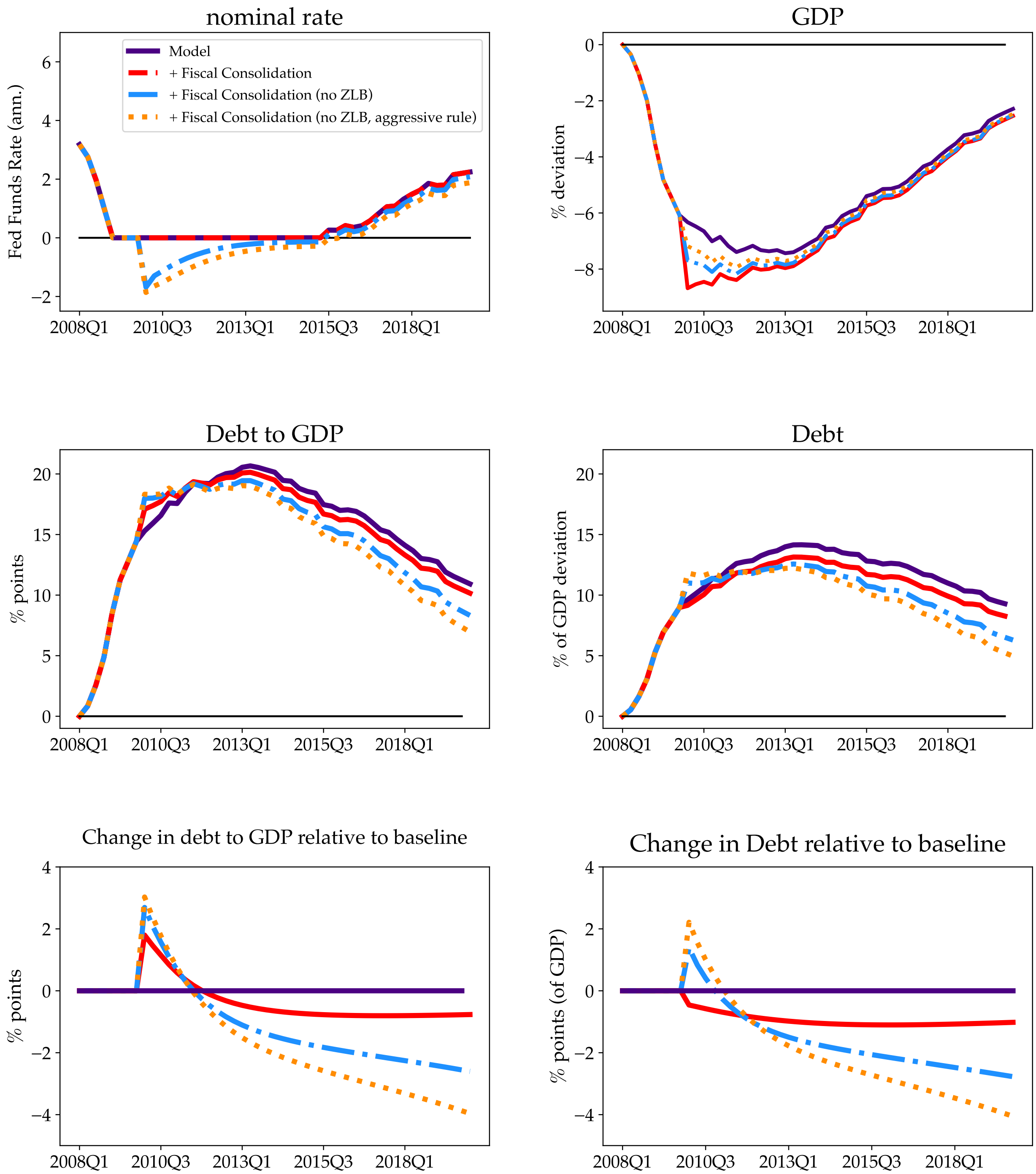


Figure 1-17. Counterfactual: Fiscal Consolidation in the US and the effects of the zero lower bound

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 macroeconomic model of incomplete markets with search and matching frictions, countercyclical unemployment risk amplifies business cycle fluctuations.[2] This amplification stems from two channels. The first is a precautionary saving channel whereby heightened fears of unemployment dampen consumption, further reducing aggregate demand. The second is an income channel, where a reduction in consumption occurs due to realized income losses from unemployment. [3]

Both these channels are typically disciplined by the realized probability of unemployment calculated from microdata. However, given the large body of evidence on how households' macroeconomic expectations deviate from the full-information-rational-expectations (FIRE), it is natural to ask whether perceptions of unemployment risk align with the true probability of losing a job. An underreaction to increased unemployment risk could lead to under-insurance,

[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 effect 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]

leaving households vulnerable as they are unable to smooth their consumption in response to shocks. In contrast, an overreaction to increased unemployment risk may induce a substantial fall in aggregate demand.[4]

This paper measures how (a) perceived, (b) objective, and (c) realized unemployment risks evolve over the business cycle. The first two measures capture ex-ante expectations of unemployment risks, while the third is the ex-post realization of the fraction of individuals transitioning into unemployment. Under rational expectations, models of the business cycle featuring countercyclical unemployment risk assume that (a) and (b) are identical. Moreover, the assumption of perfect foresight, commonly used in the empirical implementation of this class of models, implies that (b) and (c) are equivalent. We show that neither assumption proves consistent with the data.

In particular, survey expectations of job transition probabilities are used to measure (a), while the method of real-time machine learning forecasting (e.g. Bianchi et al. [2022]) is used to create a proxy of (b). Separately measuring these two allows us to characterize the difference between subjective job risk perceptions and their ex-ante rational benchmark. The conventional approach of studying expectation formation relies upon a direct comparison of (a) and (c), i.e., the forecast errors, to provide evidence for deviations from FIRE. The existence of ex-post forecast errors, however, does not necessarily imply ex-ante deviations in expectations, as the ex-post realizations may contain realized shocks that could not have been expected even by rational agents. This complements several existing studies that document biases in job beliefs by only comparing (a) and (c).[5]

Although the perceived job risks in survey data directly measure (a), such data is not available until the most recent decade. Therefore, we backcast the series of perceived job risks back to 1978 when there were no directly surveyed beliefs of the same kind. Utilizing the correlation between perceived job risks in New York Fed's *Survey of Consumer Expectations*

[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.

(SCE) since 2013 and the Michigan Survey of Consumers (MSC) in which numerous other expectations have been measured for a much longer history, we backcast the perceived job risks into the past four decades. This allows our analysis to span multiple business cycles and empirically measure the strength of precautionary motives, circumventing the assumption that ex-post outcomes are equal to ex-ante perceived risks.

To measure (b), we adopt a real-time machine-learning forecast framework following the methodology of Bianchi et al. [2022]. In particular, we generate real-time forecasts of labor market transition rates using numerous real-time variables that include economic conditions, household expectations on the future of the macroeconomy, and personal finance. We also incorporate professional forecasts and other macroeconomic series that may predict subsequent labor market changes. 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.

Specifically, for each point of the time in the sample, we perform a LASSO (least absolute shrinkage and selection operator) estimation to select a subset of variables from a set of 600 time series of real-time macroeconomic conditions and other forward-looking expectations that best predict subsequent labor market flows. We then generate a one-step-ahead forecast using the machine-efficient model. We include survey perceptions of job risks in the prediction model to account for the fact that ex-ante perceptions reported in surveys, although measures of perceptions, turn out to be predictive of ex-post transition rates. This also nests a special case where perceptions perfectly predict ex-post transition rates. Household expectations in MSC are strongly predictive of labor market transition rates, suggesting agents do incorporate useful information in forming expectations on unemployment risk. In addition, not only do real-time conditions correlate with expectations; but also forward-looking economic decisions, such as durable spending intentions. Finally, several series in the MSC provide causal attributions, e.g. not a good time to buy durables because one cannot afford them, are also important predictors.

With direct measures of (a) and (c) and a good proxy for (b), we document two main findings. First, ex-ante subjective job risks, especially regarding job-finding rates, are highly predictive of ex-post job transition rates. This suggests that average households incorporate useful information to form views about their job risks. It is also consistent with the finding in the literature that agents possess advance information about future job transitions. Second, perceived risks do not perfectly coincide with machine-efficient forecasts in that the former are upward biased and underreactive to the changes in the latter. Machine-efficient forecasts produced by the aforementioned procedure are found to be highly accurate in forecasting labor transition rates in the 3-month horizon. Average subjective perceptions of job risks, despite their predictive power, do not fully update synchronously with rational ex-ante risks, suggesting that they fail to efficiently incorporate all the information that predicts subsequent labor market changes.

The sluggish response in perceived job risks limits the ex-ante precautionary saving channel's role while amplifying the ex-post shock response channel. In addition, there is an important difference between normal times and crisis episodes in terms of the relative importance of two contributors of ex-post channel, one from misperceived risks, namely the gap between (a) and (b), and the truly unexpected unemployment shocks, namely the gap between (b) and (c). During normal times, the former was the key. This means households do not see the risks that are actually already unfolding and are therefore under-prepared when the unemployment happens. In a few crisis episodes such as the outbreak of the COVID-19 crisis, in contrast, it is the latter that matters more. The sudden increase in unemployment was a truly unexpected shock and could not have been perceived ex-ante even by the most informed forecasters in the economy.

We provide two explanations for why average perceived risks underreact to real-time macroeconomic labor risks. The first is information rigidity, in that households sluggishly learn about macroeconomic conditions. The second is heterogeneity, in that households face either conditional or unconditional heterogeneity in job risks. This implies that households do not need to react equally to aggregate labor market conditions. In particular, we find that workers across the distribution of perceived job risks react to true real-time risks by different degrees and exhibit various biases. This highlights the role of heterogeneity in true and perceived job risks workers face over business cycles. It is consistent with an increasing number of studies that emphasize the role of heterogeneity in job risks in amplifying aggregate demand fluctuations via unemployment risk channels.[6] Households are unevenly affected by increasing job risks in recessions. The heterogeneity in the effects of aggregate labor market flow rates on individual job risks, therefore, helps explain why average perceived job risks do not one-to-one react to the true real-time job risks.

