Unemployment Risk, MPC Heterogeneity, and Business Cycles*

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Abstract

This paper evaluates the quantitative importance of two channels emphasized in Heterogeneous Agent New Keynesian (HANK) models: (i) precautionary savings against countercyclical unemployment risk and (ii) MPC heterogeneity. Using the Bayesian estimation technique, I estimate a HANK model that features these two channels. I find that the business cycle dynamics in HANK are different from those in the otherwise identical complete markets benchmark, the Representative Agent New Keynesian (RANK) model. The contribution of precautionary savings against countercyclical unemployment risk on the difference in output volatility between HANK and RANK is small. The majority of the difference arises from MPC heterogeneity. Moreover, the two channels do not improve the fit of the HANK model in terms of explaining aggregate variables, as the estimated HANK model features less nominal rigidity.

Keywords: Heterogeneous Agent New Keynesian model, Bayesian estimation, Precautionary savings, Marginal propensities to consume

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1 Introduction

Do household heterogeneity and incomplete markets matter for aggregate variables? This has been one of the most fundamental questions in the quantitative macroeconomics literature at least since Krusell and Smith (1998). Emerging literature revisits this question using models that combine incomplete markets with nominal rigidities and aggregate shocks. Such models are dubbed as Heterogeneous Agent New Keynesian (HANK) models by Kaplan, Moll and Violante (2018). The HANK literature stresses two broad channels that make the aggregate dynamics in HANK models different from those in Representative Agent New Keynesian (RANK) models. These are (i) precautionary savings against the countercyclical unemployment risk and (ii) marginal propensities to consume (MPC) heterogeneity. Do these channels induce business cycle dynamics in HANK that are meaningfully different from those in RANK? If so, which factor is more important in generating different business cycle dynamics?

These questions are not fully answered in existing studies for the following reasons. First, most quantitative HANK models compare the aggregate dynamics in HANK and RANK conditional on one shock. However, business cycles are driven by multiple aggregate shocks, and thus one needs to have models that incorporate rich aggregate shocks to compare the unconditional business dynamics between HANK and RANK. Second, most quantitative HANK models have one channel out of the two, making it hard to evaluate the relative strength of each factor. For example, a popular way of endogenizing unemployment risk is to embed search and matching frictions in HANK models. These models, which Ravn and Sterk (2018) dub HANK & SAM, generate a powerful supply-demand feedback loop.[1] A rise in unemployment raises the probability of becoming unemployed for individual households, inducing a precautionary savings motive, which lowers aggregate demand, output, and employment, and so causes more unemployment risk. Most HANK & SAM models do not match realistic average MPCs for the sake of tractability. To match the MPC, one needs to have households more distributed near or at a borrowing limit. Households who are constrained do not respond to expected future income change and thus do not have a precautionary savings incentive. Therefore, models that ignore MPCs are likely to include more households that precautionary-save against unemployment risk than models that do not, potentially overestimating the effect of unemployment risk.

[1] See, e.g., Ravn and Sterk (2017, 2018), Challe et al. (2017), Den Haan, Rendahl and Riegler (2018), and Heathcote and Perri (2018) for positive analysis on aggregate fluctuations. McKay and Reis (2019), Kekre (2019), and Challe (2019) study the policy implications of this feedback loop.

The goal of this paper is to assess the importance of the two channels stressed in the HANK literature in US business cycles. To this end, I construct a HANK model that matches two key moments in steady state: the empirically relevant average MPC and the average consumption differential between employed and unemployed households that is in line with the data. Moreover, the model embeds nominal and real frictions and aggregate shock processes that are understood to be essential for explaining aggregate dynamics in medium-scale DSGE models. Exploiting a recent method for solving and estimating heterogeneous agent models introduced by Winberry (2018), I estimate the structural parameters using the US aggregate time series with a Bayesian technique in the style of Justiniano, Primiceri and Tambalotti (2010).

In the model, two channels largely contribute to the responses of aggregate consumption and output. First, a change in the current macroeconomic conditions induces a change in real wages and the number of unemployed households. The resulting change in current aggregate household income affects current aggregate consumption. The sensitivity of current aggregate consumption with respect to current aggregate income is determined by the high average MPC that arises from MPC heterogeneity. This is the MPC heterogeneity channel. Second, given the individual household income, variations in unemployment alter the *future* expected earnings of an individual household and thus change precautionary savings, affecting current aggregate consumption. This is the countercyclical unemployment risk channel. These two channels are missing in RANK.

Using the estimated model, I compare the volatility in output between HANK and RANK, the complete markets benchmark obtained by eliminating any heterogeneity on the household side. I decompose the difference in output volatility into a part that arises from the precautionary savings against countercyclical unemployment risk and the part that arises from MPC heterogeneity. The main results are as follows. I find that business cycle dynamics in HANK and RANK are very different. The contribution of precautionary savings against countercyclical unemployment risk to the difference in output volatility between HANK and RANK is 5 %. The majority of the difference arises from MPC heterogeneity.

In addition, I compare the quality of fit between HANK and RANK models in terms of the unconditional second moments of aggregate data. To do so, I also estimate the RANK version of my model and compare parameter estimates, aggregate shocks decomposition, and the log marginal likelihood between the models. I find that the estimates of price and wage stickiness are lower in HANK than in RANK, and monetary policy is more aggressive in HANK. The difference in parameter estimates arises from different predictions in response to the marginal efficiency of investment (MEI) shock, the main driver of GDP volatility. In particular, the

HANK model is capable of generating the comovement of consumption with output and investment conditional on the MEI shock due to the presence of the unemployment risk and MPC heterogeneity channels. In RANK, where these channels are absent, the only way to achieve the conditional comovement is to have a higher degree of nominal rigidity and a more accommodative monetary policy rule. With respect to the log marginal likelihood, I find the HANK model does not outperform the RANK model. Although the HANK model explains the contemporaneous correlation of quantities better than the RANK model, the HANK model has more difficulty in explaining the autocorrelations and cross-correlations of prices due to the lower degree of nominal rigidity.

The results of my paper are in contrast with those presented in existing studies that argue for the importance of unemployment risk in aggregate dynamics (Kreamer, 2016; Ravn and Sterk, 2017, 2018; Challe et al., 2017; Den Haan et al., 2018; Heathcote and Perri, 2018; McKay and Reis, 2019; Challe, 2019). [2] Most existing studies simplify wealth distribution or do not target the average MPCs. [3] Therefore, relative to my paper, the contribution of precautionary savings in amplification is larger. An exception is Kekre (2019), who studies the effect of unemployment insurance in a model in which MPC heterogeneity is considered. As in my paper, aggregate demand expansion is a result of the combined effect of MPC heterogeneity and precautionary savings against unemployment risk. However, he does not decompose the two effects.

Studies that highlight MPC heterogeneity argue that a positive covariance of MPC and individual income elasticities with respect to aggregate income is the key to the amplification. (Galí et al., 2007; Oh and Reis, 2012; Kaplan et al., 2018; Auclert et al., 2018; Auclert, 2019; Bilbiie, 2019b; Hagedorn et al., 2019) In my model, patient households have the lowest MPC and receive all profits that are countercyclical, implying a positive covariance of MPC and individual income elasticities. Therefore, the amplification of aggregate shocks via MPC heterogeneity that these studies stress is operative. In contrast to these studies, I have additional channels that lead to further amplification: precautionary savings that arise from counteryclical unemployment risk.

Moreover, my paper is related to active literature on the Bayesian estimation of HANK models. [4] Bayer, Born and Luetticke (2019a) use an estimated two-asset HANK model with

[2] Other important works that model cyclical earnings risk that are unrelated to unemployment risk include Acharya and Dogra (2019), Werning (2015), and Bilbiie (2019a). They analytically study the implications of cyclical earnings risk on various issues in monetary economics such as determinacy and the forward guidance puzzle.

[3] Gornemann, Kuester and Nakajima (2016) study the redistributive effects of monetary policy shocks rather than aggregate fluctuations.

[4] Alternative to Winberry (2018), Auclert et al. (2019) provide a fast estimation method for heterogeneous

portfolio choice to study the contribution of exogenous shock to household earnings risk in aggregate fluctuations. In contrast, earnings risk in my model takes the form of unemployment risk, which is an endogenous object due to search and matching frictions. The closest work to mine with respect to method and question is Challe et al. (2017). They study the importance of precautionary savings against unemployment risk in business cycle dynamics in their estimated model. However, they make assumptions on risk-sharing and market structure in order to construct an analytically tractable equilibrium with the wealth distribution of finite support, which restricts them to match MPCs. Exploiting the method by Winberry (2018), I can produce a wealth distribution that is consistent with empirical MPCs, allowing me to distinguish the countercyclical unemployment risk channel from the MPC heterogeneity channel.

Lastly, the present paper builds on the work by Eusepi and Preston (2015), who emphasize the effect of compositional changes between employed and unemployed households on aggregate consumption. As the average consumption level of employed households is higher than that of unemployed households, the compositional changes directly affect aggregate consumption. They show that this effect is powerful enough to solve the comovement problem of consumption with hours, investment, and output in response to non-productivity shocks, namely Barro and King (1984) problem. The composition effect is included in my model and is a part of the MPC heterogeneity channel. However, they assume asset markets are complete, and thus households do not have a precautionary savings motive.

The paper proceeds as follows. Section 2 presents the baseline HANK model. Section 3 discusses how the model is solved. Section 4 describes fixed and estimated parameters, properties of the stationary equilibrium, and estimation results. In section 5, I compare business cycle dynamics in HANK and RANK. Section 6 compares estimation results and the quality of fit between the HANK and RANK models. Section 7 concludes.

2 Model

The economy is populated by households that self-insure against the idiosyncratic incidence of unemployment due to the incomplete asset markets. As in McKay and Reis (2016) and Hagedorn, Manovskii and Mitman (2019), I allow for two groups of households, which permanently differ in the discount factor. I label the households with low discount factor as impatient households and those with high discount factor as patient households. As will

agent models that include a two-asset HANK model.

be discussed in subsection 4.1, heterogeneous discount factors are necessary to match the realistic MPC and the supply of liquid assets available in the economy. The remaining parts are standard ingredients in medium-scale DSGE models with a frictional labor market, as in Gertler, Sala and Trigari (2008). There are a representative final goods firm, a continuum of wholesale firms producing differentiated goods subject to price rigidity, a representative intermediate goods firm that hires and invest, a monetary authority, and a fiscal authority. The model resembles that of Challe et al. (2017), who have all these ingredients except for one – a wealth distribution that is consistent with empirical MPCs.

2.1 Households

There are a fraction $1-\Omega$ of households that are impatient and indexed by $i \in [0, 1-\Omega]$. An impatient household transitions between two states: employed and unemployed. It receives the real wage when employed and unemployment insurance when unemployed. As will be discussed in subsection 4.1, I choose the level of unemployment insurance to match the average consumption difference between employed and unemployed households. Therefore, in my model, unemployment insurance should be interpreted as the degree of partial insurance that includes other insurance devices such as home production.

Impatient households can only self-insure through trading riskless liquid assets, but they cannot take short positions.[5] The budget constraint of impatient household i at period t is given by

$$C_{i,t} + a_{i,t+1} = (1-\tau_t)\frac{W_t}{P_t}e_{i,t} + (1-\tau_t)b^u\frac{W_t}{P_t}(1-e_{i,t}) + \frac{R_{t-1}}{\pi_t}a_{i,t}, \tag{2.1}$$

together with borrowing constraint, $a_{i,t+1} \geq 0$, where $C_{i,t}$ denotes the consumption of the impatient household i, π_t denotes the gross inflation rate, R_{t-1} is the gross nominal interest rate paid on liquid assets purchased in period $t-1$. τ_t denotes the tax rate on labor and transfer income, and $e_{i,t}$ refers to an indicator for employment status where $e_{i,t} = 1$ if the household is employed and $e_{i,t} = 0$ if it is unemployed.

Impatient households choose a stream of consumption and savings that maximizes

$$\mathbb{E}_0 \sum_{t=0}^{\infty} (\beta_L^t \zeta_t) \left[\frac{(C_{i,t})^{1-\sigma} - 1}{1-\sigma}\right],$$

[5] An alternative way to generate a realistic MPC is to work with an incomplete markets model with two assets, liquid and illiquid assets, as in Kaplan and Violante (2018). The assumption on asset holdings in my model can be interpreted as households using liquid savings rather than costly illiquid savings to insure against unemployment risk, which is relatively short-lived.

subject to the budget constraint (2.1) and a borrowing constraint. β_L is the discount factor for impatient households. ζ_t is a common exogenous preference shifter to all households and evolves according to

$$\log(\zeta_t) = \rho_\zeta \log(\zeta_{t-1}) + \epsilon_t^\zeta, \qquad \epsilon_t^\zeta \overset{iid}{\sim} \mathcal{N}(0, {\sigma_\zeta}^2).$$

A fraction Ω of households are patient and are assumed to be unconstrained, and thus their liquid asset Euler equation holds with equality. These households act as a representative family, in which all members share all types of income. Therefore, all members enjoy the same consumption level regardless of their employment status. Patient households' preferences are the same as those of impatient households, except for the discount factor. Their period t budget constraint is

$$C_{H,t} + a_{H,t+1} \quad = \quad (1-\tau_t)(\frac{W_t}{P_t} n_t + b^u \frac{W_t}{P_t}(1-n_t)) + \frac{R_{t-1}}{\pi_t} a_{H,t} + \frac{D_t}{P_t}, \tag{2.2}$$

where $C_{H,t}$ and $a_{H,t+1}$ are consumption and savings of liquid assets by a patient household, respectively. n_t is the employment rate, and D_t denotes the sum of dividends collected from wholesale and intermediate goods firms. Werning (2015) and Bilbiie (2019a,b) argue that the cyclicality and distribution of dividends affect the amplification in HANK models. In particular, in New Keynesian models, it is well-known that dividends are countercyclical, which is at odds with the data. If dividend payments are concentrated in households that have high MPCs and are exposed to unemployment risk, amplification in HANK dampens. Following most studies that stress amplification in HANK, I assume that dividends are concentrated in patient households that have low MPC and are not exposed to unemployment risk.[6] Therefore, amplification engendered by MPC heterogeneity and unemployment risk is operative in my model.

