Heterogeneous job loss risk and precautionary savings with financial frictions

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Abstract

This paper studies how heterogeneity in job loss risk across industries and regions affects households' saving behavior and welfare in an economy with incomplete markets. Using U.S. micro-level data, I show that manufacturing and construction industries exhibit significantly higher separation rates, and their uneven spatial concentration correlates with regional disparities in savings incentives. Motivated by these facts, I develop a heterogeneous-agent model in which unemployment risk depends jointly on workers' industries of employment and regions of residence, and the risk-free rate is endogenously determined. With parameters estimated using U.S. data, the model shows that the variations in risk exposure are large enough to result in significantly more savings in risky states and industries, as well as varying welfare consequences across subgroups. In a counterfactual policy experiment that tightens credit limits, the endogenous decline in the risk-free rate partially offsets welfare losses for the constrained households while widening welfare differences across regions.

Keywords: Unemployment risk, precautionary savings, financial frictions, regional disparities, heterogeneous agents
JEL classification: E21, E24, R23, D31, G51

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1 Introduction

Over time, fluctuations in capital market policies, particularly regarding interest rates and credit constraints, are important drivers of households' economic behavior. Meanwhile, labor market risks vary significantly across industries, with people working in different industries facing different job loss probabilities and different expected unemployment durations. The variation in unemployment risk creates distinct exposure to income volatility. Motivated by this phenomenon, this paper asks three main questions. First, how large is the heterogeneity in job loss risk across industries in the U.S.? Second, how much does the variation affect households' consumption and savings decisions and welfare? Third, how do changes in credit availability result in different savings decisions and welfare distributions across sectors and regions?

The main source of heterogeneity in the model is sector-specific job loss risks, which affect people through two channels. First, employed workers face idiosyncratic job separation probabilities conditional on their sector of employment. Second, households in different regions face distinct probabilities of working in these sectors. The heterogeneity matters for households' consumption and savings behaviors and welfare, since different exposures to unemployment risk alter their precautionary savings incentives. Beyond the heterogeneous unemployment risks, an incomplete financial market[1] prevents households from fully insuring against risks thus affecting saving decisions.

On the empirical front, I present three main findings. First, there is statistically significant heterogeneity in job loss probabilities across industries. Specifically, workers in manufacturing and construction face significantly higher job separation rates. The predicted annual job separation probability in these industries is about 27.5%, compared to 14.4% in the lowest-risk industries. Second, the share of high-risk jobs varies substantially

[1] An incomplete financial market here means that there are no markets offering insurance against the specified risk of job loss.

across U.S. states, ranging from under 2% to approximately 36%. Third, the savings rates of states with the highest share of high-risk industries are 9.2% higher than those of states with the lowest share.

Theoretically, I build on a standard heterogeneous-agent model with an incomplete asset market and introduce new idiosyncratic unemployment shocks. The novelty is that idiosyncratic labor market shocks depend on both the industry in which households work and the region in which they live. On the one hand, households face four employment states, which are unemployment, and employment in one of the three industry groups with different job separation rates. On the other hand, even workers in the same industries may make different savings decisions depending on the region they live in. A household living in a region with a larger share of high-risk industries expects a higher probability of working in a high-risk job in the future. The geographical heterogeneity is crucial for two reasons. First, empirical evidence shows that the concentration of industries varies substantially across U.S. states. Second, spatial heterogeneity empowers the model to analyze the distributional effect of policies across regions. With parameters estimated using U.S. data, the model implies that the heterogeneous unemployment risk is large enough to induce precautionary savings and generate welfare losses for households exposed to higher job loss risk. The resulting savings gaps are more pronounced among the low-wealth group, which would not be observed in a single-sector model.

While the labor market specification is stylized, the endogenous interest rate setup is a critical feature of the model. With this framework, one can easily compare the differences in savings and welfare in an endogenous versus exogenous interest rate environment. In addition, this setup can also demonstrate how changes in separation rates change the endogenous interest rate. Furthermore, this framework enables a decomposition of credit policy shocks into two distinct channels, which are the exogenous reduction of credit limit and the endogenous decrease in the risk-free rate. Quantitative analysis demonstrates that this second channel is an important determinant of welfare outcomes.