Lastly, we quantify the aggregate demand fluctuations due to unemployment and unemployment risk allowing for sticky and heterogeneous risk perceptions in a standard Heterogeneous-agent model with persistent unemployment. Our empirical measures of perceptions and outcomes tell their time-series volatility per se, but it is together with the heterogeneous households' consumption/saving sensitivity with respect to risks and shocks that governs the degree of aggregate demand fluctuations. We therefore decompose the aggregate consumption Jacobians (in the terminology of Auclert et al. [2021]) to a given shock of future job-separation and finding probability onto the ex-ante precautionary response given perceptions of such a shock, under-insurance due to misperceived risk, and ex-post shock responses. Then the decomposed Jacobians are combined with the empirically estimated shocks to perceived risk, objective risk, and realized job transitions to quantify the consumption impacts of these three channels. The second channel largely contributes to the ex-post drop in consumption. We show that allowing for subjective and heterogeneous perceptions of risks yields a more persistent drop in aggregate consumption during recessions than a model assuming rational expectations and perfect foresight. This result suggests that the strength of unemployment and unemployment risk channels in amplifying business cycle fluctuations crucially depend on how the heterogeneous households perceive the fluctuations in job risks.

[6]For instance, Patterson [2023] shows that the group of workers whose income has the largest cyclical movements also have high marginal propensities to consume.

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.

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.[7]

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

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

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.

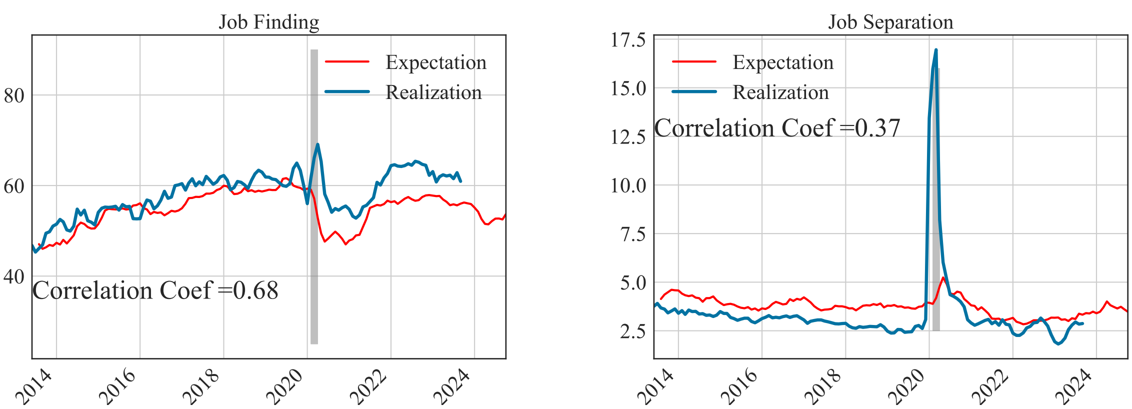


Figure 2-1. Perceived versus realized job transitions

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.

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 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 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],

(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

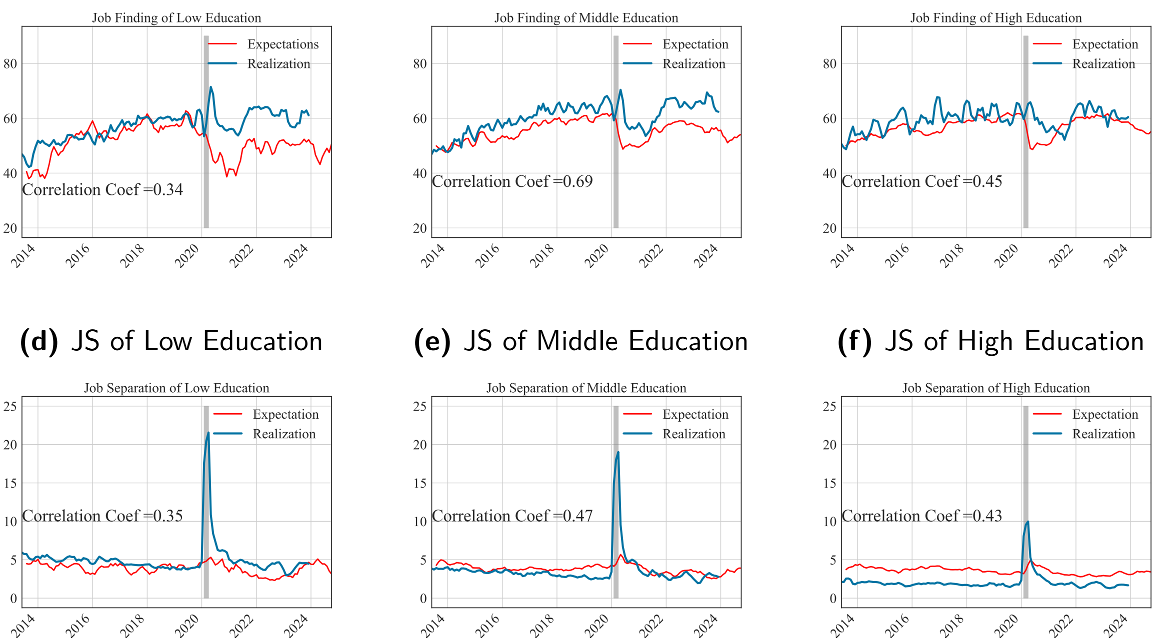


Figure 2-2. Perceived versus realized job transitions: by education

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.

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.[8] In particular, $\beta > 0$ suggests that past errors persist into future forecasts in the same direction, reflecting the presence of information rigidity.

	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.

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

[8] 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 **??**.

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.

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.[9]

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

[9] 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.

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. (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).[10] 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.").[11]

- 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 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

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

[11] 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].

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 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

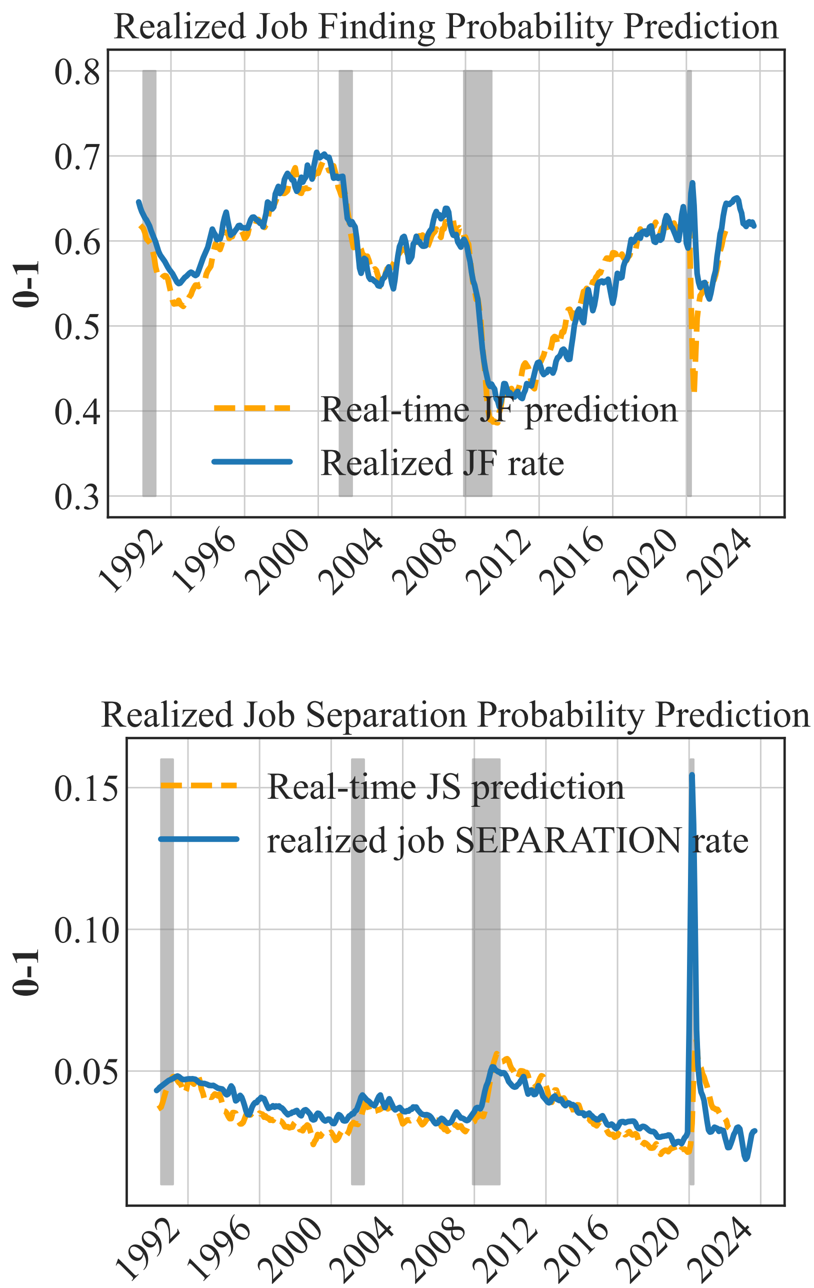


Figure 2-3. Machine prediction of labor market outcomes

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).

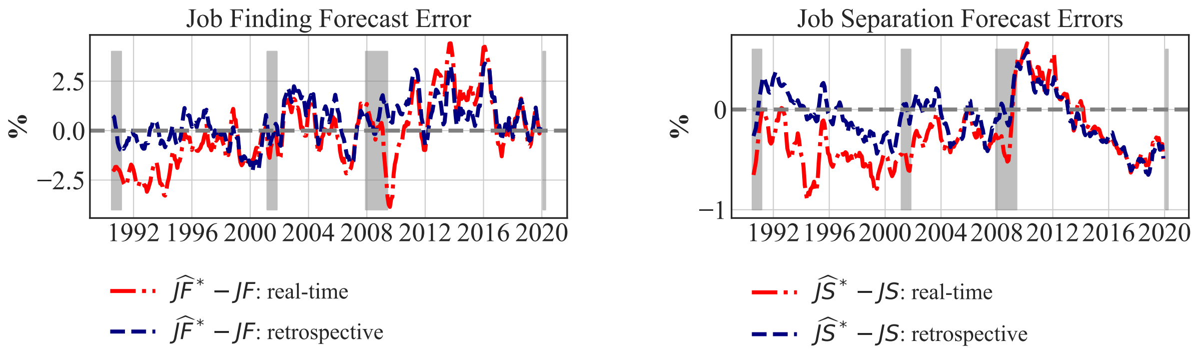


Figure 2-4. Forecast errors of real-time versus retrospective job risks

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.