2.2 Final Goods Firm

A representative final goods firm combines differentiated wholesale goods and produces a final good according to a Dixit-Stiglitz aggregator,

$$Y_t = \left[\int_0^1 Y_{h,t}^{\frac{1}{1+\eta_t^p}} \, \mathrm{d}h \right]^{1+\eta_t^p}, \tag{2.3}$$

[6] Galí et al. (2007) assume patient households receive dividends. Ravn and Sterk (2017), Challe et al. (2017), and Challe (2019) assume dividends are given to agents that do not precautionary-save.

where $\eta_t^p > 0$ denotes the price markup in the market for wholesale goods and evolves according to

$$\log(1+\eta_t^p) = (1-\rho_{\eta^p})\log(1+\eta^p) + \rho_{\eta^p}\log(1+\eta_{t-1}^p) + \epsilon_t^{\eta^p}, \qquad \epsilon_t^{\eta^p} \overset{iid}{\sim} \mathcal{N}(0, {\sigma_{\eta^p}}^2).$$

The final goods firm's problem is to minimize expenditures on wholesale goods, taking the prices as given subject to the aggregator (2.3). Its optimal choices imply the demand specification for wholesale good h

$$Y_{h,t} = \left(\frac{P_{h,t}}{P_t}\right)^{-\frac{1+\eta_t^p}{\eta_t^p}} Y_t, \tag{2.4}$$

where $P_{h,t}$ is the price of wholesale good h in period t. P_t denotes the aggregate price index, which is given by

$$P_t = \left(\int_0^1 {P_{h,t}}^{-\frac{1}{\eta_t^p}} \mathrm{d}h\right)^{-\eta_t^p}. \tag{2.5}$$

2.3 Wholesale Firms

Wholesale firm $h \in [0,1]$ converts each intermediate good into a specialized good according to

$$Y_{h,t} = Y_t^I - A_t F,$$

where F is the fixed cost of production and Y_t^I denotes the intermediate good. A_t is included to ensure the existence of a balanced growth path and will be defined below. Firm h's real profits are given by

$$\frac{D_{h,t}}{P_t} = \frac{P_{h,t}}{P_t}Y_{h,t} - \frac{MC_t}{P_t}Y_t^I = \left(\frac{P_{h,t}}{P_t} - \frac{MC_t}{P_t}\right)Y_{h,t} - \frac{MC_t}{P_t}A_t F,$$

where MC_t is the price of intermediate goods and is interpreted as the nominal marginal cost for wholesale firms.

Wholesale firms are subject to nominal price rigidity. I introduce nominal price rigidity following Calvo (1983), so that, in every period, a fraction ξ_p of the firms index their prices to lagged inflation according to

$$P_{h,t} = \pi_{t-1}^{\iota_p}\pi^{1-\iota_p}P_{h,t-1}.$$

The remaining fraction of the firms choose their period t optimal price P_t^* by maximizing the present discounted value of expected future real profits. Formally,

$$\max_{P_t^*} \mathbb{E}_t \sum_{s=0}^{\infty} (\xi_p)^s \left(\frac{1}{\Pi_{k=1}^{s} \frac{R_{t+k-1}}{\pi_{t+k}}} \right) \left\{ \left[\frac{P_t^* \chi_{t,t+s}}{P_{t+s}} - \frac{MC_{t+s}}{P_{t+s}} \right] Y_{h,t+s} - \frac{MC_t}{P_t} A_t F \right\},$$

subject to the demand constraint (2.4), where $\chi_{t,t+s} = \Pi_{k=1}^{s} \pi_{t+k-1}^{\iota_p} \pi^{1-\iota_p}$ if $s \geq 1$, and $\chi_{t,t} = 1$.

2.4 Intermediate Goods Firms

A representative competitive intermediate goods firm produces with technology

$$Y_t^I = (A_t \widetilde{A}_t)^{1-\alpha} (u_{k,t} K_{t-1})^{\alpha} n_t^{1-\alpha}, \tag{2.6}$$

where K_{t-1} denotes the installed capital, and $u_{k,t}$ is the capital utilization rate. A_t is the non-stationary aggregate technology, and its growth rate $\mu_t = \frac{A_t}{A_{t-1}}$ evolves according to

$$\log\mu_t = (1-\rho_\mu)\log\mu + \rho_\mu \log\mu_{t-1} + \epsilon_t^\mu, \qquad \epsilon_t^\mu \overset{iid}{\sim} \mathcal{N}(0, \sigma_\mu^2).$$

$\widetilde{A}_t$ is the stationary technology, and its process is

$$\log\widetilde{A}_t = \rho_{\widetilde{A}} \log\widetilde{A}_{t-1} + \epsilon_t^{\widetilde{A}}, \qquad \epsilon_t^{\widetilde{A}} \overset{iid}{\sim} \mathcal{N}(0, \sigma_{\widetilde{A}}^2).$$

In every period, the firm posts vacancies. Vacancies and households that seek for jobs are randomly matched according to the aggregate matching function

$$M(\widetilde{u}_t, v_t) = \overline{M}(\widetilde{u}_t)^{\gamma} (v_t)^{1-\gamma}, \tag{2.7}$$

where $M(\widetilde{u}_t, v_t)$ is the number of matches in period t when there are $\widetilde{u}_t$ job seekers and v_t vacancies. $\overline{M}$ is the matching efficiency, and γ represents the elasticity of matches with respect to job seekers. The mass of job seekers in period t consists of the mass of unemployment carried over from the previous period and the mass of existing employment relationships that are severed with probability $\rho_{x,t}$ at the beginning of period t. Formally,

$$\widetilde{u}_t = u_{t-1} + \rho_{x,t} n_{t-1}.$$

The job separation rate $\rho_{x,t}$ evolves according to[7]

$$\rho_{x,t} = \frac{1}{1+\exp(\overline{\rho}_x - \widetilde{\rho}_{x,t})},$$

where

$$\widetilde{\rho}_{x,t} = \rho_{\rho_x}\widetilde{\rho}_{x,t-1} + \epsilon_t^{\rho_x}, \qquad \epsilon_t^{\rho_x} \overset{iid}{\sim} \mathcal{N}(0, \sigma_{\rho_x}^2).$$

Given the matching function, the probability that a vacant job is filled and the probability that a job seeker finds a job are

$$\lambda_t = \overline{M}(v_t/\widetilde{u}_t)^{-\gamma} \quad \text{and} \quad f_t = \overline{M}(v_t/\widetilde{u}_t)^{1-\gamma},$$

respectively. In period t, a household that is severed from an employment relationship is assumed to find a job immediately with probability f_t. Therefore, the transition rate from period $t-1$ employment to period t unemployment is $\rho_{x,t}(1-f_t)$, which I label as the job-loss rate. This probability measures the degree of unemployment risk faced by employed households. Moreover, $1-f_t$ is the transition rate from period $t-1$ unemployment to period t unemployment and measures the degree of unemployment risk faced by unemployment households. Using these transition rates, I obtain the law of motion for the unemployment rate

$$u_t = (1-f_t)u_{t-1} + \rho_{x,t}(1-f_t)n_{t-1}. \tag{2.8}$$

In every period, vacancies are filled with probability λ_t. Therefore, the evolution of employment that the representative intermediate goods firm faces is

$$n_t = (1-\rho_{x,t})n_{t-1} + \lambda_t v_t. \tag{2.9}$$

The firm owns capital, invests, and chooses the capital utilization rate $u_{k,t}$. The cost of capital utilization is $\Psi(u_{k,t})$ per unit of physical capital, where $\Psi(u_{k,t}) = \rho^{u_k}\frac{u_{k,t}^{\frac{1}{1-\psi}}-1}{\frac{1}{1-\psi}}$. In the steady state, $u_k = 1$, $\Psi(1) = 0$ and $\frac{\Psi''(1)}{\Psi'(1)} = \frac{\psi}{1-\psi}$, where $\psi \in (0,1)$. Aggregate physical capital K_t accumulates according to

$$K_t = v_t I_t \left[1 - \frac{s''}{2}\left(\frac{I_t}{I_{t-1}} - \mu\right)^2\right] + (1-\delta)K_{t-1}, \tag{2.10}$$

[7]This functional form ensures $\rho_{x,t} \in [0,1]$.

where δ denotes the depreciation rate, I_t denotes investment, and s'' captures the convex investment adjustment cost. Taking into account of (2.9) and (2.10), the firm maximizes the present discounted stream of profits. Formally,

$$\max_{n_t, v_t, I_t, u_{k,t}, K_t} \mathbb{E}_t \sum_{s=0}^{\infty} \left(\frac{1}{\prod_{k=1}^{s} \frac{R_{t+k-1}}{\pi_{t+k}}} \right) \frac{D_{t+s}^I}{P_{t+s}},$$

where

$$\frac{D_{t+s}^I}{P_{t+s}} = \left(\frac{MC_{t+s}}{P_{t+s}} \right) Y_{t+s}^I - \frac{W_{t+s}}{P_{t+s}} n_{t+s} - A_t \kappa v_{t+s} - I_t - \Psi(u_{k,t}) K_{t-1}.$$

The costs for the firm are the wage bill paid to all employees, expenditures on investment goods, and forgone resources from searching for new employees and utilizing capital. κ is the cost associated with posting a vacancy.

Nominal wages In the presence of frictional labor markets, there is a surplus in the employment relationship. An intermediate goods firm's surplus is the expected profits from hiring a new employee net of searching costs of finding a new employee. A household's surplus comes from the wage income net of the cost of unemployment. To keep the employment relationship, the real wage must be bilaterally efficient so that both household and firm surplus is positive. Moreover, as the real wage stickiness affects the cyclicality of unemployment and thus unemployment risk, one needs to have a wage specification that allows for real wage rigidity. To ensure the bilateral efficiency and to incorporate real wage rigidity, following Challe et al. (2017), I adopt a wage rule[8]

$$W_t = W_{t-1}^{\iota_w} \left(P_t A_t \overline{w} \left(\frac{n_t}{n} \right)^{\xi_w} \right)^{1-\iota_w}, \tag{2.11}$$

where $P_t A_t$ is a scaling factor that ensures the existence of a balanced growth path. $\overline{w}$ is a constant that ensures the existence of a steady state real wage in the detrended equilibrium. $\xi_w \in [0, 1]$ is the elasticity of the nominal wage with respect to deviations of employment from its steady state, and ι_w measures the degree of nominal wage indexation. Both ξ_w and ι_w controls the extent of nominal stickiness. Nominal wage stickiness, together with price stickiness, determines real wage stickiness.

[8]Challe et al. (2017) show that a sequence of real wages predicted in their estimated model lies within the bargaining set over their sample period. I found that this is also the case in my estimated model.

2.5 Government

In my model, the government is the only provider of liquid assets. The government raises tax revenue and issues liquid assets to finance government expenditures on unemployment insurance, government purchases, and interest payments on liquid assets. The government budget constraint at each date is

$$\begin{aligned} B^g_{t+1} + \tau\left(\frac{W_t}{P_t}n_t + b^u\frac{W_t}{P_t}u_t\right) &= b^u\frac{W_t}{P_t}u_t + G_t + \frac{R_{t-1}}{\pi_t}B^g_t \\ B^g_{t+1} &= A_t\overline{B}^g, \end{aligned}$$

where B^g_{t+1} and G_t denote the supply of liquid assets available in the economy and government purchases, respectively. $\overline{B}^g$ is the detrended quantity of liquid assets, premultiplied by a scaling factor A_t to ensure the existence of a balanced growth path. I assume that the government cannot adjust the supply of liquid assets and hence $\overline{B}^g$ to be constant. Although governments issue debts to finance its spending in practice, especially during recessions, government debt only accounts for a very small fraction of household liquid assets. Kaplan, Moll and Violante (2018) document that most of the liquid assets are held as deposits in financial institutions and the share of government bonds in households' liquid assets is less than 10 %. Therefore, interpreting $\overline{B}^g$ as public debt and making it countercyclical in my model might overstate the stock of liquid assets that households use to self-insure. Letting $g_t = \frac{G_t}{A_t}$, I assume that the government purchases evolve according to

$$\log\left(\frac{g_t}{g}\right) = \rho_g \log\left(\frac{g_{t-1}}{g}\right) + \epsilon^g_t, \qquad \epsilon^g_t \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_g).$$

I assume the monetary policy follows a feedback rule, which has been found to be a good description of the Federal Funds rate. Following Justiniano, Primiceri and Tambalotti (2013), the nominal interest rate reacts to the previous nominal interest rate, deviations of annual inflation from its steady state counterpart, and deviations of observed annual GDP growth from its steady state level

$$\begin{aligned} \log\left(\frac{R_t}{R}\right) = \rho_R \log\left(\frac{R_{t-1}}{R}\right) + (1-\rho_R)[\phi_\pi\left(\frac{1}{4}\sum_{\iota=0}^{3}\log\left(\frac{\pi_{t-\iota}}{\pi}\right)\right) \\ +\phi_X\left(\frac{1}{4}\sum_{\iota=0}^{3}\log\left(\frac{X_{t-\iota}}{\mu X_{t-1-\iota}}\right)\right)] + \epsilon^R_t, \end{aligned} \tag{2.12}$$

where ϵ_t^R is the monetary policy shock with $\epsilon_t^R \overset{iid}{\sim} \mathcal{N}(0, \sigma_R^2)$. X_t is real GDP, defined as $X_t = C_t + I_t + G_t$. I express the model's equilibrium conditions in terms of stationary variables by applying a standard detrending technique. The full set of equilibrium conditions is outlined in Appendix B.

3 Solution Method

3.1 Discretization

The equilibrium conditions are infinite-dimensional due to the presence of infinite-dimensional objects: decision rules of impatient households and the distribution of households over liquid wealth. It is well-known that these objects pose a challenge in solving incomplete markets models. I use the method proposed by Winberry (2018) to overcome the computational hurdle of this class of models. I discretize the equilibrium conditions and represent these by finite-dimensional objects. In particular, I approximate the distribution using a parametric function, so that the distribution is summarized by the parameters of the function and the finite number of moments of the distribution. Moreover, I approximate the conditional expectation of the future consumption function using a linear combination of polynomials, so that the household decision rule is represented by the coefficients of these polynomials. Therefore, the equilibrium of the model is approximated by a set of finite-dimensional objects. For further details and the definition of the approximated equilibrium of the model, see Appendix C.

3.2 Aggregate Dynamics

To solve for aggregate dynamics, I apply a standard technique to the approximated model. That is, I compute the model's stationary equilibrium, an equilibrium with no aggregate shocks. I then linearize the model's equilibrium conditions around their stationary values. Finally, I solve for the dynamics of all variables using a standard method that solves linear rational expectation models.[9]

[9] Linearization, solving for the dynamics, and estimation were executed using `Dynare`.

4 Estimation

I solve the model using the method outlined above and estimate it using a Bayesian method. This section discusses the calibration, the property of the stationary equilibrium, the data, and the parameter estimates.