In the policy experiments, I quantify the effects of credit tightening policy and interest rate changes on household dynamics. A 75% reduction in credit limits lowers the aggregate welfare by 5.4%. However, the welfare effects differ sharply across regions and industries. For instance, people living in a region concentrated in high-risk industries experience welfare losses, whereas those in more diversified regions experience welfare gains. The divergence reflects differences in baseline precautionary saving motives and endogenous interest rate responses to the credit policy change. In the baseline economy, households in diversified region save less, so tighter credit constraint encourage them to save more and raise welfare. By contrast, households in high-risk regions already hold more savings; the resulting increase in aggregate savings lowers the equilibrium interest rate, reducing returns for these net savers and generating welfare losses. Such cross-subgroup divergence can not be observed in a representative-agent model with a single-sector setup. In addition, while the credit shock reduces wealth inequality within regions, it exacerbates inequality across regions, highlighting the necessity of accounting for both sectoral and spatial heterogeneity in policy evaluation.

Literature Review The paper makes several contributions to the empirical and theoretical literature. Empirically, this paper integrates individual-level unemployment risk data, the U.S. geographical industry distribution data, and state-level savings statistics. With the data, the paper estimates job separation rates across industries and attempts to relate the labor market risks with household savings at a disaggregated level. To the author's knowledge, there is no other paper that quantifies the differences in job separation rates across industries and reveals the links between savings profiles and industry concentrations using disaggregated U.S. data.

Theoretically, this work contributes to the literature on a standard incomplete market model (SIM) with heterogeneous agents. As summarized by Heathcote et al. (2009), there are three dimensions to extending the SIM. The first dimension is the alteration of the idiosyncratic endowment shock. In the basic model setup, the endowment shock is exogenous. A few papers endogenize the endowment shock by introducing labor market decisions or search frictions, as seen in Heathcote et al. (2010), Guerrieri and Lorenzoni (2017), and Griffy (2021). Also, some papers introduce other market frictions, such as a consumption market friction by introducing service consumption (Huo and Ríos-Rull, 2015) or credit utilization frictions (Herkenhoff et al., 2016). Secondly, the model can be extended by introducing more insurance channels, including alternative assets to hedge against risks (Mian et al., 2013), intergenerational transfers, or government policy support. Lastly, the SIM can be enriched by adding interactions between idiosyncratic risks and aggregate dynamics as in Krusell and Smith (1998) and Kaplan and Violante (2018). This paper extends the model by broadening the dimension of idiosyncratic unemployment shocks with a sectoral approach and calibrates the model closely with micro-level data in the U.S.. The sectoral approach is beneficial to understand whether the sectoral differences are large enough to affect people's behaviors.

This paper's counterfactual analysis relates to research on financial frictions, which lead to persistent and amplifying effects of a shock as summarized by Brunnermeier et al. (2012). With an incomplete market, agents cannot insure against uncertain fluctuations in income, giving rise to additional precautionary motives. Much of the related work is associated with aggregate shocks, such as financial crises (Hall, 2011). Some papers focus on specific markets, such as the housing market collapse. Mian et al. (2013) investigates the impact of the housing market collapse on the geographical distribution of wealth and household balance sheets. Brunnermeier et al. (2012) also emphasizes that liquidity considerations become essential, and wealth distribution matters with financial frictions. This paper introduces financial frictions to a heterogeneous-agent model with an endogenous risk-free rate. With micro-level labor market risk, the paper can study the wealth distributions and welfare implications for subgroups of people, which are absent in a representative-agent model.

In addition, the paper's discussion on the credit crunch exercise is closely related to Guerrieri and Lorenzoni (2017), which studies the impact of a sudden borrowing capacity decrease on aggregate demand. Their framework assumes a standard idiosyncratic income process, and the probability of becoming unemployed is a uniform shock process across the economy. Alternatively, the risks in my paper come from labor market and is determined by both sector of employment and region of residence. This structured heterogeneity in my paper is based on the empirical quantification of sectoral risks. In addition, my paper's focus is not on aggregate dynamics, but the distributional impacts across population subgroups.

Further, this work relates to recent studies on labor market and credit policy. Rendon (2006) posits that more initial wealth and access to larger amounts of credit, increase wages and unemployment duration. In another paper, Herkenhoff et al. (2016) combines a heterogeneous-agent consumption-saving model with a searching and matching model in the labor market. This study demonstrates that young workers are more responsive to credit access and more credit access increases the unemployment spell. Herkenhoff (2019) indicates that expanded credit access to unemployment will affect the labor market searching and matching rate with two opposite effects. Griffy (2021) finds that poor people have more precautionary savings and are more likely to accept low-paid jobs. This paper assumes that the labor market dynamics remain unchanged after the shifts in credit constraints since the main focus of the paper is to evaluate the cross-industry and regional effects of the policy shocks.

This paper is organized into six sections. Section 2 presents the empirical motivations of the research question. A detailed presentation of the model and equilibrium is in Section 3. Section 4 describes model computation, calibration, and baseline model dynamics. Section

5 discusses the counterfactual. Section 6 concludes.