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 **??** 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[12], 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 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

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

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 **??** 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%. [13]

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 **??** 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 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].

[13] Figure **??** 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.

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 **??**, 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.

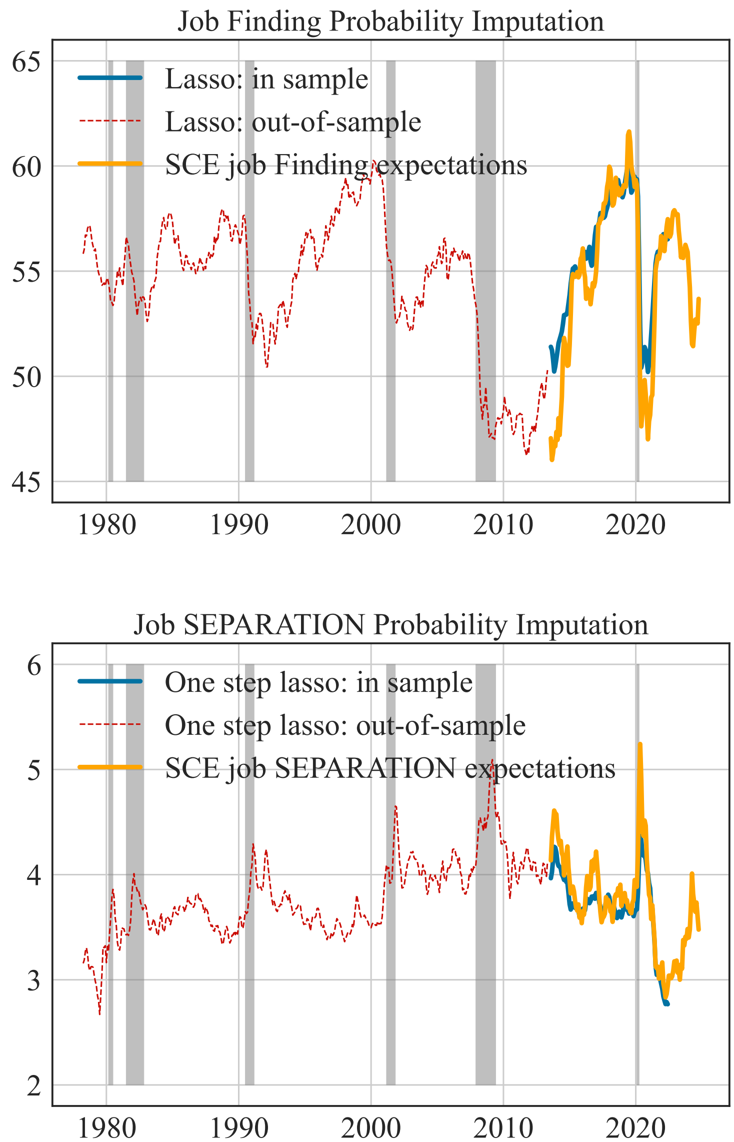


Figure 2-5. Imputed Perceived Job Risks

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.

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.

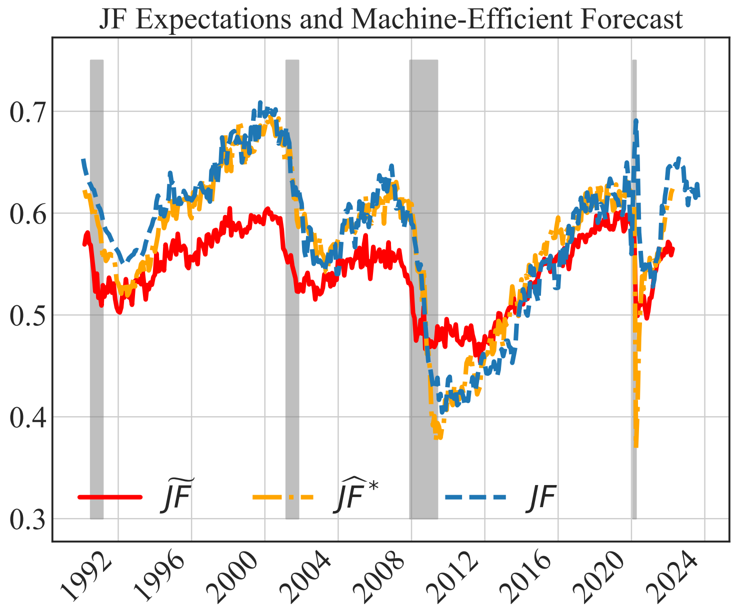
For each one percentage point increase in real-time job-finding forecast, the average perceived job-finding rate increases by 0.5 percentage points. This suggests that perceived job finding follows real-time job finding rate forecasts relatively well. But a coefficient of only half is still indicative 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, implying on average an upward bias in the perceived job separation rate.

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



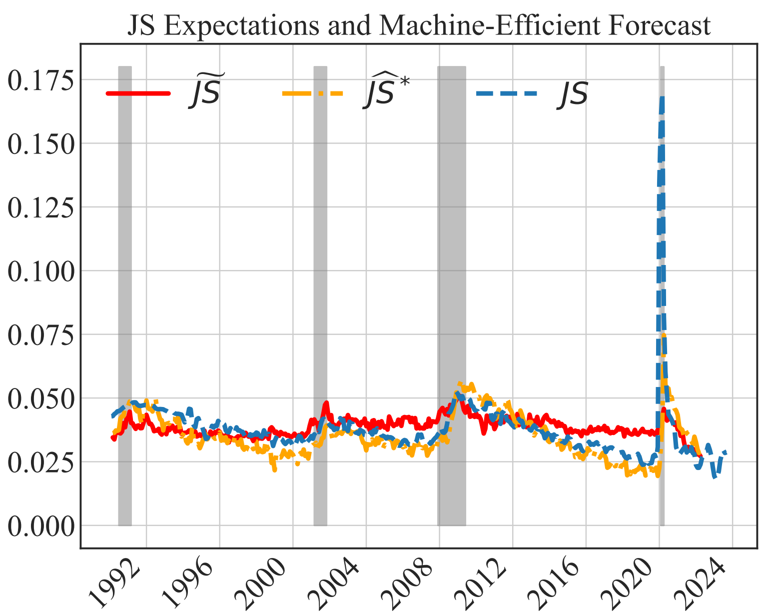


Figure 2-6. Survey perceived job risks versus machine-efficient risk forecasts (0-1)

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

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).[14]

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.[15]

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

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

[15] 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.

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 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

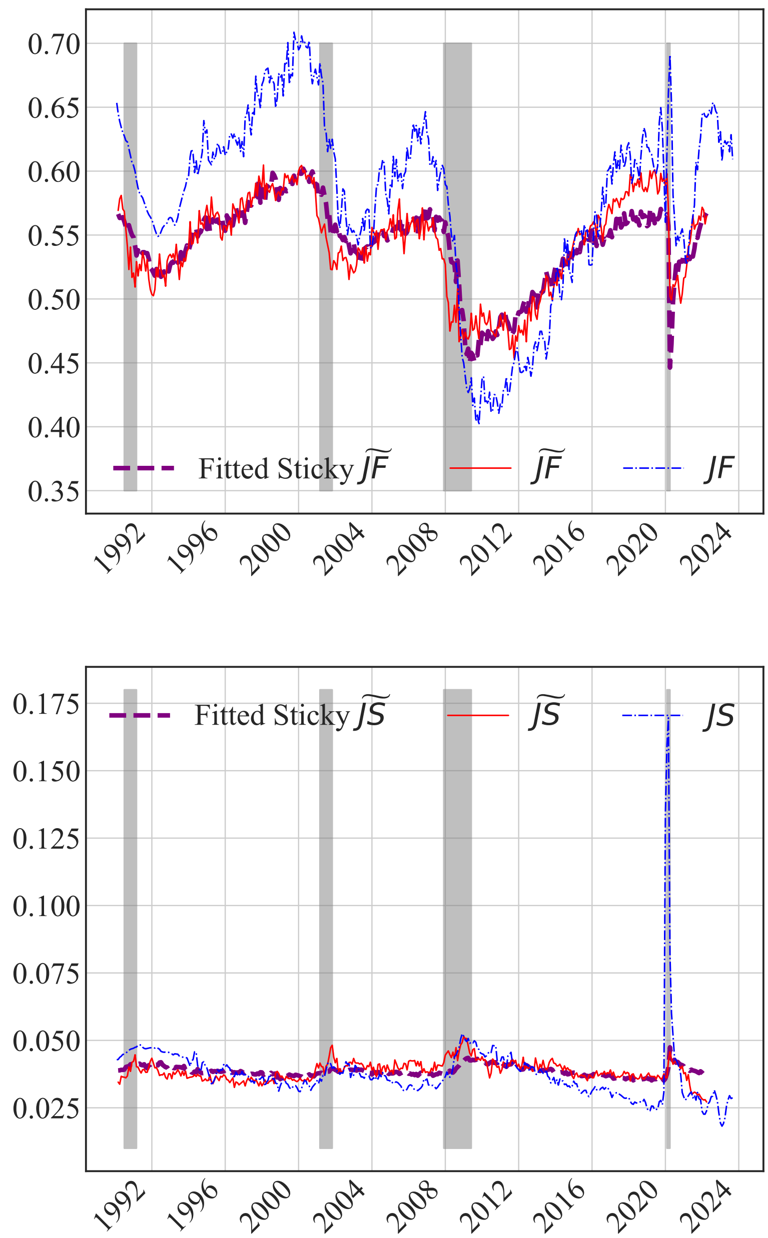


Figure 2-7. The Estimated Sticky Expectation Model of Perceived Job Risks (0-1)

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.