4.1 Calibration

In this section, I describe parameters that are not subject to estimation. The model period is one quarter. The capital share in the production function α is 0.33. The capital depreciation rate δ is 0.02, implying 8 % annual depreciation of physical capital. I set the utility function's curvature parameter σ to 2, as in McKay, Nakamura and Steinsson (2016). I fix the steady state markup η_p to 0.2, in line with Basu and Fernald (1997). The matching function elasticity to job seekers γ is 0.5, as suggested by Petrongolo and Pissarides (2001).

The steady state non-stationary technology growth is chosen to match the average quarterly GDP growth rate of 0.47 %. The steady state inflation rate is 0.96 % quarterly. The discount factor of patient households β_H is 1.0032, so that the steady state nominal interest is 1.58 % quarterly.[10] The steady state ratio of government purchases to GDP is set to 0.2. All these targets correspond to the sample average. I set the share of liquid-wealthy patient households Ω to 0.1, motivated by the evidence that the top 10 percent hold 86 percent of the total liquid wealth (Kaplan, Moll and Violante, 2018). The fixed cost F is set so that the steady state profits of monopolistic competitive wholesale firms are zero. The steady state unemployment rate is 6 %.

The steady state job-finding rate f and the job-separation rate ρ_x are determined as follows. I use the quarterly job finding rates constructed by Challe et al. (2017), who use unemployment and short-term unemployment data from the Current Population Survey (CPS) following the approach of Shimer (2005). The job-finding rate averaged 0.78 from 1964Q2 to 2008Q3. Using equation (2.8), I then compute ρ_x. For the matching efficiency $\overline{M}$, I target a quarterly vacancy-filling rate of 0.71, computed by Den Haan, Ramey and Watson (2000). The expected cost of hiring an employee κ/λ is calibrated to match 4.5 percent of quarterly wages, following Hagedorn and Manovskii (2008), whose calculation is based on the time spent hiring one worker. The value of the steady state real wage is obtained from

[10] Note $\beta_H = \frac{\mu^\sigma}{R/\pi}$.

Table 1. Parameters that are not estimated

Symbol	Description	Value	Target (Source)
δ	Capital depreciation rate	0.02	8 % annual depreciation rate
α	Capital share	0.33	
σ	Risk aversion coeff.	2	McKay et al. (2016)
η_p	Markup	0.2	Basu and Fernald (1997)
γ	Matching elasticity	0.5	Petrongolo and Pissarides (2001)
μ	TFP growth	1.0047	GDP growth
β_H	Pat. households discount factor	1.0032	1.58 % quarterly Federal funds rate
Ω	Share of pat. households	0.1	See the text
ρ_x	Job separation rate	0.23	Average job-finding rate
$\overline{M}$	Matching efficiency	0.74	Average vacancy-filling rate
κ	Cost of posting vacancy	0.06	4.5 % of quarterly wages
b^u	Replacement rate	0.62	Average E-U consumption difference
β_L	Imp. households discount factor	0.985	Average MPC of 0.2

the optimal vacancy-posting condition under the free entry assumption.

One of the objectives of this paper is to decompose the aggregate consumption responses into the part that is attributable to precautionary savings against unemployment risk and the part due to the high average MPC. Accordingly, it is crucial for the model to match both the extent of consumption insurance upon unemployment and the average MPC in steady state. As for the extent of consumption insurance, I target the average consumption difference between employed and unemployed households of 23 %, an estimate obtained by Eusepi and Preston (2015) using data from the Consumer Expenditure Survey (CEX). The value implies that unemployed households consume 23 % less than employed households on average.[11] Recent estimates on the decline in consumption during unemployment are smaller. For example, Ganong and Noel (2019) estimate that the spending of unemployed households falls by 9 % during the receipt of unemployment insurance and a further 10 % after its exhaustion using the JPMorgan Chase panel. Therefore, my chosen value of 23 % implies that my model does not understate the extent of precautionary savings. I target the average MPC of 0.2, a value that is in the range of available estimates.[12] I choose the values of the replacement rate b^u and the discount factor of impatient households β_L that jointly

[11] Note that the average consumption difference between employed and unemployed households is different from the temporary consumption loss upon an unemployment shock. See Den Haan, Rendahl and Riegler (2018) for a discussion of the evidence on the latter. I target the former as this is a more relevant counterpart to the steady state consumption difference between employed and unemployed households.

[12] See Johnson, Parker and Souleles (2006), Parker et al. (2013), and Broda and Parker (2014) among many others for evidence on MPCs. While the estimates are often imprecise because of the small sample size, these studies suggest that households spend approximately 15–25 % of the tax rebates or fiscal stimulus payments on nondurables in the quarter that they are received.

Figure 1. Stationary decision rules and wealth distribution

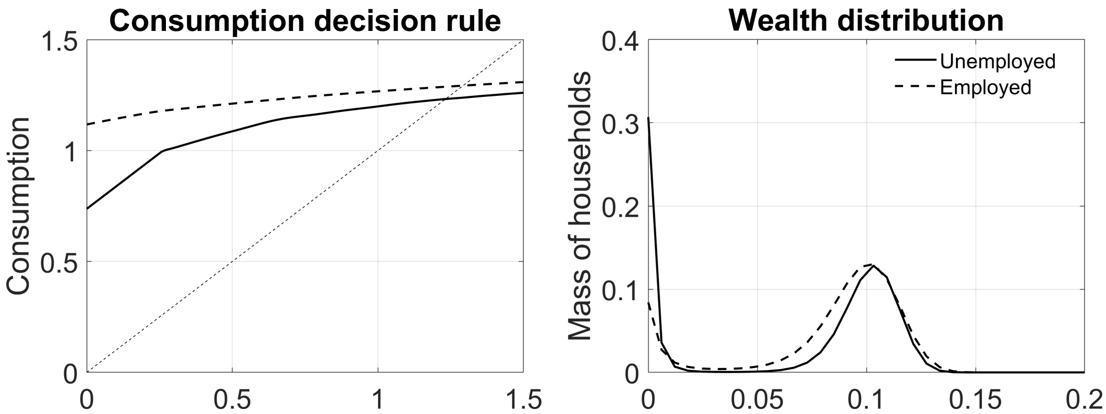


Table 2. MPC and wealth by group

Group	MPC	Wealth (as a share of output)
Impatient (U)	0.70	0.017
Impatient (E)	0.18	0.02
Patient	approx. 0	0.27
Aggregate	0.20	0.26

Note: Wealth is expressed as a fraction of annual output.

match the empirical MPC and the consumption differential between the employed and the unemployed households. Table 1 lists the parameters discussed in this subsection.

The total quantity of liquid assets $\overline{B}^g$ is assumed to be 26 % of annual GDP following Kaplan, Moll and Violante (2018). Targeting the realistic average MPC leads impatient households to hold less liquid wealth than the total amount of liquid assets. The difference between the total amount of liquid assets and the amount held by impatient households gives the wealth holdings of patient households.[13]

[13]In my setup, the total amount of liquid assets does not determine the amount of liquid assets that impatient households' can use for self-insurance. The amount of liquid assets that impatient households hold is disciplined by the average MPC, given the return on liquid assets. The main reason I target the total amount of liquid assets is realism.

4.2 Stationary Equilibrium

There are two individual states, unemployed and employed.[14] The distribution for each state is approximated using a smoothed parametric function with the degree of approximation 3. Figure 1 represents the stationary consumption policy functions and the distribution of wealth for impatient households, where the x-axis denotes the wealth position. The slope of the consumption function is 1 for households, whose asset position is close to the borrowing limit. Consumption of these households responds very strongly to an additional increase in transitory income. The slope converges to zero as the asset position moves further away from the borrowing limit. Moreover, conditional on the asset position, while the consumption level is higher for employed households than unemployed households, the slope is higher for unemployed households than employed households. Therefore, the difference in average MPCs between employed and unemployed households depends on how the employed and unemployed households are distributed over the asset positions. The right panel of the figure indicates that the unemployed households are more likely to hit the borrowing constraint than employed households, implying that the unemployed households are expected to have a higher MPC.

Table 2 summarizes the distribution of MPCs over households of different employment statuses and discount factors. Among the impatient group, unemployed households have a much higher MPC than employed households, consistent with the shape of the wealth distribution. Patient households whose consumption rule follows the permanent income hypothesis react little to a transitory income change, and thus their MPC is close to zero. In addition, MPCs are negatively correlated with the level of liquid wealth, with unemployed households in the impatient group holding the least amount of wealth and having the largest MPC. The patient households' wealth, which is the difference between aggregate liquid wealth and the wealth of impatient households, is extremely high. In terms of wealth share, patient households who account for 10 percent of the population, hold 92 percent of the total liquid wealth. The number is close to the one reported by Kaplan, Moll and Violante (2018) who show that the top 10 percent holds 86 percent of the total liquid wealth using data from the Survey of Consumer Finances (SCF).

[14] One can think of including more states by taking into account idiosyncratic wage risk conditional on being employed. I experimented with 6 states (3 for employed and 3 for unemployed) and found that the computer ran out of memory during the step of computing the posterior mode based on numerical optimization. This step is required to compute the proposal density. However, under the parameter values fixed at the posterior mean estimated from the baseline model, I found the aggregate dynamics in the 6 state model are very similar to those in the baseline model given the equal average MPC and the average consumption differential between employed and unemployed households.

Table 3. Prior and posterior distribution in HANK

Parameter	Description	Prior dist.			Posterior dist.		
		Distribution	Mean	SD	Mean	5 %	95 %
s''	Invest. adjustment cost	Gamma	4	1	1.25	0.55	2.01
ψ	Capital utilization cost	Beta	0.5	0.15	0.76	0.61	0.91
ξ_p	Price stickiness	Beta	0.5	0.1	0.51	0.46	0.56
ι_p	Price indexation	Beta	0.5	0.15	0.56	0.34	0.78
ξ_w	Wage stickiness	Gamma	1	0.2	0.79	0.65	0.92
ι_w	Wage indexation	Beta	0.5	0.15	0.66	0.59	0.73
ρ_R	Taylor rule: smoothing	Beta	0.6	0.1	0.73	0.69	0.77
ϕ_π	Taylor rule: inflation	Norm	1.7	0.3	2.28	2.03	2.54
ϕ_X	Taylor rule: GDP	Norm	0.4	0.3	1.03	0.75	1.32
ρ_{η_p}	Auto. price markup	Beta	0.6	0.1	0.61	0.52	0.70
ρ_μ	Auto. non-stat. tech.	Beta	0.4	0.1	0.34	0.22	0.47
ρ_υ	Auto. MEI	Beta	0.6	0.1	0.76	0.65	0.86
ρ_ζ	Auto. preference	Beta	0.6	0.1	0.96	0.95	0.98
ρ_{ρ_x}	Auto. job-separation	Beta	0.6	0.1	0.80	0.75	0.86
ρ_g	Auto. gov. purchase	Beta	0.6	0.1	0.96	0.94	0.97
$\rho_{\tilde{A}}$	Auto. stat. tech.	Beta	0.6	0.1	0.89	0.87	0.92
$100\sigma_{\eta_p}$	Std price markup	Inv. Gamma	0.15	1	0.91	0.73	1.07
$100\sigma_\mu$	Std non-stat. tech.	Inv. Gamma	1	1	0.41	0.33	0.48
$100\sigma_\upsilon$	Std MEI	Inv. Gamma	0.5	1	2.79	1.93	3.73
$100\sigma_R$	Std mon. policy	Inv. Gamma	0.15	1	0.28	0.25	0.31
$100\sigma_\zeta$	Std preference	Inv. Gamma	1	1	7.91	6.50	9.35
$100\sigma_{\rho_x}$	Std job-separation	Inv. Gamma	1	1	12.7	11.6	13.8
$100\sigma_g$	Std gov. purchase	Inv. Gamma	0.5	1	0.89	0.80	0.98
$100\sigma_{\tilde{A}}$	Std stat. tech.	Inv. Gamma	1	1	0.84	0.75	0.94
$100\sigma_w$	Std wage measurement	Inv. Gamma	0.5	1	0.26	0.23	0.29

Although the model targets the average MPC, the model's prediction of MPCs by employment status and liquid wealth position is qualitatively consistent with the data. Using the 2010 Survey of Household Income and Wealth, Kekre (2019) finds that the self-reported annual MPC is higher for unemployed versus employed households. Moreover, Broda and Parker (2014) find much stronger consumption responses to the 2008 fiscal stimulus payments among households with low liquid funds, implying a pattern of MPCs declining in liquid wealth.

4.3 Data and Estimation Results

I estimate the remaining structural parameters using the following quarterly US series: the inflation rate, the Federal funds rate, the log difference of real per-capita consumption, investment, and government purchases, the wage inflation rate, the job-finding rate, and the job-loss rate. The job-finding rate and the job-loss rate are included because the cyclicality of these two rates directly measures the evolution of the degree of unemployment risk over the business cycle. The inflation rate is the growth rate of the GDP deflator, while the wage inflation rate is the growth of average hourly earnings of production and non-supervisory employees. Real per-capita consumption is nominal consumption divided by the civilian non-institutional population (16 years and older) and the GDP deflator. The real series for per-capita investment and government purchases are obtained in the same manner. Consumption corresponds to the sum of non-durables and services, while investment is the sum of consumer durables and total private investment. Government purchases are constructed by adding government consumption and investment. I use the job-finding and the job-loss rates constructed by Challe et al. (2017), who follow the procedure adopted by Shimer (2005). As the job-finding and the job-loss rates exhibit trends, I detrend those using the filtering method proposed by Hamilton (2018). The sample starts from 1964Q2 due to the limited availability of the wage data and ends in 2008Q3, which is the quarter right before the nominal interest rate hit the zero lower bound. All series are demeaned before estimation.

The data series on wage inflation imperfectly match the model's concept of wage inflation due to well-known difficulties in measuring aggregate nominal wages. To tackle the absence of wage markup shocks and the mismatch between the data and the model in nominal wages, I augment the wage inflation rates in the model with measurement errors, as in Boivin and Giannoni (2006) and Justiniano, Primiceri and Tambalotti (2013).[15] I obtain 200,000 draws of a set of parameters to recover the posterior distribution by relying on the Random Walk Metropolis-Hastings algorithm. Estimated parameters and information on the prior and posterior distributions of these parameters are listed in Table 3.