2 Empirical Motivation

In this section, I apply the U.S. micro-level data to document three salient patterns related to job separation risk and household savings behavior. Firstly, I demonstrate the heterogeneity of job loss probabilities in different sectors with controls for other key variables. Empirical evidence shows that some sectors, such as manufacturing, have significantly higher job loss probabilities than others. Secondly, I observe geographical differences in sector prevalence across the U.S. states. Lastly, the geographical sector dominance is statistically correlated with disaggregated household savings rates. These empirical observations motivate my model construction in Section 3.

2.1 Industry heterogeneity in unemployment shocks

The labor market risk I want to focus on is the probability of job loss. To show the heterogeneity of job separation risk across industries, I use the person-level survey data, Annual Social and Economic (ASEC) of the Current Population Survey (CPS) [2], from 1990 to 2022. Each individual in the survey can be identified by the person ID - "CPSIDP" and about half of the individuals are surveyed over two years. The advantages of using a person-level survey database are twofold. On the one hand, compared with an aggregate-level dataset, I can control for individual characteristics that might affect the probability of job loss. In addition, as opposed to other survey-based databases, ASEC data reports the industry codes of the job that lasted the longest in the previous year and that helps to identify the sector more accurately. The industry code identifier "IND90LY" is used for industry classification since it harmonizes different versions of industry codes, providing

[2]Data are sourced from Integrated Public Use Microdata Series (IPUMS) CPS data through `https://cps.ipums.org/cps/`(Flood et al.)

consistency from 1968 onwards. Detailed industry classification on the 1990 system is shown in Appendix B.

The empirical strategy is shown in the Equation 1. The dependent variable is either a binary dependent variable, which takes the value of 1 if being unemployed [3], or categorical variable representing the length of being unemployed [4]. $ind2$ and $ind3$ are two of the three defined industry groups, "Agriculture, some services and public sectors" and "Transportation, trade and main business sectors" respectively [5]. X contains other control variables related to individual characteristics, such as gender, education, and experience[6]. δ_t is the year fixed effect.

$$unem_{i,t} = \beta_0 + \beta_1 ind2_{i,t} + \beta_2 ind3_{i,t} + \alpha X_{i,t} + \delta_t + \sigma_{i,t} \tag{1}$$

Empirical results of the logistic regressions in the column (1) and (2) in Table 1 show that the default industry group, manufacturing and construction sectors, have higher odds of being unemployed compared to the other two groups. Specifically, as in Figure 1, the annual job loss probability in the manufacturing, and construction industry group is estimated to be around 0.27, which is statistically higher than those in the other two industries groups, which are 0.21 and 0.14, respectively.

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[3]Results showing in columns (1) and (2) in Table 1

[4]This variable inherently follows a sequence based on unemployment durations. I defined 4 levels of unemployment length. The value is 0 if an individual has zero weeks of unemployment. This value will be 1, 2, or 3 if the number of unemployed weeks is less than one quarter, less than two quarters, or more than half a year respectively. Results based on the unemployment length are reported in columns (3) and (4) in Table 1.

[5]I grouped all the 14 industries according to the Census industry classification into 3 industry groups based on their differences in job loss probabilities. Details on the classifications are shown in Appendix B

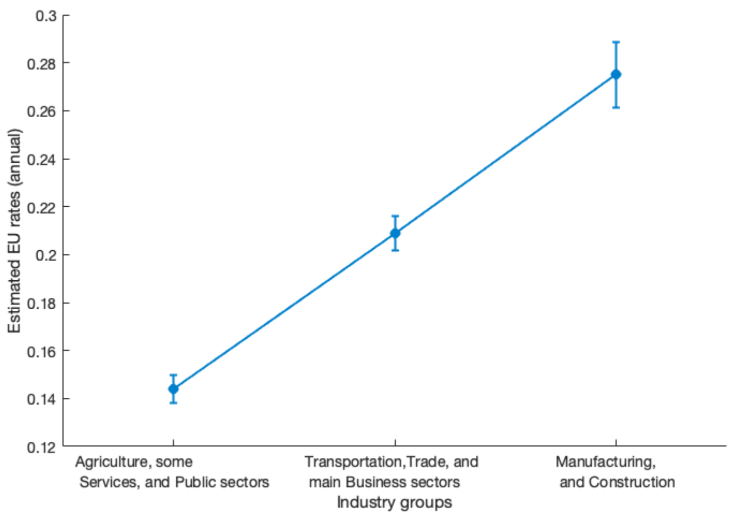
[6]Working experience is measured by $age - 16$.