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.

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

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.

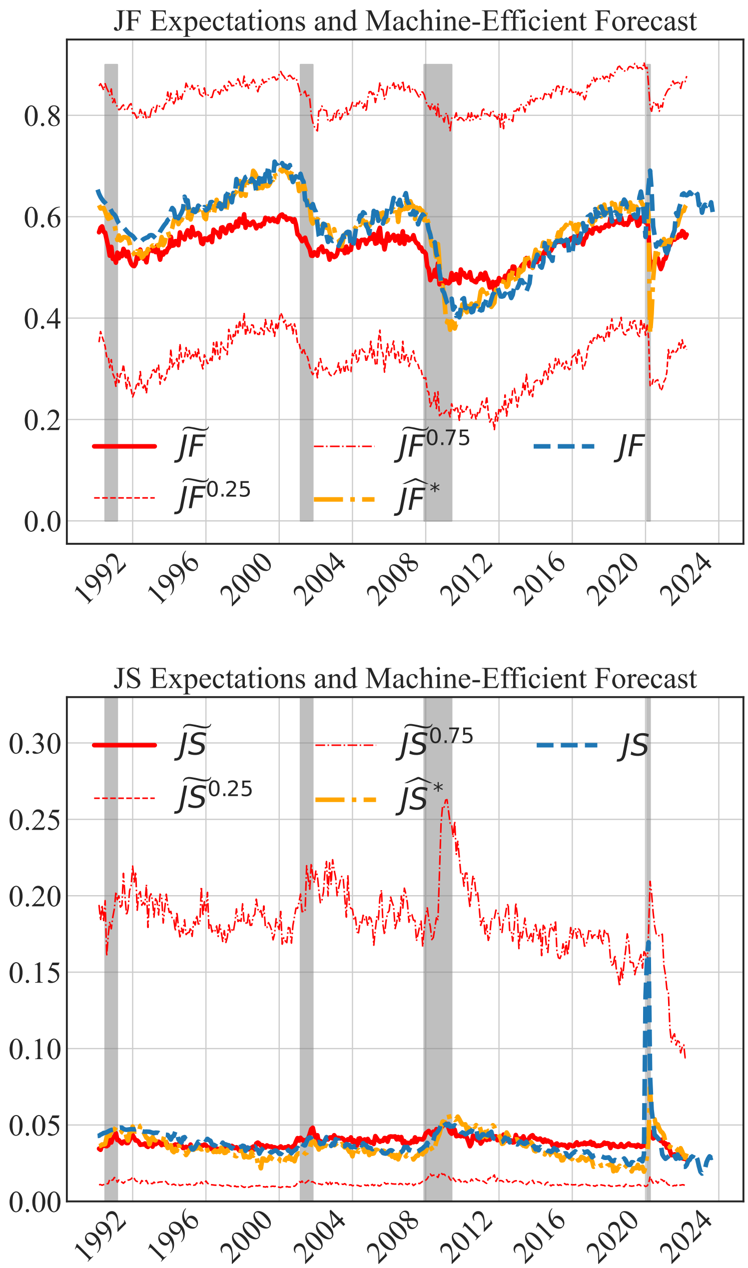
The heterogeneous sensitivities of perceptions with respect to common aggregate risk are probably sensible. In particular, the perceptions of those who perceive high job risks (high separation and low finding risk perceptions) show the highest sensitivity. Business cycles are not just characterized by 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.

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



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) 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.

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

2.5 Macro implications of perceived job risks

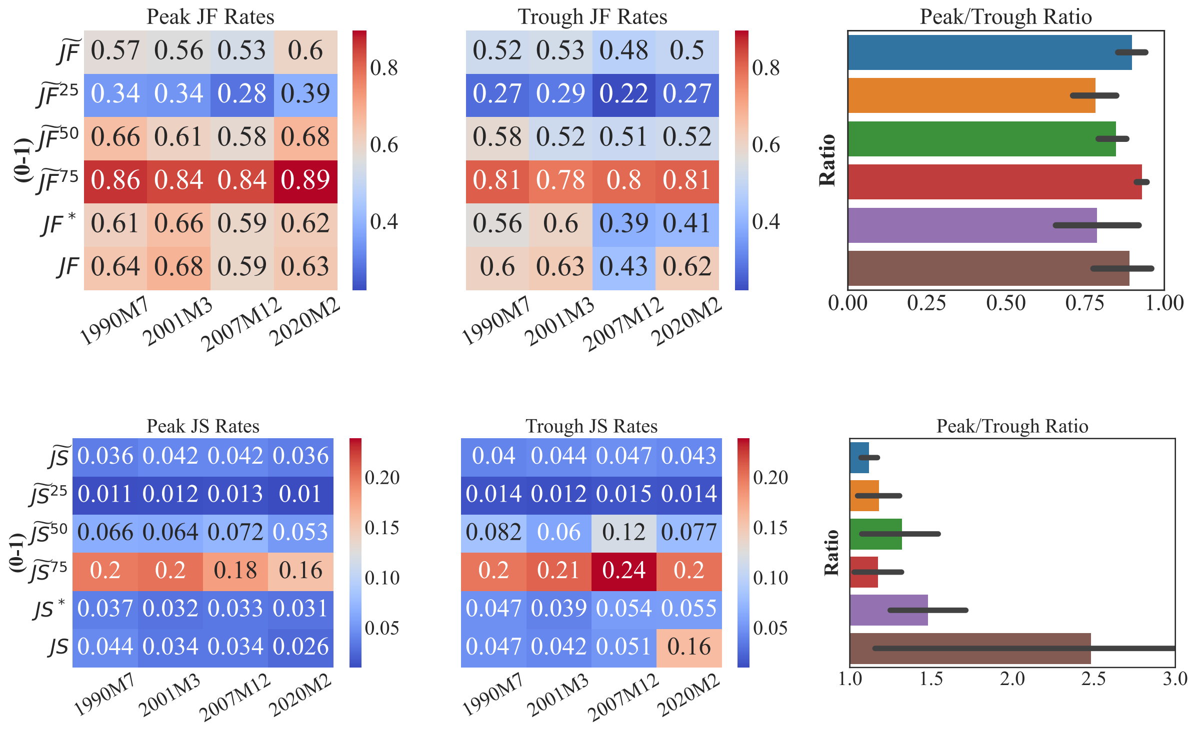
2.5.1 Shocks or risks?

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.



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

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 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

Despite its debatable quantitative importance, an expanding literature has demonstrated that counter-cyclical unemployment risk is an important mechanism that amplifies business cycle fluctuations.[16] Almost all of these models, however, assume perfect foresight and full-information-rational expectations. That is, (a), (b), and (c) are assumed to be the same object.[17] Unlike them, we pay special attention to implications of the fact that it is subjectively perceived job risks, as we measured separately, that effectively govern ex-ante precautionary saving behaviors. We show in this section that the quantitative importance of the unemployment risk channel crucially depends on how such risks are perceived by the households.

[16] Challe and Ragot [2016], McKay [2017], Bayer et al. [2019], Ravn and Sterk [2021].

[17] Bardóczy and Guerreiro [2023] is an exception, which incorporates deviation in perceived job risks in an otherwise standard HANK model.

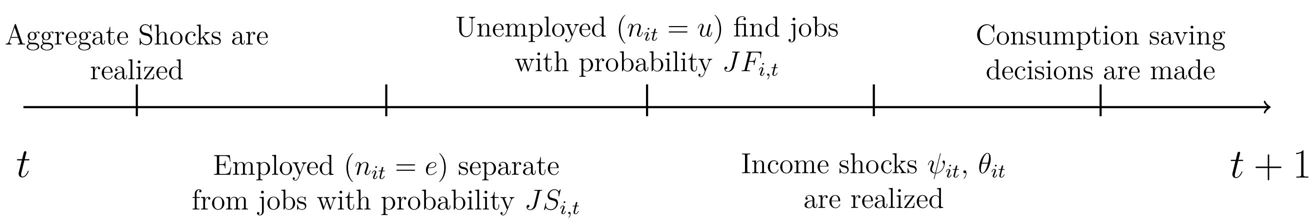


Figure 2-10. Timeline of the Model

Decomposition of consumption Jacobians

The overall impacts of unemployment risks on consumption not only depend on how big the fluctuation of the actual and perceived risks is, which is the primary focus of the paper but also the sensitivity of the aggregate consumption response to changes in unemployment risks. We discipline such sensitivity with a heterogeneous-agent consumption-saving model featuring persistent unemployment under a set of standard calibrations commonly seen in the literature. In our model, households make a consumption-saving decision in the face of both productivity shocks and unemployment risk. Unemployment risk is dictated by the job separation and job finding probability. Self-insurance is achieved by saving money on a risk-free bond. Figure 2-10 illustrates the timeline of the model and we document other model specifications in the Appendix **??**. Table 1-IV reports all the parameter calibrations. What's particularly important is the unemployment insurance replacement ratio, which we set to be 0.5. We indirectly infer the discount factor β to be 0.97 to match a steady state quarterly MPC of 0.16, which falls well in the median range of the estimates seen in the literature. The model is set at a quarterly frequency. footnote [18]

In the model, the dynamic aggregate consumption response comes from both the optimally chosen consumption policies of heterogeneous households given their perceived risks and the resulting changes in the wealth distribution, which come from both choices and the realized unemployment shocks. We summarize such responses using the Sequence Space Jacobian method by Auclert et al. [2021].

[18] In the Appendix, we reproduce our experiments with a monthly model with several modifications. The main messengers to be conveyed in the following discussions remain intact.

As an illustration, the consumption Jacobians concerning a future positive shock to job separation rate at a given horizon are shown in Figure 2-11 under the standard perfect foresight assumption, in that the shock to future job risks at $t+h$ (h=10 here) is perfectly anticipated by agents at the time t. The ex-ante component Jacobians include both the consumption response between t and $t+h$ and the subsequent impacts of such self-insurance behaviors on the consumption response after the shock realization. The ex-post Jacobians capture the consumption impacts in effect from $t+h$ when the shock happens. It is calculated by fixing the consumption policy of the agents but unexpectedly increasing the job risks at $t+h$. Essentially, it measures the aggregate consumption impacts of a higher share of people who unexpectedly find or lose their jobs. The total Jacobians consist of both the ex-ante and ex-post responses. Intuitively, because of the ex-ante responses before the realization of the shock, the hypothetical ex-post responses to the realized shock at $t+h$ are partially insured, resulting in a more moderate total response at the moment of the shock.