All parameters except for two are standard, and their prior distributions are in line with the literature. The two exceptions are the wage elasticity with respect to employment and the wage indexation, which are embedded in the wage rule (2.11). Because this rule is borrowed from Challe et al. (2017), I adopt their prior distribution for these two parameters. The

[15] Justiniano, Primiceri and Tambalotti (2013) find that the wage inflation dynamics are largely attributable to wage measurement errors.

covariance matrix of the vector of shocks is diagonal. For posterior estimates, I only comment on parameters that govern price stickiness, nominal wage stickiness, and the responsiveness of the policy rate. These New Keynesian ingredients determine the strength of aggregate demand externality and thus the degree of amplification in any New Keynesian models.

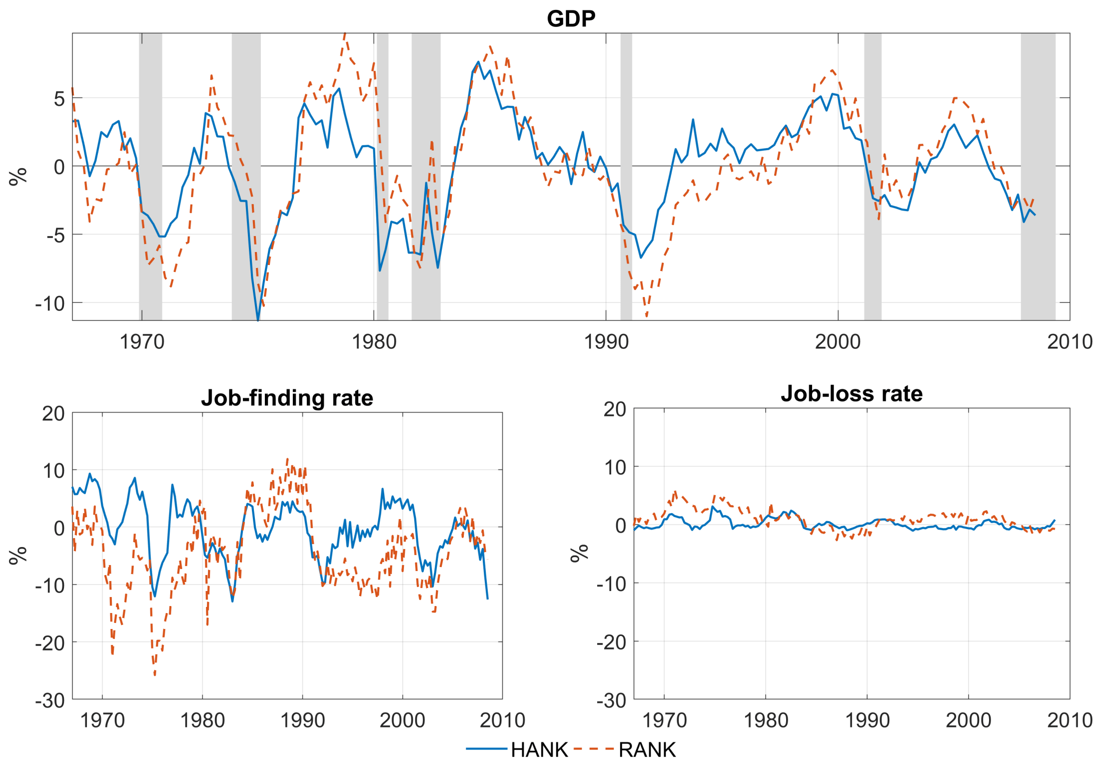
The posterior mean of ξ_p implies that prices are adjusted approximately every two quarters, which is lower than the typical estimates obtained from most RANK models. In section 6, I discuss why this is the case by comparing the parameter estimates with those obtained from the RANK version of my model. The posterior mean of ι_p is quite high relative to most RANK models, perhaps due to the absence of habit formations in my model. With habit formations, aggregate demand and inflation become persistent, and thus there is less need to rely on price indexation for models to generate the high persistence of inflation seen in the data. The posterior mean of ξ_w is lower than its prior mean, and the posterior mean of ι_w is higher than its prior mean. These estimates suggest that there is a relatively strong degree of nominal wage stickiness. The coefficient of inflation and the GDP growth rate in the monetary policy rule has a posterior mean of 2.28 and 1.03, respectively. These coefficient estimates suggest that the monetary policy authority reacts fairly strongly to inflation and economic activity. The value of these coefficients is larger than most existing calibrated HANK models, in which inflation and output growth coefficients are set around 1.5 and 0, respectively.

5 Amplification in HANK

In this section, I first explore whether the HANK model generates different business cycle dynamics from those in the RANK model. Although there are studies that compare HANK and RANK in response to a particular shock, there are few studies that do so in response to *all shocks*. The RANK benchmark is obtained from the HANK model by setting the share of patient households to 1. Therefore, the RANK model shares the same preferences, degree of nominal rigidity, the production side, government, monetary authority, and shock processes featured in HANK. Steady state prices and aggregate quantities are also the same between the two models. The only departure from HANK is the absence of heterogeneity in discount factors and consumption levels.

The experiment works as follows. Conditional on the sample information, I use the Kalman smoother to recover the historical shocks and state variables from the estimated HANK model. I then feed these shocks and state variables to simulate the counterfactual path of

Figure 2. Historical dynamics in response to all shocks



Note: GDP is detrended using the Hamilton filter.

aggregate variables in the RANK economy.[16] I compare the volatility of aggregate variables from the two economies.

Figure 2 compares the historical evolution of the level of GDP, the job-finding rate, and the job-loss rate. The parameter values in both models are fixed at the posterior mean estimated from the HANK model. These variables are expressed as deviations from their respective trends, which are obtained from the filtering method proposed by Hamilton (2018). Two results stand out. First, in line with Challe et al. (2017), the job-loss rate in the HANK model moves little over the business cycle, implying that most of the unemployment fluctuation and thus the unemployment risk arises from variations in the job-finding rates. This observation implies that the job-separation rate $\rho_{x,t} = \frac{s_t}{1-f_t}$ moves little and has a negligible role in unemployment fluctuations, consistent with Shimer (2005). Second, more importantly, the

[16] To do so, I collect the equilibrium conditions of the HANK model and those of the RANK model in a system of rational expectation difference equations. I then recover shocks and state variables from the system. Justiniano, Primiceri and Tambalotti (2013) use a similar approach to obtain the historical path of a counterfactual economy.

Table 4. Conditional GDP volatility

Model	Conditional standard deviation							
	Markup	Non-stat. tech.	MEI	Stat. tech.	Monetary	Pref.	Separation	Gov.
HANK	1.35	0.91	1.11	3.48	0.70	0.71	0.28	0.09
RANK	1.18	0.83	1.17	3.44	0.65	2.73	0.36	0.20

Note: The standard deviations are computed conditional on each shock. The data are detrended using the Hamilton filter.

RANK economy is more unstable relative to the HANK economy. To identify the shocks that have contributed to the destabilizing property of the RANK economy, I report the comparison of GDP volatility in Table 4 conditional on each shock. The MEI, preference, job-separation, and government purchase shocks are innovations that induce destabilizing results in RANK. Among these innovations, the preference shock is most responsible for the destabilization, making the GDP in RANK 4 times as volatile as the GDP in HANK.

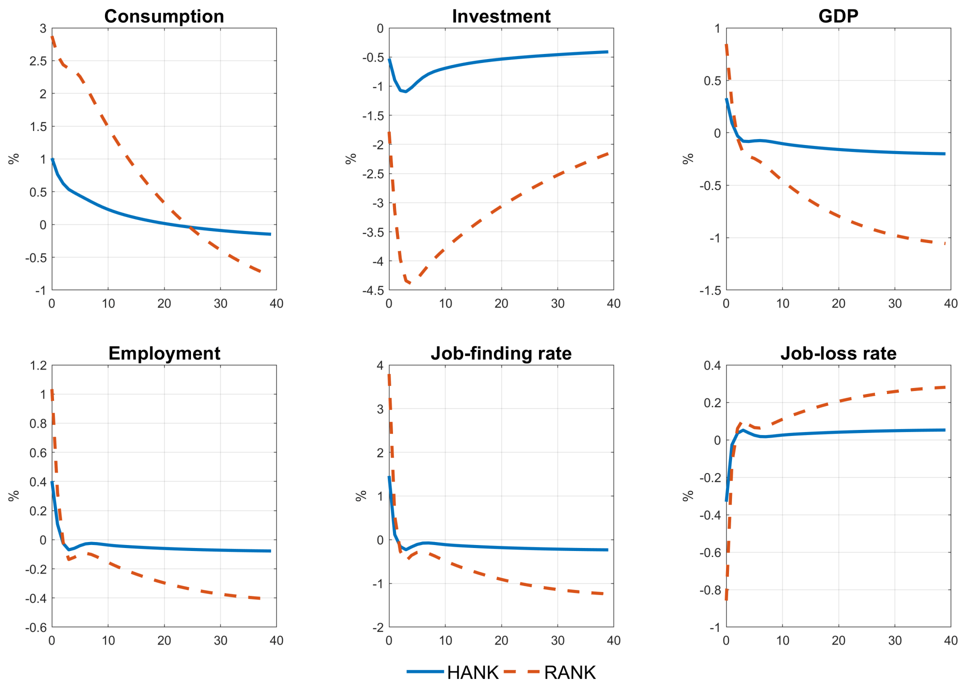
To understand the destabilizing result emanated from the preference shock, Figure 3 portrays the impulse responses to a positive preference shock. In RANK, a positive preference shock makes all households impatient, causing all households to consume more and save less. The resulting rise in the real interest rate depresses investment. In HANK, in which the empirical MPC is targeted, the responses of consumption are much more muted than in RANK. This is because for households that are at the borrowing limit, there are no savings to use for consumption. Hence, their consumption is not affected by a direct shift in time-preferences. It is only the households that are far away from the borrowing limit that respond sensitively to the preference shock, causing a mild aggregate consumption expansion.

One might argue that preference shocks are hard to interpret, as we know less about the exogenous forces that change households' desire to save.[17] For this reason, I exclude the preference shock and repeat the experiment of comparing the volatility of the aggregate variables in HANK and RANK. Results are reported in Figure 4 and Table 5. As noted in the figure and the table, the GDP and the job-finding rate in HANK are more volatile than in RANK. The larger fluctuations of the GDP arise from the larger fluctuations of consumption.

Two channels lead to the more volatile consumption and GDP in HANK. Take recessions

[17] One example is tighter credit limits that reduce households' borrowing capacity as in Guerrieri and Lorenzoni (2017). This causes unconstrained households to save more as they want to move further away from the tightened borrowing limit. Other examples are the idiosyncratic earning uncertainty shock (Bayer et al., 2019b) and the macro uncertainty shock (Basu and Bundick, 2017) that change households' precautionary savings motive.

Figure 3. IRFs to a positive preference shock



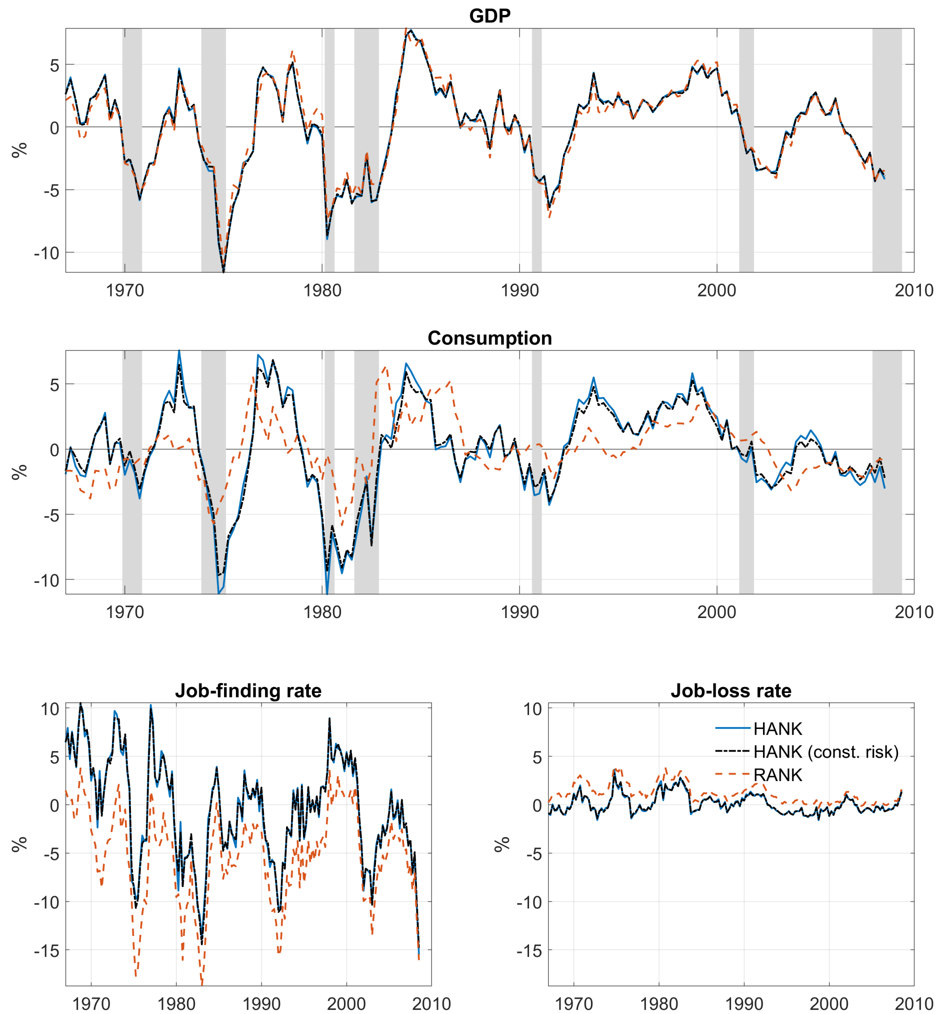
Note: For employment, the job-finding rate, and the job-loss rate, the IRFs correspond to the deviation from the steady state. For the other variables, the IRFs are reported as the percent deviation from the steady state.

as an example. First, aggregate household income falls as a result of two effects: a fall in real wages and an increase in unemployment. As the average MPC household in HANK is higher than in RANK, aggregate consumption drops by more in HANK. Second, even if its employment status does not change, an individual household cuts consumption due to a strong precautionary savings motive that arises from the increased probability of becoming unemployed.

I now assess the quantitative importance of each channel to the difference in GDP volatility between HANK and RANK. To do so, I introduce a benchmark in which an endogenous risk wedge in the impatient households' consumption Euler equation is assumed to be constant. This endogenous risk wedge takes the form of the job-loss rate for employed households and the job-finding rate for unemployed households. By fixing these two rates in the Euler equation to their steady state values, the baseline model collapses to a HANK model with constant (acyclical) idiosyncratic risk.[18] In words, impatient households do not take into

[18]HANK models that adopt constant idiosyncratic risk are McKay, Nakamura and Steinsson (2016), Kaplan, Moll and Violante (2018), and Hagedorn, Manovskii and Mitman (2019) among many others.