Table 1: *Probability of job loss by industries*

VARIABLES	(1) Job loss probability	(2) Robust S.E.	(3) Unemployment length	(4) Robust S.E.	(5) Unemployment length	(6) Robust S.E.
Agriculture, some Services, and Public sectors	-0.8128***	(0.0420)	-0.7787***	(0.0412)	-0.7060***	(0.0192)
Transportation, Trade, and main Business sectors	-0.3619***	(0.0390)	-0.3185***	(0.0379)	-0.1988***	(0.0167)
Male	0.3177***	(0.0296)	0.3046***	(0.0294)	0.4297***	(0.0141)
Less than high school	-0.0896**	(0.0406)	-0.0847**	(0.0400)	-0.0202	(0.0194)
Some college	-0.3125***	(0.0367)	-0.3161***	(0.0361)	-0.1738***	(0.0170)
Bachelor's degree	-0.4053***	(0.0469)	-0.4221***	(0.0462)	-0.2761***	(0.0215)
Master's or more	-0.7447***	(0.0660)	-0.7485***	(0.0666)	-0.5660***	(0.0303)
Black	0.5396***	(0.0495)	0.5924***	(0.0496)	0.4466***	(0.0227)
Asian	0.1843*	(0.1103)	0.2287**	(0.1130)	0.0673	(0.0506)
Other single race	0.2618***	(0.0859)	0.2573***	(0.0825)	0.1422***	(0.0415)
Two or more races	0.2980**	(0.1430)	0.2406*	(0.1344)	0.3121***	(0.0707)
Potential experience	0.0548***	(0.0033)	0.0546***	(0.0033)	0.0679***	(0.0017)
Potential experience^2	-0.0014***	(0.0001)	-0.0013***	(0.0001)	-0.0015***	(0.0000)
Year fixed effect	Y		Y		Y	
Constant	-0.9942***	(0.0806)				
Observations	51,938		51,938		153,048	
Pseudo R^2	0.0715		0.0514		0.0533	

Heteroskedasticity-robust standard errors are reported in the parantheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Notes: columns (1) and (2) show the results of having the probability of unemployment as the dependent variable; columns (3) and (4) show the results of having the length of being unemployed. The default industry group 1 includes the manufacturing and construction sectors. Each observation in the regression is a person in the survey. Regressions are adjusted using ASEC weights.

Figure 1: *Estimated effects on job separation probabilities by industry groups*



Notes: The figure plots the predicted probabilities and their 95% confidence intervals.

In addition, people working in the manufacturing and construction sectors not only have a higher probability of losing their jobs but also spend a longer time finding a new job after a layoff. Columns (3) and (4) in Table 1 present the results of an ordered logistic regression by having the categorical unemployment duration variable as the dependent variable in the equation 1. Consistent with the previous results, compared with the reference industry group, the two other industry groups exhibit statistically significant shorter unemployment spells. Noticeably, the rank of the first two coefficient values in column (3) is the same as that in column (1). In other words, if people work in an industry group that has a higher job loss probability, they will also need to spend more time finding a new job after being laid off. So, for people working in the manufacturing and construction sectors, it is more likely to lose a job and will take more time to reenter the job market after becoming unemployed.

Based on the empirical evidence, I define the three industry groups as high-risk industries, medium-risk industries, and low-risk industries, and the details of the classification are in the appendix Table B.1.

2.2 Geographical heterogeneity in industry shares

Across the U.S., the prevalence of the high-risk industry group is quite different. With county-level employment data from the Quarterly Census of Employment and Wages (QCEW) database, I calculate average state-level high-risk industry group shares[7].

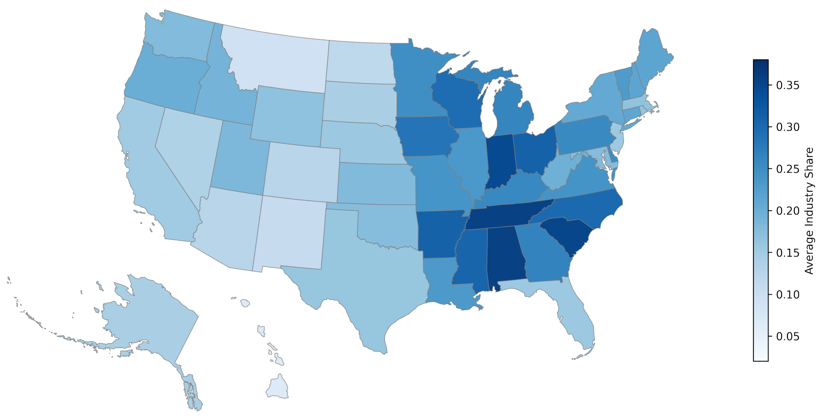
The geographical industry distribution map is presented in Figure 2. The high-risk industry employment share is quite dispersed, with the highest at 35.7% and the lowest at 1.5%. Specifically, over 33% of the people are employed in the high-risk industry group in some states in the South and Midwest, such as Alabama, Tennessee, and Indiana. While the share of high-risk industry employment is below 10% for states such as Hawaii and New Mexico.