With the same logic, we can decompose the aggregate consumption Jacobians into ex-ante and ex-post responses under subjective perceptions of job risks, as shown in Figure 2-12. The total response with belief rigidity differs from its objective benchmark, which ultimately comes from a different ex-ante response. In particular, the ex-ante subjective response is entirely based on how the imagined shock at $t+h$ is perceived by the agent at time t. Because of belief stickiness, subjective ex-ante Jacobian jumps downward less than the full-information one. This also results in a more drastic drop in consumption following the shock at $t+h$ than in the full-information case ("Subjective (Total)"), simply because the consumption insurance induced by ex-ante response was more limited ("Subjective ex-ante") to counteract the impacts of uninsured ex-post shock ("ex-post").

What is more interesting is that we can understand the difference between the objective and subjective perceptions of job risks through the lens of ex-ante/ex-post decomposition. In particular, the total subjective responses ("Subjective (Total)") can be further thought of as a combination of the contributions from the ex-ante response under sticky expectations

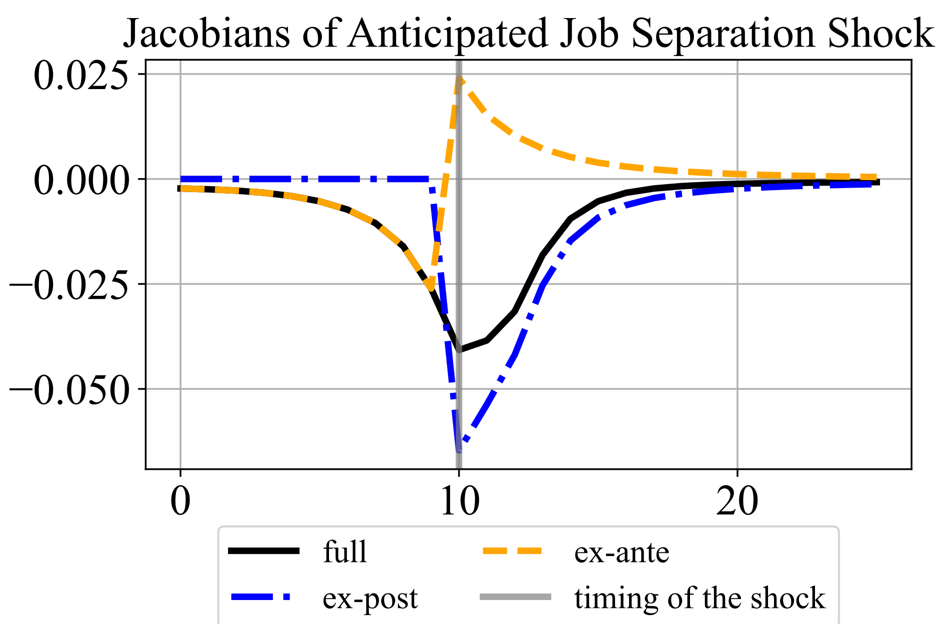
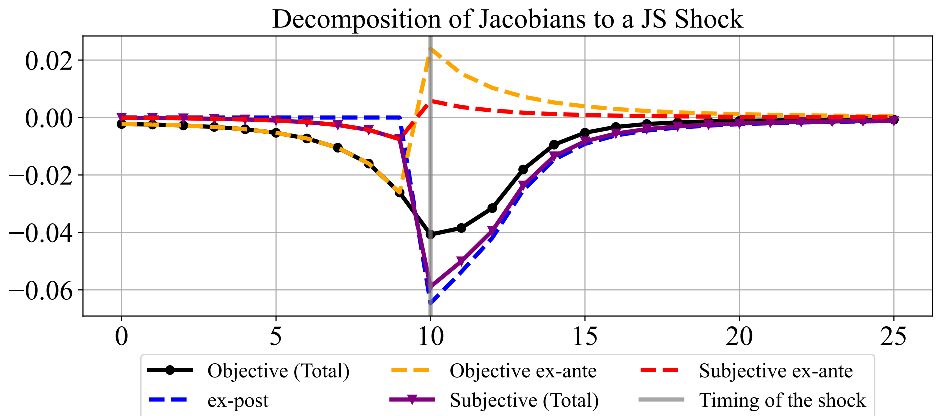


Figure 2-11. Consumption Jacobian to an anticipated 10-period-ahead shock to the job separation

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. [2021].



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

("Subjective ex-ante"), underinsurance due to misperceived risks due to stickiness (the area between "Subjective ex-ante" and "Objective ex-ante"), and the responses under full-information ("Objective (Total)"). Due to the under-insurance toward the increased job separation risk, the consumption drop following the shock is bigger than that under full information.

Quantification of consumption impacts

With the decomposed Jacobians, we simulate the path of aggregate consumption from 1988 to 2020 due to unemployment and unemployment risk fluctuations. For this simulation, expectations are disciplined by the beliefs series we have estimated, and the unemployment rate is disciplined by the realized path of job transition rates.

In particular, we empirically estimate the persistence and realized shocks to job flow rates JS_t and JF_t using an AR(1) model. We confirm that the unemployment rate dynamics implied by such an estimated law of motion and shocks to separation and finding match the empirical patterns of the realized unemployment rate reasonably well. Such shocks, combined with the ex-post Jacobians in Figure 2-12 yield the consumption deviations that only come from ex-post shock responses.

Next, respectively, we add to the ex-post response the ex-ante precautionary response stemming from either objective job risks according to rational expectation as measured by real-time risk forecast or measured subjective perceptions to obtain the total simulated path of consumption deviation from its steady state. We combine the estimated perceived law of motion and the realized shocks to the perceived job finding and separation rates ($\widetilde{JF}_t/\widetilde{JS}_t$), and $\widehat{JF}^*_t/\widehat{JS}^*_t$.) with the ex-ante Jacobians to obtain such responses.

Figure 2-13 plots the results from such comparisons based on only job separation, job finding, and the combined impacts of both. Three findings are worth discussing. First, with only a separation rate, the stickiness in job separation beliefs induces a very limited degree of ex-ante precautionary saving responses during each recession. This explains why the total consumption fluctuations according to subjective perceptions fall short of objective perceptions and are very close to the ex-post impacts. Intuitively, consumption drops mostly due to the realized job losses, instead of precautionary responses.

Second, with job-finding beliefs, however, the subjective total response indeed largely precedes that of ex-post shock response, suggesting an important role of precautionary saving behaviors. Take the Great Recession as an example, such precautionary responses imply an additional 1.5-2 percentage point drop in aggregate consumption at the onset of the crisis compared to the drop that solely stems from realized lower job-finding rates. Furthermore, because of the partial response in job finding beliefs to true finding risk, there is also a sizable gap between subjective and objective responses throughout the sample. During the Great Recession, for instance, the objective response implies an even sharper drop in consumption by an additional 1 percentage point. Meanwhile, the slowly reacting job beliefs induce a slower recovery from the recession, a defending feature of the post-crisis consumption patterns.

Lastly, the combined impacts of job finding and separation, shown at the bottom of Figure 2-13, are primarily driven by the impacts of job finding. This is due to two reasons. First, as established by Fujita and Ramey [2009] and a few follow-up studies, job finding overall contributes more than job separation to the business cycle fluctuations of the unemployment rate, although the exact relative importance is debated in the literature. For instance, Broer et al. [2021a] argue that job separations are important for the immediate impact and job finding rates have a long lasting effect. Second, our model assumes that job finding affects not only people currently unemployed but also those currently employed. The unemployment risk a worker faces stems from the possibility of losing their current job and being unable to find a new job. In addition, the importance of job finding also comes from a higher sensitivity in perceptions in the former than that in separation. This makes the precautionary saving behaviors due to unemployment risk quantitatively significant. Note that this model focuses on non-durable consumption. As Carroll and Dunn [1997] and Harmenberg and Öberg [2021] argue that the unemployment risk channel for durable goods is much stronger than for non-durables, our estimates provide rather a lower bound.