Figure 4. Counterfactual dynamics in response to non-preference shocks



Note: GDP and consumption are detrended using the Hamilton filter.

account the probability of becoming unemployed when they make consumption and savings decisions, even if the job-finding and the job-loss rates vary due to the intermediate goods firms' vacancy posting decisions. The only departure of this benchmark from the baseline HANK model is the absence of a precautionary savings motive against countercyclcial unemployment risk. The MPCs, consumption difference between employed and unemployed households, prices, and aggregate quantities and prices in the steady state remain the same. Therefore, comparing the baseline HANK model with the constant risk benchmark allows one to gauge the pure effect of countercylical unemployment risk. The difference in the aggregate dynamics between the constant risk benchmark and the RANK model captures the effect of MPC heterogeneity.

Table 5. Volatility subject to non-preference shocks

Model	Standard deviation				
	GDP	Consumption	Investment	Job-finding rate	Job-loss rate
HANK	3.521	3.661	6.093	5.449	0.978
HANK (c. risk)	3.515	3.334	6.435	5.423	0.953
RANK	3.400	2.259	8.903	4.953	0.998

Note: In all models, aggregate fluctuations are driven by non-preference shocks. GDP, consumption, and investment are detrended using the Hamilton filter. HANK (c. risk) denotes the model in which households face constant (acyclical) unemployment risk.

The black dash-dotted line in Figure 4 corresponds to the dynamics in the constant risk benchmark. GDP, consumption, the job-finding rate, and the job-loss rate in this benchmark are visually indistinguishable from those in HANK. The standard deviations of the aggregate variables in the three models are reported in Table 5. The contribution of countercyclical unemployment risk to the difference in GDP volatility between HANK and RANK is $\frac{(3.521-3.515)}{(3.521-3.4)} \times 100 \approx 5$ %. 95 % of the difference is driven by MPC heterogeneity.

Recently, Challe (2019) shows that amplification induced by unemployment risk in HANK models is neutralized under the optimal monetary policy. Similarly, Ravn and Sterk (2017) and McKay and Reis (2019) show that a more accommodative monetary policy is the stronger the effect of unemployment risk on the precautionary savings motive, causing a more volatile business cycle. Given these findings, one might argue that the fairly small contribution of unemployment risk in my HANK model is driven by the monetary policy rule that is estimated to be quite aggressive. To investigate this possibility, I introduce a more accommodative monetary policy rule than the baseline. In particular, I set $\phi_\pi = 1.2$ and $\phi_X = 0$, whereas the baseline is $\phi_\pi = 2.21$ and $\phi_X = 1.18$. Table 6 reports the volatility in HANK, HANK with constant risk, and RANK when monetary policy is accommodative. Relative to the estimated monetary policy, volatilities are increased in all three economies. However, the contribution of countercyclical unemployment risk to the difference in GDP volatility between HANK and RANK is 18 %, which is still small.

In sum, regardless of monetary policy, I find that unemployment risk, the only source of countercyclical earnings risk in this model, plays a relatively minor role in shaping the aggregate dynamics. However, such a result does not necessarily imply that countercyclical earnings risk that households face is not important. Recent empirical literature documents there are other sources of countercyclical earnings risk that might be unrelated to unemployment, such as the one documented by Guvenen, Ozkan and Song (2014). By omitting other

Table 6. Volatility under an accommodative monetary policy

Model	Standard deviation				
	GDP	Consumption	Investment	Job-finding rate	Job-loss rate
HANK	4.434	7.274	3.944	18.011	3.787
HANK (c. risk)	4.140	6.494	4.258	16.965	3.528
RANK	2.796	2.769	7.466	11.797	2.393

Note: In all models, aggregate fluctuations are driven by non-preference shocks. GDP, consumption, and investment are detrended using the Hamilton filter. HANK (c. risk) denotes the model in which households face constant (acyclical) unemployment risk.

sources of risk, my analysis may be understating the role of countercyclical earnings risk in business cycle dynamics.

6 Comparison of Model Fit: HANK vs. RANK

In this section, I compare parameter estimates, aggregate shocks decomposition, and the quality of fit between the HANK and RANK models. To do so, I estimate the RANK model using the same aggregate series that were used to estimate the HANK model. Table 7 reports the prior and posterior distributions of structural parameters in RANK. To save space, the results for the parameters of the shock processes are presented in Appendix D. A notable difference between HANK and RANK comes from the degree of nominal rigidity and the stance of monetary policy. For price stickiness, based on the posterior mean, it is $\xi_p = 0.71$ in RANK, implying prices are adjusted approximately every 3.5 quarters, while $\xi_p = 0.51$ in HANK. For nominal wage stickiness, it is $\xi_w = 0.68$ and $\iota_w = 0.70$ in RANK, while $\xi_w = 0.79$ and $\iota_w = 0.66$ in HANK. For inflation and output growth rate coefficients in the monetary policy rule, they are $\phi_\pi = 1.58$ and $\phi_X = 0.77$ in RANK, while $\phi_\pi = 2.28$ and $\phi_X = 1.03$ in HANK. In sum, the RANK model prefers a higher degree of nominal rigidity and a more accommodative monetary policy than its HANK counterpart.

Next, I compare the contributions of aggregate shocks to the volatility of aggregate series in HANK and RANK. Table 8 reports the variance decomposition in the two economies, evaluated at their own posterior mean. In RANK, the numbers are broadly in line with those reported in Justiniano, Primiceri and Tambalotti (2010). In particular, the MEI shock accounts for the largest fraction of the fluctuations in investment and GDP. However, it only accounts for a modest fraction of consumption fluctuations, which are mainly driven by the preference shock. The preference and monetary policy shocks play a relatively minor

Table 7. Prior and posterior distribution in RANK

Parameter	Description	Prior dist.			Posterior dist.		
		Distribution	Mean	SD	Mean	5 %	95 %
s''	Invest. adjustment cost	Gamma	4	1	3.84	2.43	5.31
ψ	Capital utilization cost	Beta	0.5	0.15	0.42	0.27	0.57
ξ_p	Price stickiness	Beta	0.5	0.1	0.71	0.66	0.76
ι_p	Price indexation	Beta	0.5	0.15	0.25	0.10	0.39
ξ_w	Wage stickiness	Gamma	1	0.2	0.68	0.56	0.81
ι_w	Wage indexation	Beta	0.5	0.15	0.70	0.64	0.77
ρ_R	Taylor rule: smoothing	Beta	0.6	0.1	0.67	0.63	0.71
ϕ_π	Taylor rule: inflation	Norm	1.7	0.3	1.58	1.44	1.73
ϕ_X	Taylor rule: GDP	Norm	0.4	0.3	0.77	0.60	0.94

role in GDP and inflation variations. In HANK, the contribution of the MEI shock to GDP fluctuations is smaller but remains to be the most important driver. Its reduced role in the variance of GDP is replaced by an increased role of the markup and monetary policy shocks. The most notable difference between RANK and HANK is that the contribution of the MEI shock to consumption fluctuations in HANK is twice as large as those in RANK, while its contribution to investment volatility is smaller.

To understand why the MEI shock has a quantitatively different role in the consumption and investment dynamics between the two models, I present the impulse responses to a positive MEI shock in Figure 5. The responses in HANK and RANK are computed at their own posterior mean. As observed in the figure, in RANK, investment rises, while consumption falls, consistent with the pattern presented in the estimated RANK model of Justiniano, Primiceri and Tambalotti (2010). The inability to generate a positive comovement of consumption with investment, employment, and output is the main reason that the MEI shock in the RANK model explains only a small fraction of consumption volatility. This conditional comovement problem arises in most representative agent models. In particular, when prices are flexible, in response to a shock that raises the demand for investment goods, market forces work to drive up the price of goods, depressing consumption. The problem can be solved if prices are more rigid, or monetary policy is more accommodative. If prices are fixed, a fall in consumption is dampened, and the investment boom induces an expansion in output, increasing households' income and consumption. If the nominal interest rate is fixed, a rise in prices results in a fall in the real interest rate, causing consumption to go up. However, in most estimated RANK models, such an extreme degree of nominal rigidity and

Table 8. Variance decomposition

Shock/series	GDP	C	I	Job-finding	Job-loss	π^w	π	R
				HANK				
Markup	13.00	17.79	3.23	9.40	9.94	2.70	10.67	0.58
Non-stat. tech.	5.98	3.78	1.28	15.45	16.32	7.10	4.63	1.52
MEI	32.65	14.56	49.66	23.06	24.37	46.44	38.28	77.64
Stat. tech.	22.96	10.11	30.43	28.26	29.86	10.44	32.47	3.18
Mon. policy	14.17	18.72	3.28	4.79	5.06	12.43	9.65	12.45
Preference	10.63	32.49	11.62	11.90	12.58	5.90	3.67	4.56
Job-separation	0.51	0.42	0.40	7.06	1.81	0.08	0.59	0.04
Gov. purchase	0.11	2.12	0.10	0.06	0.06	0.06	0.03	0.04
Wage measurement	0	0	0	0	0	14.84	0	0
				RANK				
Markup	10.59	7.39	6.02	9.67	10.29	0.62	25.43	2.95
Non-stat. tech.	7.40	8.06	0.29	5.63	5.99	7.16	3.20	1.06
MEI	40.19	7.58	78.59	40.33	42.95	58.31	40.44	74.15
Stat. tech.	23.63	22.39	12.39	33.42	35.59	11.41	26.39	3.79
Mon. policy	8.73	17.64	1.49	1.84	1.96	3.37	2.11	15.78
Preference	7.53	34.98	0.81	1.55	1.65	2.25	1.53	1.67
Job-separation	0.23	0.16	0.14	6.95	0.91	0.18	0.40	0.05
Gov. purchase	1.69	1.81	0.26	0.62	0.66	0.64	0.50	0.56
Wage measurement	0	0	0	0	0	16.07	0	0

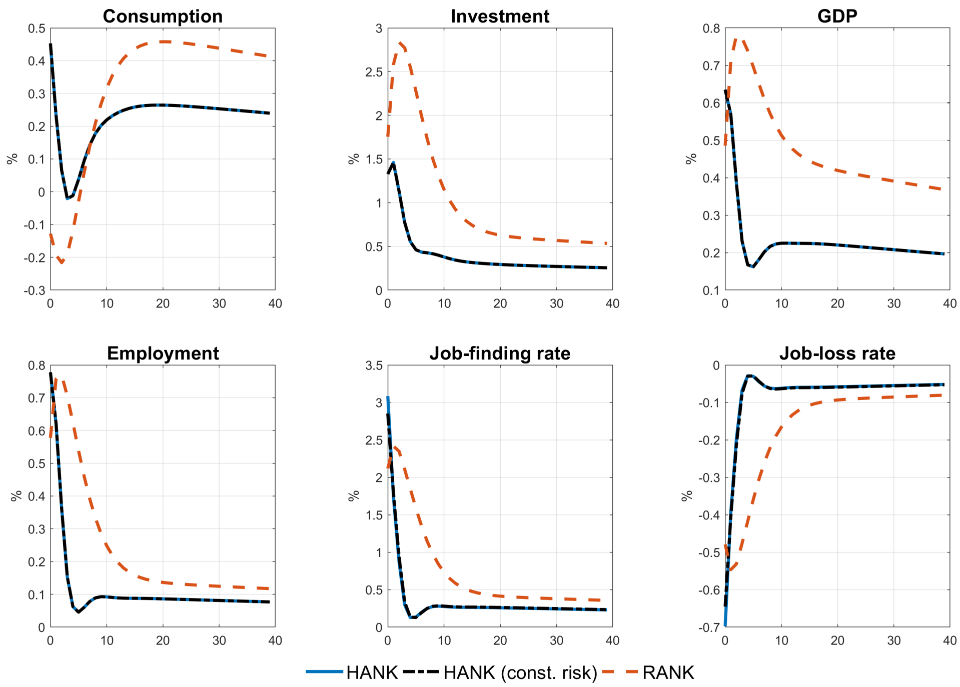
Note: Decomposition is computed at the posterior mean and expressed in percentages. GDP, consumption, and investment are in growth. π^w denotes nominal wage inflation.

interest rate inertia is not obtained, and hence the comovement problem persists.

In the estimated HANK economy, the comovement problem appears to be no longer an issue. Two channels work to increase consumption in response to a positive MEI shock. First, higher investment leads to a higher level of future capital stock, raising the marginal product of labor. Accordingly, intermediate goods firms hire more, inducing higher aggregate household income. Aggregate consumption in HANK expands more than in RANK because of the high average MPC. Second, higher employment lowers the unemployment risk, weakens the precautionary savings motive, and so raises aggregate consumption.[19] These two channels

[19]It is proposed that the unemployment risk channel can help to solve other problems present in standard New Keynesian models. Ravn and Sterk (2018) argue that mild deflation during the financial crisis can be explained in HANK with search and matching frictions. Oh and Rogantini Picco (2019) show that introducing this channel generates a comovement between consumption and inflation in response to macro uncertainty

Figure 5. IRFs to a positive MEI shock



Note: For employment, the job-finding rate, and the job-loss rate, the IRFs correspond to the deviation from the steady state. For the other variables, the IRFs are reported as the percent deviation from the steady state.

are reinforced in the presence of nominal rigidity, which generates the aggregate demand externality. The two channels are completely absent in the RANK model. Therefore, the data, in which aggregate consumption and investment have a positive correlation, instructs the RANK model to have a higher degree of nominal rigidity and a more accommodative monetary policy than in HANK. Put differently, the HANK model achieves the conditional comovement by relying less on New Keynesian ingredients due to the presence of channels that amplify consumption. Increased consumption in HANK implies fewer savings, smaller drop in the real interest rates, and so smaller increase in investment in response to the MEI shock, lowering its explanatory power in investment volatility.

For completeness, I explore whether a rise in aggregate consumption conditional on the MEI shock is caused by countercyclical unemployment risk or a high average MPC. The black dash-dotted line in Figure 5 corresponds to the case in which countercyclical unemployment risk is ineffective. Again, consistent with the analysis in the previous section, the precau-

shocks.

tionary savings motive against unemployment risk has a small contribution in achieving the conditional comovement. The high average MPC that arises from MPC heterogeneity is the main determinant.

Finally, Table 9 evaluates the fit of the HANK model in explaining aggregate variables relative to the RANK model. The data strongly favors the RANK model over the HANK model, implying that unemployment risk and MPC heterogeneity in HANK is not supported by the aggregate data. Why does the fit of the HANK model fall behind compared to the RANK model? To understand the reason, it is useful to compare the model-based and empirical cross-correlations of the data. These second moments are displayed in Figure 6. Solid black lines represent the moments predicted in HANK, while solid red lines indicate the moments predicted in RANK, computed at their own posterior mean. The solid blue lines and the dashed blue lines correspond to the empirical correlations and 95 % confidence intervals, respectively.

Observe the upper-left 4 by 1 block of graphs, which includes correlations of quantities and consumption growth of different lags. The HANK model does a fairly good job in capturing the contemporaneous correlation between the quantities and consumption. The success is primarily driven by the HANK model's capability in generating the comovement of consumption with investment and employment in response to the MEI shock, the most important source of GDP fluctuations. The RANK model does not do a good job in capturing the contemporaneous correlation, owing to its difficulties in generating the conditional comovement. Focus on the bottom-right 3 by 3 block of graphs, which includes cross-correlations of prices. Both HANK and RANK models do not capture the full extent of autocorrelations and cross-correlations of price and wage inflation and the nominal interest rate, even in the presence of inflation indexation and high policy rate persistence in the monetary policy rule. The HANK model has more difficulty in explaining the second moment of prices than its RANK counterpart. Such a challenge occurs mostly due to the low degree of nominal rigidity in the estimated HANK model. Lower success in matching price dynamics tells us why the HANK model is worse than the RANK model in terms of log marginal likelihood. Comparing the value of the log marginal likelihood between the HANK model and the constant risk benchmark, one can conclude that the unemployment risk channel does not improve the fit of the HANK model in terms of aggregate data.

Table 9. Model fit

	Model		
	HANK	HANK (c. risk)	RANK
Log Marginal likelihood	-1677.2	-1645.5	-1497.0

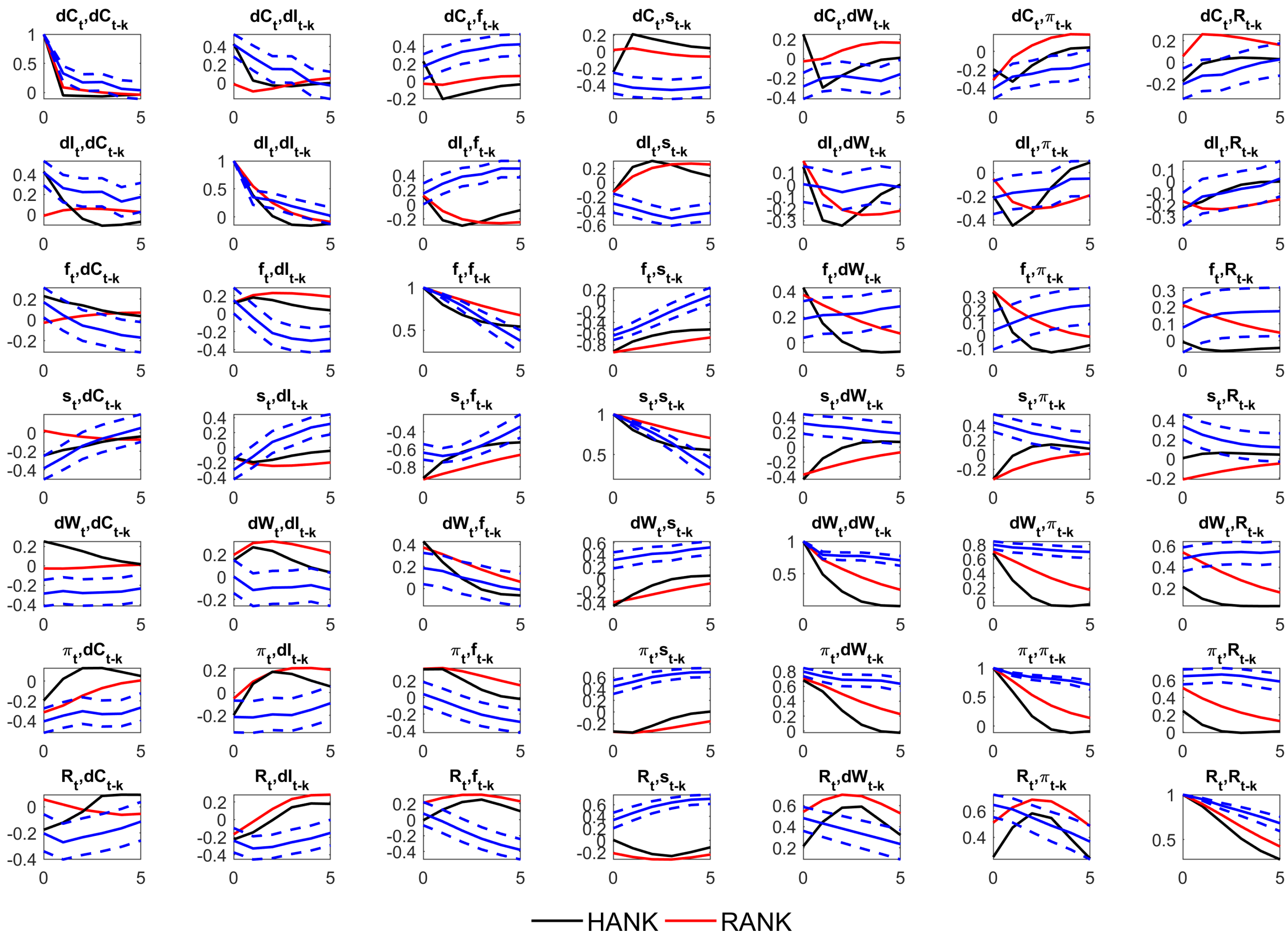
Note: HANK (c. risk) denotes the model in which households face constant (acyclical) unemployment risk.

7 Conclusion

I have assessed the quantitative importance of (i) precautionary savings against the countercyclical unemployment risk and (ii) MPC heterogeneity in business cycle dynamics. I did so in an estimated Heterogeneous Agent New Keynesian model with search and matching frictions. I found that these channels in HANK matter substantially, generating different output volatility compared to the otherwise identical complete markets benchmark, the RANK model. Precautionary savings engendered from unemployment risk plays a minor role in explaining the differences in the aggregate dynamics between HANK and RANK. The majority of the differences stem from MPC heterogeneity. In addition, the HANK model does not outperform the RANK model in terms of explaining aggregate data. This is because the HANK model has more difficulty than its RANK counterpart in explaining autocorrelations and cross-correlations of prices.

In this paper, the asset structure is fairly simple in the sense that it does not embed households' portfolio choice between liquid and illiquid assets. Bayer et al. (2019b) investigate the effect of exogenous earning risk on consumption and output in a two-asset HANK model and found the interaction between precautionary savings and portfolio choices has a substantial effect on consumption and output. Future work might explore the impact of endogenous unemployment risk on aggregate fluctuations in a two-asset HANK model and see whether the results differ from those in the present paper. Therefore, my quantitative results should be regarded as benchmarks against which future models with a rich asset and labor market structure can be compared.

Figure 6. Cross-correlogram of the observable variables in the models and the data



Note: The solid blue lines are the empirical correlations, and the blue dashed lines are 95 % confidence intervals centered around the empirical correlations. Solid black lines correspond to the HANK model's prediction evaluated at its posterior mean. The solid red line corresponds to the RANK model's prediction evaluated at its posterior mean.

Appendices

A Agents' Optimal Conditions

A.1 Household

Patient households' optimization yields

$$C_{H,t}^{-\sigma} = \beta_H \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} (C_{H,t+1})^{-\sigma} \right].$$

Impatient households' optimization yields

$$C(a,e)^{-\sigma} \geq \beta \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} C(a'(a,e),e')^{-\sigma} | e \right],$$

with equality if $a'(a,e) > 0$, where

$$C(a,e) = (1-\tau)\frac{W_t}{P_t} e + (1-\tau) b^u \frac{W_t}{P_t}(1-e) + \frac{R_{t-1}}{\Pi_t} a + \frac{D_t}{P_t} - a'(a,e)$$

is the optimal consumption for impatient household with liquid asset position a and income state e. Dividend to households is

$$\frac{D_t}{P_t} = Y_t - \frac{W_t}{P_t} n_t - A_t \kappa v_t - I_t - \Psi(u_t) K_{t-1}.$$

A.2 Wholesale Firms

The first order condition with respect to P_t^* is

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\xi_p)^s \left(\frac{1}{\Pi_{k=1}^{s} \frac{R_{t+k-1}}{\pi_{t+k}}} \right) \frac{\Lambda_{t+\nu}}{\Lambda_t} \frac{Y_{h,t+s}}{P_{t+s} \eta_{t+s}^p} \left[(1+\eta_{t+s}^p) MC_{t+s} - P_t^* \chi_{t,t+s} \right] = 0.$$

Given the Calvo assumption, the sectoral price index evolves according to

$$P_{j,t}^{-\frac{1}{\eta_{j,t}^p}} = (1-\xi_{pj})(P_{j,t}^*)^{-\frac{1}{\eta_{j,t}^p}} + \xi_{pj}(\pi_{j,t-1}^{\iota_{pj}} \pi_j^{1-\iota_{pj}} P_{j,t-1})^{-\frac{1}{\eta_{j,t}^p}}.$$

A.3 Intermediate goods firms

Combining the first-order conditions with respect to v_t and n_t yields

$$\frac{A_t\kappa}{\lambda_t} = \left(\frac{MC_t}{P_t}\right)(1-\alpha)A_t^{1-\alpha}(u_t^k K_{t-1})^\alpha n_t^{-\alpha} - \frac{W_t}{P_t} + \mathbb{E}_t\left[\frac{1}{R_t/\pi_{t+1}}(1-\rho_{x,t+1})\frac{A_{t+1}\kappa}{\lambda_{t+1}}\right]. \quad \text{(A.1)}$$

The first-order conditions with respect to I_t, K_t, and $u_{k,t}$ are

$$1 = q_t\upsilon_t\left[1 - \frac{s''}{2}\left(\frac{I_t}{I_{t-1}} - \mu\right)^2 - s''\frac{I_t}{I_{t-1}}\left(\frac{I_t}{I_{t-1}} - \mu\right)\right] + s''\mathbb{E}_t\left[\frac{1}{R_t/\pi_{t+1}}q_{t+1}\upsilon_{t+1}\frac{I_{t+1}^2}{I_t^2}\left(\frac{I_{t+1}}{I_t} - \mu\right)\right]$$

$$q_t = \mathbb{E}_t\frac{1}{R_t/\pi_{t+1}}[(1-\delta)q_{t+1} + r_{t+1}^k u_{k,t+1} - \Psi(u_{k,t+1})]$$

$$\Psi'(u_{k,t}) = r_t^k,$$

where $r_t^k \equiv \alpha\left(\frac{MC_t}{P_t}\right)A_t^{1-\alpha}(u_{t,k}K_{t-1})^{\alpha-1}n_t^{1-\alpha}$.

A.4 Market Clearing and Output

The market clearing condition for liquid assets and the final goods market are

$$\int a'(a,e)\mathrm{d}\Gamma_t(a,e) = B_{t+1}^g \quad \text{(A.2)}$$

$$\int C(a,e)\mathrm{d}\Gamma_t(a,e) + I_t + G_t = Y_t - A_t\kappa v_t - \Psi(u_t)K_{t-1}. \quad \text{(A.3)}$$

Using the demand for wholesale goods (2.4) and intermediate goods firms' technology (2.6), it can be shown that the output can be expressed as

$$\Delta_t^p Y_t = (u_{k,t}K_{t-1})^\alpha(A_t n_t)^{1-\alpha} - A_t F$$

where $\Delta_t^p \equiv \int_0^1 \left(\frac{P_{h,t}}{P_t}\right)^{-\frac{1+\eta_t^p}{\eta_t^p}} dh$ is a measure of price dispersion across wholesale firms.

B Full Set of Equilibrium Conditions

To solve the model, it is necessary to detrend variables that feature a unit root. Let the following variables denote detrended variables

$$y_t = \frac{Y_t}{A_t}, \quad x_t = \frac{X_t}{A_t} \quad g_t = \frac{G_t}{A_t}, \quad x_t = \frac{X_t}{A_t}, \quad \mu_t = \frac{A_t}{A_{t-1}}, \quad w_t = \frac{W_t}{P_t A_t}, \quad p_t^* = \frac{P_t^*}{P_t},$$
$$mc_t = \frac{MC_t}{P_t}, \quad d_t = \frac{D_t}{P_t A_t}, \quad a^* = \frac{a}{A_{t-1}}, \quad c = \frac{C}{A_t}, \quad i_t = \frac{I_t}{A_t}, \quad k_t = \frac{K_t}{A_t}.$$

The full set of equilibrium conditions, expressed in terms of stationary variables are as follows.

Patient households:

$$c_{H,t}^{-\sigma} = \beta_H \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} (\mu_{t+1} c_{H,t+1})^{-\sigma} \right] \tag{B.1}$$

Impatient households:

$$c(a^*, e)^{-\sigma} \geq \beta_L \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} (\mu_{t+1} c(a^{*\prime}(a^*, e), e'))^{-\sigma} | e \right], \tag{B.2}$$

with equality if $a^{*\prime}(a^*, e) > 0$, where

$$c(a^*, e) = (1-\tau) w_t e + (1-\tau) b^u w_t (1-e) + \frac{R_{t-1}}{\Pi_t} \frac{a^*}{\mu_t} - a^{*\prime}(a^*, e)$$

.