Allowing for heterogeneous risks and beliefs

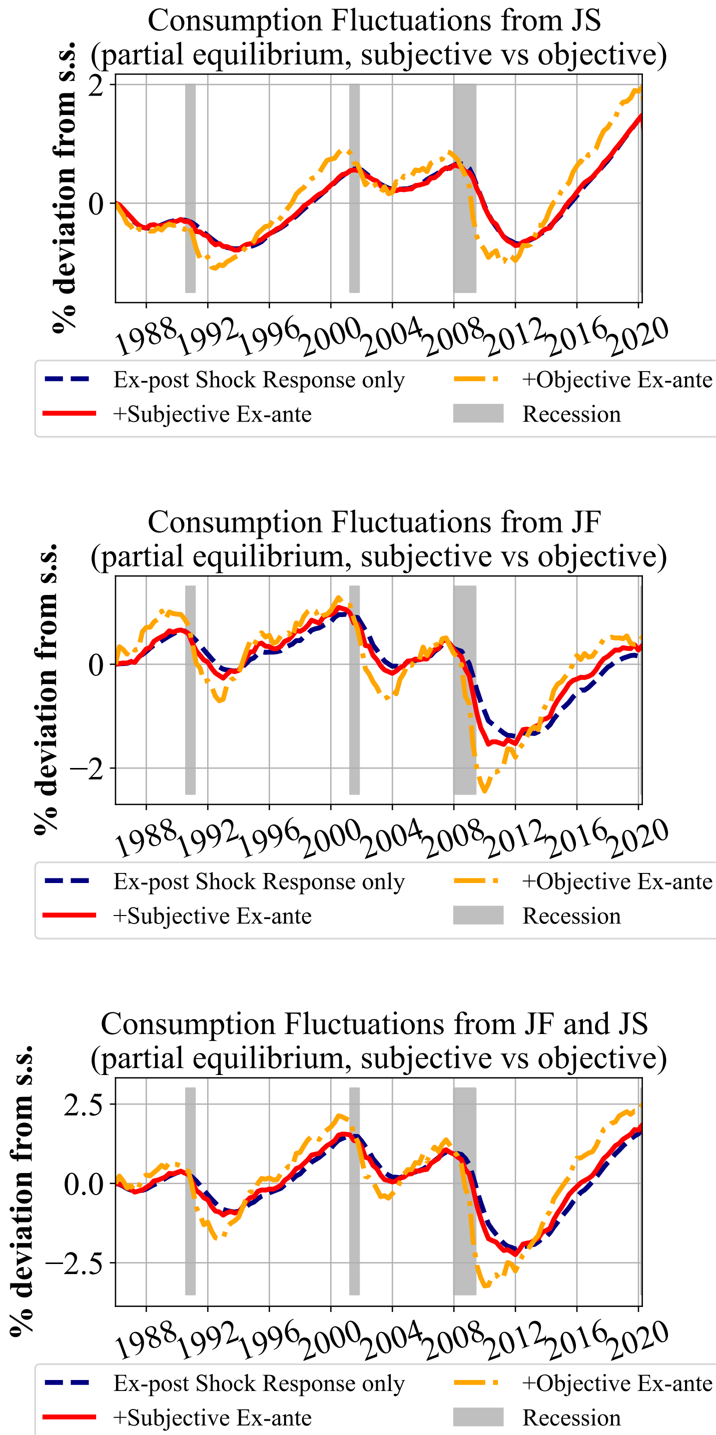
Figure 2-14 simulates consumption fluctuations for each education group, separately, under the alternative assumption of ex-ante heterogeneity in job risks along education level. This is motivated by the results in section 2.4.3, which suggests that compared to the higher separation risk fluctuations than the others, the low education groups' perceptions are particularly sluggish in reacting to such changes. Meanwhile, it is the middle-education group whose beliefs on job finding are the most underreactive to real-time changes. We quantify the importance of misperceived risks and overall precautionary saving motives for each group, respectively. It should be noted that the Jacobians we used to calculate such responses are identical for all groups. This means that we do not assume any other heterogeneity by education besides the one on the objective risks they face and on those as perceived.

Two findings emerge. First, not surprisingly, the ex-post shock response by the low education group was the biggest in recessions, which is attributable to an overall higher volatility of realized job transitions of this group. Second, because the group with the highest education also has the highest sensitivity of the beliefs, they overall have a larger precautionary response. This is indicated by a smaller gap between the subjective and objective response and a larger gap between the subjective and ex-post response for the high-education group.

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.

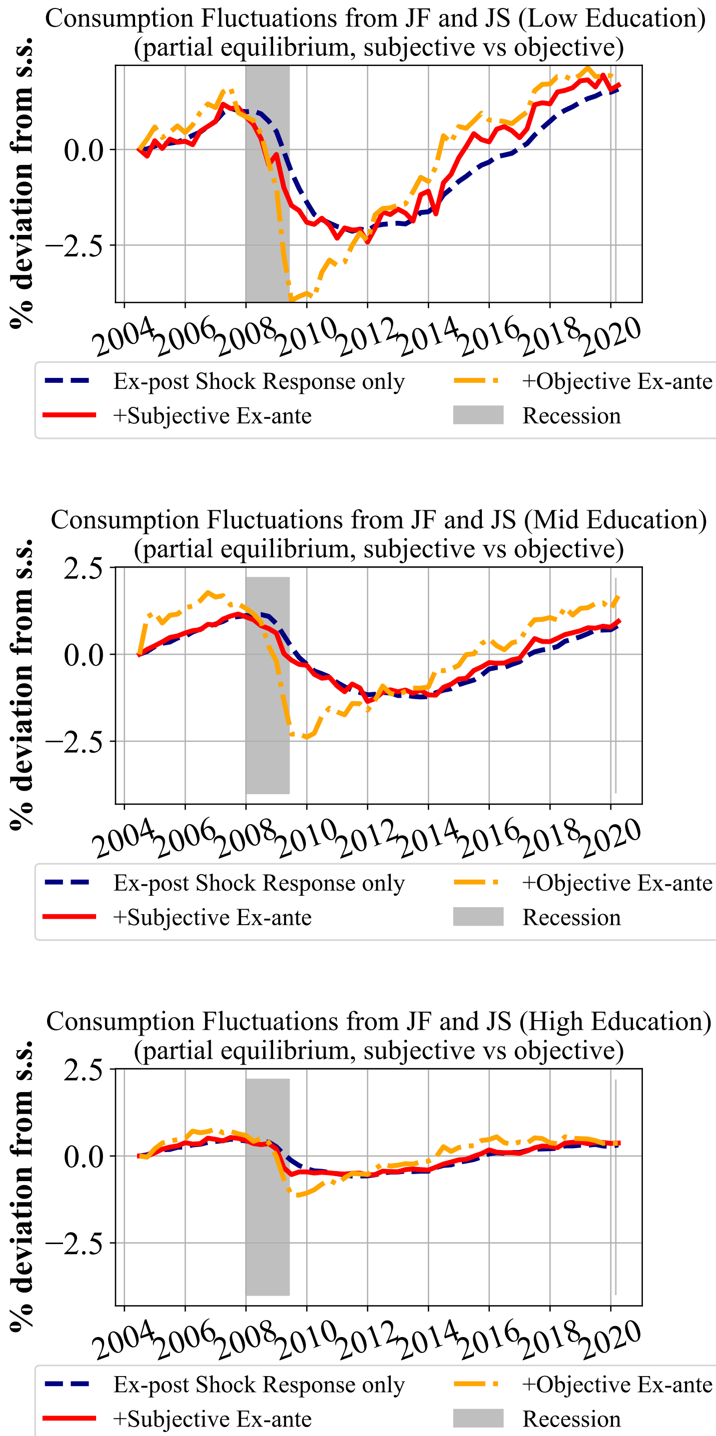
2.6 Conclusion

More people lose jobs and fewer people find jobs in recessions than in normal times. But do people see these changes coming? This paper asks if business cycle movements in job risks are perceived by the average and heterogeneous households who are exposed to different degrees of job risks. The answer to such a question matters because it affects the relative importance of consumption slump in recessions due to ex-ante heightened risks or unexpected ex-post shocks. This paper finds that the average risk perceptions, primarily those regarding job loss, are slow to reflect the unfolding job risk movements along business cycles, therefore limiting the ex-ante channel in driving consumption response and the degree of self-insurance, resulting in a larger impact by ex-post shock response. Meanwhile, job finding beliefs are less rigid and even overreactive, inducing sizable precautionary saving responses. In addition, the footprints of aggregate market labor conditions are widely heterogeneous, as revealed by substantial heterogeneity in perceived job risks. It is not the average worker, but the marginal one who is particularly exposed to business cycle fluctuations that matter for aggregate demand fluctuations due to counter-cyclical job risks. We show the quantitative importance of aggregate and distributional consumption drop due to precautionary savings, misperceived risks, and unexpected income shock response.



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 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 2-14. 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 **?**. 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 (**?**).

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 **?**, 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 **?**'s definition of liquid wealth) and the entire pattern of the iMPC from **?** (see Figure **??** 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.

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,

[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 **??**.

[3]For example, the model in **?**.

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 **?**'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, 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.

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

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 **??**).

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 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,

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 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

quantitatively, all of these effects are small.

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 **?** 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. **?** 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 [2021], and ? 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 ? 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 ?, 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 ? and ?. 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 ?, 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"). ? 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.

? 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 **?** and **?**. However, the literature is conflicted on this subject and **?** and **?** find that extensions of unemployment insurance affect both search decisions and vacancy creation leading to a rise in unemployment. **?**, 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 **?** and **?**, who argue that fiscal multipliers are higher in such circumstances. **?** 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. **?** 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. **?** 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 **?** and **?** 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 **??** 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 **??** describes the steps we take to parameterize the model and discusses the implications for some moments that we do not target. In section **??** 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 **??** presents a general equilibrium HANK and SAM model where we compare the multipliers of the same three policies to the partial equilibrium results. Section **??** 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 **??**.

Conclusions and general discussion

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem.

Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

Fusce mauris. Vestibulum luctus nibh at lectus. Sed bibendum, nulla a faucibus semper, leo velit ultricies tellus, ac venenatis arcu wisi vel nisl. Vestibulum diam. Aliquam pellentesque, augue quis sagittis posuere, turpis lacus congue quam, in hendrerit risus eros eget felis. Maecenas eget erat in sapien mattis porttitor. Vestibulum porttitor. Nulla facilisi. Sed a turpis eu lacus commodo facilisis. Morbi fringilla, wisi in dignissim interdum, justo lectus sagittis dui, et vehicula libero dui cursus dui. Mauris tempor ligula sed lacus. Duis cursus enim ut augue. Cras ac magna. Cras nulla. Nulla egestas. Curabitur a leo. Quisque egestas wisi eget nunc. Nam feugiat lacus vel est. Curabitur consectetuer.

Suspendisse vel felis. Ut lorem lorem, interdum eu, tincidunt sit amet, laoreet vitae, arcu. Aenean faucibus pede eu ante. Praesent enim elit, rutrum at, molestie non, nonummy vel, nisl. Ut lectus eros, malesuada sit amet, fermentum eu, sodales cursus, magna. Donec eu purus. Quisque vehicula, urna sed ultricies auctor, pede lorem egestas dui, et convallis elit erat sed nulla. Donec luctus. Curabitur et nunc. Aliquam dolor odio, commodo pretium, ultricies non, pharetra in, velit. Integer arcu est, nonummy in, fermentum faucibus, egestas vel, odio.