Dividends:

$$d_t = y_t - w_t n_t - \kappa v_t - i_t - \Psi(u_{k,t}) \frac{k_{t-1}}{\mu_t} \tag{B.3}$$

Production function:

$$\Delta_t^p y_t = (u_{k,t} k_{t-1})^\alpha n_t^{1-\alpha} - F \tag{B.4}$$

Price setting of wholesale firms:

$$p_t^* = \frac{h_{1,t}^p}{h_{2,t}^p} \tag{B.5}$$

$$h_{1,t}^p = (1+\eta_t^p) mc_t + \xi_p \mu_{t+1} \mathbb{E}_t \left(\frac{1}{R_t/\pi_{t+1}} \right) h_{1,t+1}^p \tag{B.6}$$

$$h_{2,t}^p = 1 + \xi_p \mu_{t+1} \mathbb{E}_t \left(\frac{1}{R_t/\pi_{t+1}} \right) \frac{\pi_t^{\iota_p} \pi^{1-\iota_p}}{\pi_{t+1}} h_{2,t+1}^p \tag{B.7}$$

$$1 = (1-\xi_p)(p_t^*)^{-\frac{1}{\eta_t^p}} + \xi_p \left(\frac{\pi_{t-1}^{\iota_p} \pi^{1-\iota_p}}{\pi_t} \right)^{-\frac{1}{\eta_t^p}} \tag{B.8}$$

$$\Delta_t^p = (1-\xi_p)(p_t^*)^{-\frac{1+\eta_t^p}{\eta_t^p}} + \xi_p \left(\frac{\pi_{t-1}^{\iota_p} \pi^{1-\iota_p}}{\pi_t} \right)^{-\frac{1+\eta_t^p}{\eta_t^p}} \Delta_{t-1}^p. \tag{B.9}$$

Intermediate goods firms:

$$\frac{\kappa}{\lambda_t} = mc_t(1-\alpha) \left(\frac{u_t^k k_{t-1}}{n_t} \right)^{\alpha} - w_t + \mathbb{E}_t \left[\frac{\mu_{t+1}}{R_t/\pi_{t+1}} (1-\rho_{x,t+1}) \frac{\kappa}{\lambda_{t+1}} \right]. \tag{B.10}$$

$$\begin{aligned} 1 &= q_t \upsilon_t \left[1 - \frac{s''}{2} \left(\frac{i_t \mu_t}{i_{t-1}} - \mu \right)^2 - s'' \frac{i_t \mu_t}{i_{t-1}} \left(\frac{i_t \mu_t}{i_{t-1}} - \mu \right) \right] \\ &+ s'' \mathbb{E}_t \frac{1}{R_t/\pi_{t+1}} q_{t+1} \upsilon_{t+1} \left(\frac{i_{t+1} \mu_{t+1}}{i_t} \right)^2 \left(\frac{i_{t+1} \mu_{t+1}}{i_t} - \mu \right) \end{aligned} \tag{B.11}$$

$$q_t = \mathbb{E}_t \frac{1}{R_t/\pi_{t+1}} [(1-\delta) q_{t+1} + r_{t+1}^k u_{k,t+1} - \Psi(u_{k,t+1})] \tag{B.12}$$

$$\Psi'(u_{k,t}) = r_t^k \tag{B.13}$$

$$r_t^k = \alpha mc_t \left(\frac{u_{k,t} k_{t-1}}{n_t} \right)^{\alpha-1} \tag{B.14}$$

$$k_t = \upsilon_t i_t \left[1 - \frac{s''}{2} \left(\frac{i_t \mu_t}{i_{t-1}} - \mu \right)^2 \right] + (1-\delta) \frac{k_{t-1}}{\mu_t} \tag{B.15}$$

Wage setting:

$$w_t = \left(\frac{w_{t-1}}{\pi_t \mu_t} \right)^{\iota_w} \left(w \left(\frac{n_t}{n} \right)^{\xi_w} \right)^{1-\iota_w} \tag{B.16}$$

Labor market flows:

$$n_t = (1-\rho_{x,t}) n_{t-1} + \psi \upsilon_t \left(\frac{\upsilon_t}{\widetilde{u}_t} \right)^{-\gamma} \tag{B.17}$$

$$\rho_{x,t} = \frac{1}{1 + \exp(\overline{\rho}_x - \widetilde{\rho}_{x,t})} \tag{B.18}$$

$$\widetilde{u}_t = u_{t-1} + \rho_{x,t} n_{t-1} \tag{B.19}$$

$$u_t = (1 - f_t) u_{t-1} + \rho_{x,t}(1 - f_t) n_{t-1} \tag{B.20}$$

$$u_t = 1 - n_t \tag{B.21}$$

$$\lambda_t = \overline{M}(v_t / \widetilde{u}_t)^{-\gamma} \tag{B.22}$$

Monetary policy:

$$\begin{aligned} \log\left(\frac{R_t}{R}\right) &= \rho_R \log\left(\frac{R_{t-1}}{R}\right) + (1 - \rho_R)[\phi_\pi \left(\frac{1}{4}\sum_{\iota=0}^{3} \log\left(\frac{\pi_{t-\iota}}{\pi}\right)\right) \\ &\quad + \phi_X \left(\frac{1}{4}\sum_{\iota=0}^{3} \log\left(\frac{x_{t-\iota}\mu_{t-\iota}}{\mu x_{t-1-\iota}}\right)\right)] + \epsilon_t^R \end{aligned} \tag{B.23}$$

Government budget constraint:

$$\overline{B}^g + \tau_t (w_t n_t + b^u w_t u_t) = b^u w_t u_t + g_t + \frac{R_{t-1}}{\pi_t} \frac{\overline{B}^g}{\mu_t} \tag{B.24}$$

Market clearing:

$$c_t + i_t + g_t = y_t - \kappa v_t - \Psi_t(u_{k,t}) \frac{k_{t-1}}{\mu_t} \tag{B.25}$$

Real GDP and aggregate consumption:

$$x_t = c_t + i_t + g_t \tag{B.26}$$

$$c_t = \Omega \int c(a^*, e) \mathrm{d}\Gamma_t(a^*, e) + (1 - \Omega) c_{H,t} \tag{B.27}$$

Evolution of distribution for all measurable set $\mathcal{A}$:

$$\Gamma_{t+1}(\mathcal{A}, e') = \sum_{\epsilon} \boldsymbol{\pi}_t(e'|e) \int \mathbf{1}\{a^{*\prime}(a^*, e) \in \mathcal{A}\} \Gamma_t(\mathrm{d}a^*, e), \tag{B.28}$$

where $\boldsymbol{\pi}_t(e'|e)$ is the period t transition probability from e to e'

Aggregate shocks:

$$\log(1+\eta_t^p) = (1-\rho_{\eta^p})\log(1+\eta^p) + \rho_{\eta^p}\log(1+\eta_{t-1}^p) + \epsilon_t^{\eta^p} \tag{B.29}$$

$$\log\mu_t = (1-\rho_\mu)\log\mu + \rho_\mu\log\mu_{t-1} + \epsilon_t^\mu \tag{B.30}$$

$$\log \upsilon_t = \rho_\upsilon \log \upsilon_{t-1} + \epsilon_t^\upsilon \tag{B.31}$$

$$\log \widetilde{A}_t = \rho_{\widetilde{A}} \log \widetilde{A}_{t-1} + \epsilon_t^{\widetilde{A}} \tag{B.32}$$

$$\log\zeta_t = \rho_\zeta\log\zeta_{t-1} + \epsilon_t^\zeta \tag{B.33}$$

$$\widetilde{\rho}_{x,t} = \rho_{\rho_x}\widetilde{\rho}_{x,t-1} + \epsilon_t^{\rho_x} \tag{B.34}$$

$$\log g_t = (1-\rho_g)\log g + \rho_g\log g_{t-1} + \epsilon_t^g \tag{B.35}$$

C Approximated Equilibrium

.

I describe the procedure of discretizing the infinite-dimensional representation of the equilibrium conditions. I follow the procedure presented in the user guide of Winberry (2018), which describes the discretization of the equilibrium conditions of Krusell and Smith (1998). The model contains two infinite-dimensional objects: decision rules of impatient households and their distribution over liquid wealth.

C.1 Discretizing the Household's Decision Rules

Define the conditional expectation function:

$$\chi_t(a^*, e) = \beta_L \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} (\mu_{t+1} c(a^{*\prime}(a^*, e), e'))^{-\sigma} | e \right].$$

I approximate the conditional expectation function using Chebyshev polynomials

$$\widehat{\chi}_t(a_j^*, e) = \exp\left\{ \sum_{i=1}^{n_\chi} \theta_{ej,t} T_j(\boldsymbol{\xi}(a_j^*)) \right\},$$

where n_χ is the order of approximation, and $T_j(\cdot)$ is the j^{th} order Chebyshev polynomial. $\boldsymbol{\xi}(a^*_j) = 2\frac{a^*_j - \underline{a}^*}{\overline{a}^* - \underline{a}^*} - 1 \in [-1, 1]$ is a node on which the Chebyshev polynomials are defined, where $a^*_j \in [\underline{a}^*, \overline{a}^*]$. $\{\theta_{ej,t}\}_{j=1}^{n_\chi}$ are basis coefficients. To construct grids on asset, I create n_χ Chebyshev nodes on the interval [-1,1] and then use $\boldsymbol{\xi}(a^*_j)$ to obtain asset grids $\{a^*_j\}_{j=1}^{n_\chi}$. Given the approximation of the conditional expectation function, I approximate the household's decision rules using collocation, which forces the households' optimality condition to hold exactly on the constructed asset grids. Formally, solve for $\{\theta_{ej,t}\}_{j=1}^{n_\chi}$ that satisfy

$$\exp\{\sum_{j=1}^{n_\chi} \theta_{ej,t} T_j(\boldsymbol{\xi}(a^*_j))\} = \beta_L \mathbb{E}_t \left[\frac{R_t}{\pi_{t+1}} \frac{\zeta_{t+1}}{\zeta_t} (\mu_{t+1} \widehat{c}_t(\widehat{a}^{*\prime}_t(a^*_j, e), e'))^{-\sigma} | e \right],$$

where

$$\widehat{a}^{*\prime}_t(a^*_j, e) = \max\left\{0, (1-\tau)w_t e + (1-\tau)b^u w_t(1-e) + \frac{R_{t-1}}{\Pi_t}\frac{a^*_j}{\mu_t} - \widehat{\chi}_t(a^*_j, e)^{-\frac{1}{\sigma}}\right\},$$

$$\widehat{c}_t(a^*_j, e) = (1-\tau)w_t e + (1-\tau)b^u w_t(1-e) + \frac{R_{t-1}}{\Pi_t}\frac{a^*_j}{\mu_t} - \widehat{a}^{*\prime}_t(a^*_j, e).$$

C.2 Discretizing the Distribution

The distribution of households is approximated by a parametric function, which captures the distribution away from the limit, and the mass of households at the borrowing limit.

Mass at the limit Denote the fraction of households with employment status e at the borrowing constraint with $\underline{m}_{e,t}$. The evolution of the mass at the borrowing limit is

$$\begin{aligned} \underline{m}_{e,t+1} = & \frac{1}{\boldsymbol{\pi}_t(e)}[\sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{-1})(1-\hat{m}_{e_{-1},t})\boldsymbol{\pi}_{t-1}(e|e_{-1})\mathbf{1}\{a^{*\prime}_t(a^*, e_{-1}) = 0\} g_{e_{-1},t}(a^*)da^* \\ & + \sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{-1})\hat{m}_{e_{-1},t}\boldsymbol{\pi}_{t-1}(e|e_{-1})\mathbf{1}\{a'_t(0, e_{-1}) = 0\}]. \end{aligned}$$

I approximate the integrals using Gauss-Legendre quadrature, which gives nodes $\{a^*_\iota\}_{\iota=1}^{m_g}$ and weights $\{\omega_\iota\}_{\iota=1}^{m_g}$.

Distribution away from the limit The distribution of households over assets $a^* > 0$ is approximated using the probability density function $g_{e,t}(a^*)$

$$g_{e,t}(a^*) = g_{e,t}^0 \exp\left\{ g_{e,t}^1(a^* - m_{e,t}^1) + \sum_{j=2}^{n_g} g_{e,t}^j \left[(a^* - m_{e,t}^1)^j - m_{e,t}^j \right] \right\},$$

where n_g denotes the degree of approximation, and $\{m_{e,t}^j\}_{j=1}^{n_g}$ are the centralized moments of the distribution. Given the moments $\{m_{e,t}^j\}_{j=1}^{n_g}$, the coefficients $\{g_{e,t}^{i_m}\}_{i_m=0}^{n_g}$ are determined by the following moment conditions

$$m_{e,t}^1 = \int a^* g_{e,t}(a^*) da^*, \quad m_{e,t}^{i_m} = \int (a^* - m_{e,t}^1)^{i_m} g_{e,t}(a^*) da^*,$$

for $i_m = 2, ..., n_g$, and $\int g_{e,t}(a^*) da^* = 1$. The law of motion for distribution is characterized by the evolution of moments

$$\begin{aligned} m_{e,t+1}^1 &= \frac{1}{\boldsymbol{\pi}_t(e)} [\sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{-1})(1 - \underline{m}_{e_{-1},t}) \boldsymbol{\pi}_{t-1}(e|e_{-1}) \int a_t^{*\prime}(e_{-1}, a) g_{e_{-1},t}(a^*) da^* \\ &\quad + \sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{-1}) \underline{m}_{e_{-1},t} \boldsymbol{\pi}_{t-1}(e|e_{-1}) a_t^{*\prime}(0, e_{-1})] \\ m_{e,t+1}^{i_m} &= \frac{1}{\boldsymbol{\pi}_t(e)} [\sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{t-1})(1 - \underline{m}_{e_{-1},t}) \boldsymbol{\pi}_{t-1}(e|e_{-1}) \int [a_t^{*\prime}(e_{-1}, a^*) - m_{e,t+1}^1]^{i_m} g_{e_{-1},t}(a^*) da^* \\ &\quad + \sum_{e_{-1}} \boldsymbol{\pi}_{t-1}(e_{-1}) \underline{m}_{e_{-1},t} \boldsymbol{\pi}_{t-1}(e|e_{-1}) [a_t^{*\prime}(0, e_{-1}) - m_{e_{-1},t}^1]^{i_m}], \end{aligned}$$

for $i_m = 2, ..., n_g$, where $\boldsymbol{\pi}_t(e)$ is the normalizing factor that makes the sum of weights equal to 1.

C.3 Definition of Approximated Equilibrium

Given the discretized households' decision rules and wealth distribution, we are ready to define the approximated equilibrium of the model. The approximated equilibrium is a sequence of $\{\{\{\theta_{ej,t}\}_{j=1}^{n_\chi}\}_e, \{\{g_{e,t}^{i_m}\}_{i_m=1}^{n_g}\}_e, \{\boldsymbol{\pi}_t(e'|e)\}_{e,e'}, \{\boldsymbol{\pi}_t(e)\}_e, \{\{m_{e,t}^{i_m}\}_{i_m=1}^{n_g}\}_e, \{\underline{m}_{e,t}\}_e$, c_t, $c_{H,t}$, i_t, k_t, $u_{k,t}$, d_t, y_t, x_t, u_t, $\widetilde{u}_t$, n_t, λ_t, f_t, v_t, $\rho_{x,t}$, R_t, π_t, p_t^*, $h_{1,t}^p$, $h_{2,t}^p$, Δ_t^p, mc_t, r_t^k, q_t, w_t, τ_t, η_t^p, μ_t, υ_t, $\widetilde{A}_t$, ζ_t, $\widetilde{\rho}_{x,t}$, g_t $\}_{t=0}^{\infty}$ that satisfies

$$\exp\{\sum_{i=1}^{n_\chi}\theta_{ei,t}T_j(\xi(a_j^*))\} = \beta_L \mathbb{E}_t\left[\frac{R_t}{\pi_{t+1}}\frac{\xi_{t+1}}{\xi_t}\sum_{e'}\boldsymbol{\pi}(e'|e)(\mu_{t+1}c_{t+1}(\hat{a}_t'(a_j^*,e),e'))^{-\sigma}\right], \tag{C.1}$$

$$m_{e,t}^1 = \sum_{j=1}^{m_g} a_j^* g_{e,t}(a_j^*), \tag{C.2}$$

$$m_{e,t}^{i_m} = \sum_{j=1}^{m_g}(a_j^* - m_{e,t}^1)^{i_m} g_{e,t}(a_j^*), \tag{C.3}$$

$$\begin{aligned} m_{e,t+1}^1 &= \frac{1}{\boldsymbol{\pi}_{t-1}(e)}[\sum_{e_{-1}}(1-\underline{m}_{e_{-1},t})\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_{t-1}(e|e_{-1})\sum_{\iota=1}^{m_g}\omega_\iota a_t^{*\prime}(a_\iota^*,e_{-1})g_{e_{-1},t}(a_j^*) \\ &+\sum_{e_{-1}}\underline{m}_{e_{-1},t}\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_{t-1}(e|e_{-1})a_t^{*\prime}(0,e_{-1})], \end{aligned} \tag{C.4}$$

$$\begin{aligned} m_{e,t+1}^{i_m} &= \frac{1}{\boldsymbol{\pi}_t(e)}[\sum_{e_{-1}}(1-\underline{m}_{e_{-1},t})\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_{t-1}(e|e_{-1})\sum_{\iota=1}^{m_g}\omega_\iota[a_t^{*,\prime}(a_j^*,e_{-1})-m_{e,t+1}^1]^{i_m}g_{e_{-1},t}(a_\iota^*) \\ &+\sum_{e_{-1}}\underline{m}_{e_{-1},t}\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_t(e|e_{-1})[a_t^{*\prime}(0,e_{-1})-m_{e,t+1}^1]^{i_m}], \end{aligned} \tag{C.5}$$

$$\begin{aligned} \underline{m}_{e,t+1} &= \frac{1}{\boldsymbol{\pi}_t(e)}[\sum_{e_{-1}}(1-\underline{m}_{e_{-1},t})\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_{t-1}(e|e_{-1})\sum_{j=1}^{m_g}\omega_j\mathbf{1}\{a_t^{*\prime}(a_j^*,e_{-1})=0\}g_{e_{-1},t}(a_j^*) \\ &+\sum_{e_{-1}}\underline{m}_{e_{-1},t}\boldsymbol{\pi}_{t-1}(e_{-1})\boldsymbol{\pi}_{t-1}(e|e_{-1})\mathbf{1}\{a_t^{*\prime}(0,e_{-1})=0\}], \end{aligned} \tag{C.6}$$

$$\boldsymbol{\pi}_{t-1}(0|0) = 1-f_t, \tag{C.7}$$

$$\boldsymbol{\pi}_{t-1}(1|0) = f_t, \tag{C.8}$$

$$\boldsymbol{\pi}_{t-1}(0|1) = \rho_{x,t}(1-f_t), \tag{C.9}$$

$$\boldsymbol{\pi}_{t-1}(1|1) = 1-\rho_{x,t}(1-f_t), \tag{C.10}$$

$$\boldsymbol{\pi}_t(0) = u_t, \tag{C.11}$$

$$\boldsymbol{\pi}_t(1) = n_t, \tag{C.12}$$

Table A.1. Prior and posterior distribution of shock processes in RANK

Parameter	Description	Prior dist.			Posterior dist.		
		Distribution	Mean	SD	Mean	5 %	95 %
ρ_{η_p}	Auto. price markup	Beta	0.6	0.1	0.69	0.60	0.78
ρ_{μ}	Auto. non-stat. tech.	Beta	0.4	0.1	0.35	0.22	0.47
ρ_{υ}	Auto. MEI	Beta	0.6	0.1	0.74	0.66	0.81
ρ_{ζ}	Auto. preference	Beta	0.6	0.1	0.92	0.88	0.95
ρ_{ρ_x}	Auto. job-separation	Beta	0.6	0.1	0.81	0.76	0.87
ρ_g	Auto. gov. purchase	Beta	0.6	0.1	0.95	0.94	0.97
$\rho_{\tilde{A}}$	Auto. stat. tech.	Beta	0.6	0.1	0.92	0.90	0.94
$100\sigma_{\eta_p}$	Std price markup	Inv. Gamma	0.15	1	1.46	0.99	1.94
$100\sigma_{\mu}$	Std non-stat. tech.	Inv. Gamma	1	1	0.40	0.33	0.48
$100\sigma_{\upsilon}$	Std MEI	Inv. Gamma	0.5	1	4.58	3.05	6.03
$100\sigma_R$	Std mon. policy	Inv. Gamma	0.15	1	0.27	0.24	0.30
$100\sigma_{\zeta}$	Std preference	Inv. Gamma	1	1	1.36	1.19	1.52
$100\sigma_{\rho_x}$	Std job-separation	Inv. Gamma	1	1	12.6	11.6	13.7
$100\sigma_g$	Std gov. purchase	Inv. Gamma	0.5	1	0.92	0.83	1.01
$100\sigma_{\tilde{A}}$	Std stat. tech.	Inv. Gamma	1	1	0.81	0.72	0.90
$100\sigma_w$	Std wage measurement	Inv. Gamma	0.5	1	0.23	0.20	0.26

(B.1), (B.3)-(B.27), and (B.29)-(B.35). $\{a_j\}_{j=1}^{n_\chi}$ are Chebyshev nodes, and $\{a_\iota\}_{\iota=1}^{m_g}$ are Quadrature nodes. I set $n_\chi = 25$, $n_g = 3$, and $m_g = 15$.

D Additional Tables

Table A.1 reports the prior and posterior distributions for parameters defining the shock processes in RANK. It is interesting to note that the standard deviation of the preference shock is smaller than that in HANK. As discussed in the body of the paper, in response to the preference shock, the HANK model produces a much less volatile consumption than the RANK model. Hence, a larger preference shock is required in HANK than in RANK to fit the volatility of the consumption data. Moreover, the standard deviation of the MEI shock is larger in RANK than in HANK, while the investment adjustment cost is lower in HANK than in RANK. The result arises because the ability to generate a comovement of consumption with investment conditional on the MEI shock in HANK leads to a more dampened response of investment. An increase in consumption in response to a positive MEI shock leads to reduced savings, which makes the drop in the real interest rate difficult, and hence causes a smaller rise in investment. Therefore, to explain the highly volatile investment in the data, a lower investment adjustment cost is required. Because of a lower investment adjustment cost, a less volatile MEI shock is needed to match the investment volatility in the data.

References

Acharya, Sushant and Keshav Dogra, "Understanding HANK: Insights from a PRANK," 2019. Working Paper.

Auclert, Adrien, "Monetary Policy and the Redistribution Channel," *American Economic Review*, 2019, *109* (6), 2333–2367.

_ **, Matthew Rognlie, and Ludwig Straub**, "The Intertemporal Keynesian Cross," 2018. NBER Working Paper No. 25020.

_ **, Rognlie Matthew Bardóczy Bence and, and Ludwig Straub**, "Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Model," 2019. NBER Working Paper No. 26123.

Barro, Robert J. and Robert G. King, "Time-Separable Preferences and Intertemporal-Substitution Models of Business Cycles," *Quarterly Journal of Economics*, 1984, *99* (4), 817– 839.

Basu, Susanto and Brent Bundick, "Uncertainty Shocks in a Model of Effective Demand," *Econometrica*, 2017, *85* (3), 937–958.

_ **and John G. Fernald**, "Returns to Scale in U.S. Production: Estimates and Implications," *Quarterly Journal of Economics*, 1997, *105* (2), 249–283.

Bayer, Christian, Benjamin Born, and Ralph Luetticke, "Shocks, Frictions, and Inequality in US Business Cycles," 2019. Working Paper.

_ **, Ralph Lutticke, Lien Pham-Daoz, and Volker Tjadenz**, "Precautionary Savings, Illiquid Assets, and the Aggregate Consequences of Shocks to Household Income Risk," *Econometrica*, 2019, *87* (1), 255–290.

Bilbiie, Florin O., "Monetary Policy and Heterogeneity: An Analytical Framework," 2019. Working Paper.

_ , "The New Keynesian Cross," 2019. *Journal of Monetary Economics*, forthcoming.

Boivin, Jean and Marc Giannoni, "DSGE Models in a Data-Rich Environment," 2006. NBER Working Paper No. 12772.

Broda, Christian and Jonathan A. Parker, "The Economic Stimulus Payments of 2008 and the Aggregate Demand for Consumption," *Journal of Monetary Economics*, 2014, *68* (S), S20–S36.

Calvo, Guillermo A, "Staggered Prices in a Utility-Maximizing framework," *Journal of monetary Economics*, 1983, *12* (3), 383–398.

Challe, Edouard, "Uninsured Unemployment Risk and Optimal Monetary policy in a Zero-Liquidity Economy," 2019. American Economic Journal: Macroeconomics, forthcoming.

_ , Julien Matheron, Xavier Ragot, and Juan F. Rubio-Ramírez, "Precautionary Saving and Aggregate Demand," *Quantitative Economics*, 2017, *8* (2), 435–478.

Den Haan, Wouter J., Garey Ramey, and Joel Watson, "Job Destruction and Propagation of Shocks," *American Economic Review*, 2000, *90* (3), 482–498.

Den Haan, Wouter, Pontus Rendahl, and Markus Riegler, "Unemployment (Fears) and Deflationary Spirals," *Journal of the European Economic Association*, 2018, *16* (5), 1281–1349.

Eusepi, Stefano and Bruce Preston, "Consumption Heterogeneity, Employment Dynamics and Macroeconomic Co-movement," *Journal of Monetary Economics*, 2015, *71* (2), 13–32.

Galí, Jordi, David López-Salido, and Javier Vallés, "Understanding The Effects of Government Spending on Consumption," *Journal of the European Economic Association*, 2007, *5* (1), 227–270.

Ganong, Peter and Pascal Noel, "Consumer Spending During Unemployment: Positive and Normative Implications," *American Economic Review*, 2019, *109* (7), 2383–2424.

Gertler, Mark, Luca Sala, and Antonella Trigari, "An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining," *Journal of Money, Credit and Banking*, 2008, *40* (8), 1713–1764.

Gornemann, Nils, Keith Kuester, and Makoto Nakajima, "Doves for the Rich, Hawks for the Poor? Distributional Consequences of Monetary Policy," 2016. International Finance Discussion Papers 1167, Board of Governors of the Federal Reserve System.

Guerrieri, Veronica and Guido Lorenzoni, "Credit Crises, Precautionary Savings, and the Liquidity Trap," *Quarterly Journal of Economics*, 2017, *132* (3), 1427—-1467.

Guvenen, Fatih, Serdar Ozkan, and Jae Song, "The Nature of Countercyclical Income Risk," *Journal of Political Economy*, 2014, *122* (3), 621–660.

Hagedorn, Marcus and Iourii Manovskii, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 2008, *98* (4), 1692–1706.

_ , _ , and Kurt Mitman, "The Fiscal Multiplier," 2019. Working Paper, University of Oslo.

Hamilton, James, "Why You Should Never Use the Hodrick-Prescott Filter," *Review of Economics and Statistics*, 2018, *100* (5), 831–843.

Heathcote, Jonathan and Fabrizio Perri, "Wealth and Volatility," *Review of Economic Studies*, 2018, *85* (4), 2139–2172.

Johnson, David S., Jonathan A. Parker, and Nicole S. Souleles, "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review*, 2006, *96* (5), 1589–1610.

Justiniano, Alejandro, Giorgio E Primiceri, and Andrea Tambalotti, "Is There a Trade-Off between Inflation and Output Stabilization?," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 1–31.

_ , Giorgio Primiceri, and Andrea Tambalotti, "Investment Shocks and Business Cycles," *Journal of Monetary Economics*, 2010, *57* (2), 132–145.

Kaplan, Greg and Giovanni L. Violante, "A Model of the Consumption Response to Fiscal Stimulus Payments," *Econometrica*, 2018, *82* (4), 1199–1239.

_ , Benjamin Moll, and Giovanni L. Violante, "Monetary Policy According to HANK," *American Economic Review*, 2018, *108* (3), 697–743.

Kekre, Rohan, "Unemployment Insurance in Macroeconomic Stabilization," 2019. Working Paper.

Kreamer, Jonathan, "Household Debt, Unemployment, and Slow Recoveries," 2016. Working Paper.

Krusell, Per and Anthony A. Smith, "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, 1998, *106* (5), 867–896.

McKay, Alisdair and Ricardo Reis, "The Role of Automatic Stabilizers in the US Business Cycle," *Econometrica*, 2016, *84* (1), 141–194.

_ **and** _ , "Optimal Automatic Stabilizers," 2019. Working Paper.

_ **, Emi Nakamura, and Jón Steinsson**, "The Power of Forward Guidance Revisited," *American Economic Review*, 2016, *106* (10), 3133–3158.

Oh, Hyunseung and Ricardo Reis, "Targeted Transfers and the Fiscal Response to the Great Recession," *Journal of Monetary Economics*, 2012, *59* (S), S50–S64.

Oh, Joonseok and Anna Rogantini Picco, "Macro Uncertainty and Unemployment Risk," 2019. Working Paper, EUI.

Parker, Jonathan A., S. Souleles Nicholas, David S. Johnson, and Robert McClelland, "Consumer Spending and the Economic Stimulus Payments of 2008," *American Economic Review*, 2013, *103* (6), 2530–53.

Petrongolo, Barbara and Christopher A. Pissarides, "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 2001, *39* (2), 390–431.

Ravn, Morten O. and Vincent Sterk, "Job Uncertainty and Deep Recessions," *Journal of Monetary Economics*, 2017, *90* (4), 125–141.

_ **and** _ , "Macroeconomic Fluctuations with HANK & SAM: an Analytical Approach," 2018. Working Paper.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95*, 25–49.

Werning, Iván, "Incomplete Markets and Aggregate Demand," 2015. NBER Working Paper No. 21448.

Winberry, Thomas, "A Method for Solving and Estimating Heterogeneous Agent Macro Models," *Quantitative Economics*, 2018, *9* (3), 1123–1151.