Sed commodo posuere pede. Mauris ut est. Ut quis purus. Sed ac odio. Sed vehicula hendrerit sem. Duis non odio. Morbi ut dui. Sed accumsan risus eget odio. In hac habitasse platea dictumst. Pellentesque non elit. Fusce sed justo eu urna porta tincidunt. Mauris felis odio, sollicitudin sed, volutpat a, ornare ac, erat. Morbi quis dolor. Donec pellentesque, erat ac sagittis semper, nunc dui lobortis purus, quis congue purus metus ultricies tellus. Proin et quam. Class aptent taciti sociosqu ad litora torquent per conubia nostra, per inceptos hymenaeos. Praesent sapien turpis, fermentum vel, eleifend faucibus, vehicula eu, lacus.

Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Donec odio elit, dictum in, hendrerit sit amet, egestas sed, leo. Praesent feugiat sapien aliquet odio. Integer vitae justo. Aliquam vestibulum fringilla lorem. Sed neque lectus, consectetuer at, consectetuer sed, eleifend ac, lectus. Nulla facilisi. Pellentesque eget lectus. Proin eu metus. Sed porttitor. In hac habitasse platea dictumst. Suspendisse eu lectus. Ut mi mi, lacinia sit amet, placerat et, mollis vitae, dui. Sed ante tellus, tristique ut, iaculis eu, malesuada ac, dui. Mauris nibh leo, facilisis non, adipiscing quis, ultrices a, dui.

Morbi luctus, wisi viverra faucibus pretium, nibh est placerat odio, nec commodo wisi enim eget quam. Quisque libero justo, consectetuer a, feugiat vitae, porttitor eu, libero. Suspendisse sed mauris vitae elit sollicitudin malesuada. Maecenas ultricies eros sit amet ante. Ut venenatis velit. Maecenas sed mi eget dui varius euismod. Phasellus aliquet volutpat odio. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Pellentesque sit amet pede ac sem eleifend consectetuer. Nullam elementum, urna vel imperdiet sodales, elit ipsum pharetra ligula, ac pretium ante justo a nulla. Curabitur tristique arcu eu metus. Vestibulum lectus. Proin mauris. Proin eu nunc eu urna hendrerit faucibus. Aliquam auctor, pede consequat laoreet varius, eros tellus scelerisque quam, pellentesque hendrerit ipsum dolor sed augue. Nulla nec lacus.

Suspendisse vitae elit. Aliquam arcu neque, ornare in, ullamcorper quis, commodo eu, libero. Fusce sagittis erat at erat tristique mollis. Maecenas sapien libero, molestie et, lobortis in, sodales eget, dui. Morbi ultrices rutrum lorem. Nam elementum ullamcorper leo. Morbi dui. Aliquam sagittis. Nunc placerat. Pellentesque tristique sodales est. Maecenas imperdiet lacinia velit. Cras non urna. Morbi eros pede, suscipit ac, varius vel, egestas non, eros. Praesent malesuada, diam id pretium elementum, eros sem dictum tortor, vel consectetuer odio sem sed wisi.

Sed feugiat. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Ut pellentesque augue sed urna. Vestibulum diam eros, fringilla et, consectetuer eu, nonummy id, sapien. Nullam at lectus. In sagittis ultrices mauris. Curabitur malesuada erat sit amet massa. Fusce blandit. Aliquam erat volutpat. Aliquam euismod. Aenean vel lectus. Nunc imperdiet justo nec dolor.

Etiam euismod. Fusce facilisis lacinia dui. Suspendisse potenti. In mi erat, cursus id, nonummy sed, ullamcorper eget, sapien. Praesent pretium, magna in eleifend egestas, pede pede pretium lorem, quis consectetuer tortor sapien facilisis magna. Mauris quis magna varius nulla scelerisque imperdiet. Aliquam non quam. Aliquam porttitor quam a lacus. Praesent vel arcu ut tortor cursus volutpat. In vitae pede quis diam bibendum placerat. Fusce elementum convallis neque. Sed dolor orci, scelerisque ac, dapibus nec, ultricies ut, mi. Duis nec dui quis leo sagittis commodo.

Appendix I

Oligonucleotide and probe sequences

Table I-I. Oligonucleotide and probe sequences

№	Name	Note	Sequence
		General	
1	SP6-F	*SP6 Promoter Primer*	`GATTTAGGTGACACTATAG`
2	T7-F	*T7 Promoter Primer*	`TAATACGACTCACTATAGG`
		qPCR oligos & probes	
3	EGFP-615F		`GTCCGCCCTGAGCAAAGA`
4	EGFP-668R		`TCCAGCAGGACCATGTGATC`
5	EGFP-634T	*EGFP probe*	`CCCAACGAGAAGCG`

Appendix II

A few scripts with syntax styling

A. Perl script

```perl
#!/usr/bin/perl

# The traditional first program.

# Strict and warnings are recommended.
use strict;
use warnings;

# Print a message.
print "Hello,␣World!\n";
```

B. R script

```r
# My first program in R Programming

# Store string in variable
myString <- "Hello,␣World!"

# Print variable
print (myString)
```

Bibliography

Hie Joo Ahn and James D Hamilton. Heterogeneity and unemployment dynamics. *Journal of Business & Economic Statistics*, 38(3):554–569, 2020.

Felipe Alves and Gianluca Violante. Some like it hot: Monetary policy under okun's hypothesis. 2023.

Felipe Alves and Giovanni L. Violante. From Micro to Macro Hysteresis: Long-Run Effects of Monetary Policy. Staff Working Papers 24-39, Bank of Canada, October 2024. URL https://ideas.repec.org/p/bca/bocawp/24-39.html.

Donald WK Andrews. Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, pages 821–856, 1993.

Patrick Arni. What's in the blackbox? the effect of labor market policy on search behavior & beliefs. a field experiment. Technical report, IZA Working papers, 2013.

Adrien Auclert, Ludwig Straub, and Matthew Rognlie. Micro Jumps, Macro Humps: monetary policy and business cycles in an estimated HANK model. 2019 Meeting Papers 1449, Society for Economic Dynamics, 2019. URL https://ideas.repec.org/p/red/sed019/1449.html.

Adrien Auclert, Bence Bardoczy, Matthew Rognlie, and Ludwig Straub. Using the sequence-space jacobian to solve and estimate heterogeneous-agent models. *Econometrica*, 89(5):2375–2408, 2021.

Laurence Ball, Davide Furceri, Daniel Leigh, and Prakash Loungani. The distributional effects of fiscal consolidation. *IMF Working Paper*, 2013.

Almut Balleer, Georg Duernecker, Susanne Forstner, and Johannes Goensch. The effects of biased labor market expectations on consumption, wealth inequality, and welfare. 2021.

Almut Balleer, Georg Duernecker, Susanne Forstner, and Johannes Goensch. Biased expectations and labor market outcomes: Evidence from german survey data and implications for the east-west wage gap. 2023.

Bence Bardóczy. Spousal insurance and the amplification of business cycles. 2020.

Bence Bardóczy and Joao Guerreiro. Unemployment insurance in macroeconomic stabilization with imperfect expectations. Technical report, mimeo, 2023.

Christian Bayer, Ralph Lütticke, Lien Pham-Dao, and Volker Tjaden. Precautionary savings, illiquid assets, and the aggregate consequences of shocks to household income risk. *Econometrica*, 87(1):255–290, 2019.

Antoine Bertheau, Edoardo Maria Acabbi, Cristina Barcelo, Andreas Gulyas, Stefano Lombardi, and Raffaele Saggio. The unequal consequences of job loss across countries. *American Economic Review: Insights*, 5(3):393–408, September 2023.

Francesco Bianchi, Howard Kung, and Gonzalo Morales. Growth, slowdowns, and recoveries. *Journal of Monetary Economics*, 101:47–63, 2019.

Francesco Bianchi, Sydney C Ludvigson, and Sai Ma. Belief distortions and macroeconomic fluctuations. *American Economic Review*, 112(7):2269–2315, 2022.

Serdar Birinci. Spousal Labor Supply Response to Job Displacement and Implications for Optimal Transfers. Working Papers 2019-020, Federal Reserve Bank of St. Louis, September 2019. URL https://ideas.repec.org/p/fip/fedlwp/88548.html.

Olivier Blanchard and Jordi Gali. Labor markets and monetary policy: A new keynesian model with unemployment. *American Economic Journal: Macroeconomics*, 2(2):1–30, April 2010.

Christopher Boone, Arindrajit Dube, Lucas Goodman, and Ethan Kaplan. Unemployment insurance generosity and aggregate employment. *American Economic Journal: Economic Policy*, 13(2):58–99, 2021.

Pedro Bordalo, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. Overreaction in macroeconomic expectations. *American Economic Review*, 110(9):2748–2782, 2020.

Tobias Broer, Jeppe Druedahl, Karl Harmenberg, and Erik Öberg. The unemployment-risk channel in business-cycle fluctuations. 2021a.

Tobias Broer, Alexandre Kohlhas, Kurt Mitman, and Kathrin Schlafmann. Information and wealth heterogeneity in the macroeconomy. 2021b.

Christopher Carroll, Jiri Slacalek, Kiichi Tokuoka, and Matthew N White. The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, 8(3):977–1020, 2017.

Christopher D Carroll. Macroeconomic expectations of households and professional forecasters. *the Quarterly Journal of economics*, 118(1):269–298, 2003.

Christopher D Carroll and Wendy E Dunn. Unemployment expectations, jumping (s, s) triggers, and household balance sheets. *NBER macroeconomics annual*, 12:165–217, 1997.

Valerie Cerra, Antonio Fatas, and Sweta C. Saxena. Hysteresis and business cycles. *Journal of Economic Literature*, 61(1):181–225, March 2023.

Edouard Challe and Xavier Ragot. Precautionary saving over the business cycle. *The Economic Journal*, 126(590):135–164, 2016.

Lawrence J. Christiano, Martin S. Eichenbaum, and Mathias Trabandt. Unemployment and Business Cycles. *Econometrica*, 84:1523–1569, July 2016. URL https://ideas.repec.org/a/wly/emetrp/v84y2016ip1523-1569.html.

Olivier Coibion and Yuriy Gorodnichenko. What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, 120(1):116–159, 2012.

Olivier Coibion and Yuriy Gorodnichenko. Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–78, 2015.

Olivier Coibion, Yuriy Gorodnichenko, and Saten Kumar. How do firms form their expectations? new survey evidence. *American Economic Review*, 108(9):2671–2713, 2018.

Roberto Colarieti, Pierfrancesco Mei, and Stefanie Stantcheva. The how and why of household reactions to income shocks. Technical report, National Bureau of Economic Research, 2024.

Diego Comin and Mark Gertler. Medium-term business cycles. *American Economic Review*, 96(3):523–551, June 2006.

John J Conlon, Laura Pilossoph, Matthew Wiswall, and Basit Zafar. Labor market search with imperfect information and learning. Technical report, National Bureau of Economic Research, 2018.

Steven J. Davis and Till Von Wachter. Recessions and the costs of job loss [with comments and discussion]. *Brookings Papers on Economic Activity*, pages 1–72, 2011. ISSN 00072303, 15334465. URL http://www.jstor.org/stable/41473597.

Wouter J Den Haan, Pontus Rendahl, and Markus Riegler. Unemployment (fears) and deflationary spirals. *Journal of the European Economic Association*, 16(5):1281–1349, 2018.

Andy Dickerson and Francis Green. Fears and realisations of employment insecurity. *Labour economics*, 19(2):198–210, 2012.

Antonio Fatás and Lawrence H. Summers. The permanent effects of fiscal consolidations. *Journal of International Economics*, 112:238–250, 2018.

Jeffrey C Fuhrer. Intrinsic expectations persistence: evidence from professional and household survey expectations. *Available at SSRN 3296152*, 2018.

Shigeru Fujita. All layoffs are not created equal. *Economic Insights*, 1(3):1–8, July 2016.

Shigeru Fujita and Giuseppe Moscarini. Recall and unemployment. *American Economic Review*, 107(12):3875–3916, December 2017.

Shigeru Fujita and Garey Ramey. The cyclicality of separation and job finding rates. *International Economic Review*, 50(2):415–430, 2009.

Mark Gertler, Christopher K Huckfeldt, and Antonella Trigari. Temporary layoffs, loss-of-recall and cyclical unemployment dynamics. Working Paper 30134, National Bureau of Economic Research, June 2022. URL http://www.nber.org/papers/w30134.

Nils Gornemann, Keith Kuster, and Makoto Nakajima. Doves for the rich, hawks for the poor? distributional consequences of systematic monetary policy. 2021.

Sebastian Graves. Does unemployment risk affect business cycle dynamics? *International Finance Discussion Paper*, (1298), 2020.

Sebastian Graves, Christopher K. Huckfeldt, and Eric T. Swanson. The Labor Demand and Labor Supply Channels of Monetary Policy. NBER Working Papers 31770, National Bureau of Economic Research, Inc, October 2023. URL https://ideas.repec.org/p/nbr/nberwo/31770.html.

Victoria Gregory, Guido Menzio, and David G Wiczer. The alpha beta gamma of the labor market. Technical report, National Bureau of Economic Research, 2021.

Fatih Guvenen, Serdar Ozkan, and Jae Song. The nature of countercyclical income risk. *Journal of Political Economy*, 122(3):621–660, 2014.

Ingar K Haaland, Christopher Roth, Stefanie Stantcheva, and Johannes Wohlfart. Measuring what is top of mind. Technical report, National Bureau of Economic Research, 2024.

Robert E Hall and Marianna Kudlyak. Job-finding and job-losing: A comprehensive model of heterogeneous individual labor-market dynamics. Technical report, National Bureau of Economic Research, 2019.

Karl Harmenberg and Erik Öberg. Consumption dynamics under time-varying unemployment risk. *Journal of Monetary Economics*, 118:350–365, 2021.

Ida Maria Hartmann and Søren Leth-Petersen. Subjective unemployment expectations and (self-) insurance. *Labour Economics*, page 102579, 2024.

Nathaniel Hendren. Knowledge of future job loss and implications for unemployment insurance. *American Economic Review*, 107(7):1778–1823, 2017.

Chenyu Hou and Tao Wang. Uncovering subjective models from survey expectations. Technical report, mimeo, 2024.

Christopher L. House, Christian Proebsting, and Linda L. Tesar. Austerity in the aftermath of the great recession. *Journal of Monetary Economics*, 115:37–63, 2020.

Christopher Huckfeldt. Understanding the scarring effect of recessions. *American Economic Review*, 112(4):1273–1310, April 2022. doi: 10.1257/aer.20160449. URL https://www.aeaweb.org/articles?id=10.1257/aer.20160449.

Louis S. Jacobson, Robert J. LaLonde, and Daniel G. Sullivan. Earnings losses of displaced workers. *The American Economic Review*, 83(4):685–709, 1993. ISSN 00028282. URL http://www.jstor.org/stable/2117574.

Oscar Jorda and Alan M. Taylor. The time for austerity: Estimating the average treatment effect of fiscal policy. *The Economic Journal*, 126(590):219–255, 2016.

Oscar Jorda, Alan Taylor, and Sanjay Singh. The long-run effects of monetary policy. *Federal Reserve Bank of San Francisco Working Paper*, 2023.

Kyle Jurado, Sydney C Ludvigson, and Serena Ng. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015.

Greg Kaplan, Giovanni L. Violante, and Justin Weidner. The wealthy hand-to-mouth. *Brookings Papers on Economic Activity*, 45(1 (Spring)):77–153, 2014. URL https://EconPapers.repec.org/RePEc:bin:bpeajo:v:45:y:2014:i:2014-01:p:77-153.

Greg Kaplan, Benjamin Moll, and Giovanni L Violante. Monetary policy according to hank. *American Economic Review*, 108(3):697–743, 2018.

Rohan Kekre. Unemployment insurance in macroeconomic stabilization. *Review of Economic Studies*, 90(5):2439–2480, 2023a.

Rohan Kekre. Unemployment insurance in macroeconomic stabilization. *Review of Economic Studies*, 90(5):2439–2480, 2023b.

Marta Lachowska, Alexandre Mas, and Stephen A. Woodbury. Sources of displaced workers' long-term earnings losses. *American Economic Review*, 110(10):3231–66, October 2020.

Sylvain Leduc and Zheng Liu. Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35, 2016.

N Gregory Mankiw and Ricardo Reis. Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics*, 117(4): 1295–1328, 2002.

Alisdair McKay. Time-varying idiosyncratic risk and aggregate consumption dynamics. *Journal of Monetary Economics*, 88:1–14, 2017.

Alisdair McKay and Ricardo Reis. The role of automatic stabilizers in the u.s. business cycle. *Econometrica*, 84(1):141–194, 2016.

Alisdair McKay and Ricardo Reis. Optimal automatic stabilizers. *The Review of Economic Studies*, 88(5):2375–2406, 2021.

Alisdair McKay and Johannes F Wieland. Lumpy durable consumption demand and the limited ammunition of monetary policy. *Econometrica*, 89(6):2717–2749, 2021.

Guido Menzio. Stubborn beliefs in search equilibrium. *NBER Working Paper*, (w29937), 2022.

Brendan Moore and Judith Scott-Clayton. The firm's role in displaced worker earnings losses. 2019.

Camilo Morales-Jiménez. The cyclical behavior of unemployment and wages under information frictions. *American Economic Journal: Macroeconomics*, 14(1):301–331, 2022.

Patrick Moran and Albert Queralto. Innovation, productivity, and monetary policy. *Journal of Monetary Economics*, 93:24–41, 2018.

Andreas I Mueller and Johannes Spinnewijn. Expectations data, labor market, and job search. *Handbook of Economic Expectations*, pages 677–713, 2023.

Andreas I Mueller, Johannes Spinnewijn, and Giorgio Topa. Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias. *American Economic Review*, 111(1):324–63, 2021.

Evi Pappa, Morten O Ravn, and Vincent Sterk. Expectations and incomplete markets. In *Handbook of Economic Expectations*, pages 569–611. Elsevier, 2023.

Christina Patterson. The matching multiplier and the amplification of recessions. *American Economic Review*, 113(4):982–1012, 2023.

Yuri Pettinicchi and Nathanael Vellekoop. Job loss expectations, durable consumption and household finances: Evidence from linked survey data. 2019.

Maxim Poletaev and Chris Robinson. Human capital specificity: Evidence from the dictionary of occupational titles and displaced worker surveys, 1984–2000. *Journal of Labor Economics*, 26(3):387–420, 2008. doi: 10.1086/588180. URL https://doi.org/10.1086/588180.

Garey Ramey, Wouter J. den Haan, and Joel Watson. Job Destruction and Propagation of Shocks. *American Economic Review*, 90(3):482–498, June 2000. URL https://ideas.repec.org/a/aea/aecrev/v90y2000i3p482-498.html.

Morten O Ravn and Vincent Sterk. Job uncertainty and deep recessions. *Journal of Monetary Economics*, 90:125–141, 2017.

Morten O Ravn and Vincent Sterk. Macroeconomic fluctuations with hank & sam: An analytical approach. *Journal of the European Economic Association*, 19(2):1162–1202, 2021.

Marta Garcıa Rodrıguez. The role of wage expectations in the labor market. 2023.

Barbara Rossi and Tatevik Sekhposyan. Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review*, 105(5):650–655, 2015.

Julio J Rotemberg. Sticky prices in the united states. *Journal of political economy*, 90(6):1187–1211, 1982.

Johannes F. Schmieder, Till von Wachter, and Jorg Heining. The costs of job displacement over the business cycle and its sources: Evidence from germany. *American Economic Review*, 113(5):1208–54, May 2023.

Jose Silva and Manuel Toledo. Labot turnover costs and the cyclical behavior of vacancies and unemployment. *Macroeconomic Dynamics*, 13(S1):76–96, 2009. URL https://EconPapers.repec.org/RePEc:cup:macdyn:v:13:y:2009:i:s1:p:76-96_08.

Johannes Spinnewijn. Unemployed but optimistic: Optimal insurance design with biased beliefs. *Journal of the European Economic Association*, 13(1):130–167, 2015.

Melvin Stephens Jr. Job loss expectations, realizations, and household consumption behavior. *Review of Economics and statistics*, 86(1):253–269, 2004.

Tao Wang. Perceived versus calibrated income risks in heterogeneous-agent consumption models. Technical report, Bank of Canada, 2023.