With this observation, I rank the 50 U.S. states and D.C. based on their shares of high-risk industry employment and define three region groups. The "Vulnerable Region"

[7] Industry codes in the QCEW follow the North American Industry Classification System (NAICS). The matching between NAICS and the Census industrial classification is explained in the Appendix C.

contains the top 6 states in the list, whose high-risk industry share is above 31%, and are assumed to be exposed to job separation risks to the largest extent. The bottom 6 states are grouped as the "Diversified Region", whose shares are less than 12% and have a more diversified industry composition. The states ranked in the middle are classified as the "Stable Region".[8,9]

Figure 2: *Geographical difference of employment in high-risk industries*



Notes: The map shows the 50 U.S. states and one federal district, Washington, D.C. The color bar on the right shows the share of high-risk industries (including manufacturing and construction industries). The darker shades indicate a higher share.

2.3 Different savings behaviors across the U.S. regions

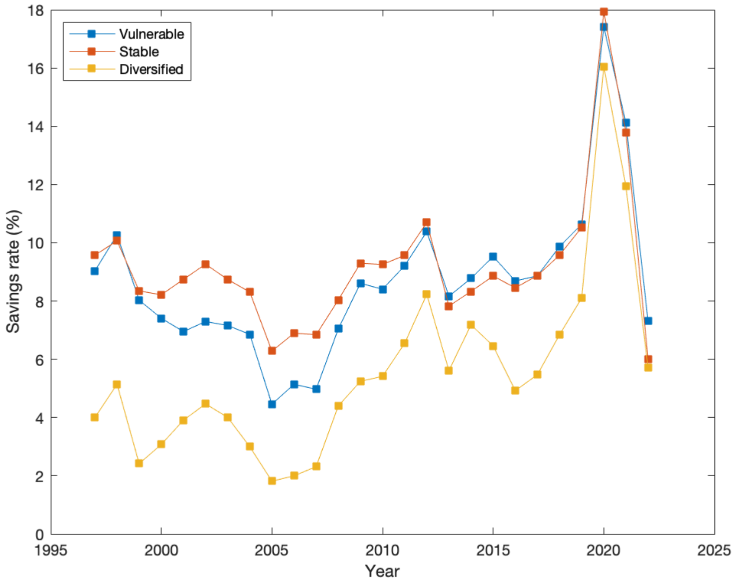
This section seeks empirical evidence on the correlation between regional labor market risk and savings behavior. Figure 3 plots savings rates across the defined regions. With the state-level savings rate series, I find that the diversified region, defined as being exposed to the smallest labor market risk, tends to have the lowest savings rate among all three regions over time, although the differences between the vulnerable region and the stable

[8]The classification of regions group is not affected by taking average shares over time. As shown in Figure D.1 in the Appendix D, the ranking remains the same over time, which means the high-risk industry is prevalent in the vulnerable region over time.

[9]List of states in each region group is exhibited in Table D

region seem small.

Figure 3: *Savings rate across regions over time*



Notes: State-level disposable personal income and personal consumption expenditures data is collected from the U.S. Bureau of Economic Analysis (BEA). The savings rate is defined as the percentage of disposable income that people leave after personal spending following BEA's definition. The state-level savings rate is calculated by the author. The region-level savings rate is weighted by the population of each state. Data is plotted from 1997 to 2022.

To control for other factors that might affect the savings rate, I follow the empirical strategy detailed in the Equation 2. The regression is run on a constructed state-level panel dataset. The dependent variable is the savings rate of each state. I set the vulnerable region as the reference region, such that $Reg2$ and $Reg3$ represent the stable region and the diversified region, respectively. Control variables, embedded in Xs, include state-level education, gender, and age profiles which are from the U.S. Census [10] as well as disposable income. I use the 5-year estimates for these variables and take the last year of the 5-year range as the year in regression. For instance, if it is a 2006-2010 estimate, I treat it as the data for 2010. The control variable also has state-level unemployment which is from the

[10] I use the IPUMS National Historical Geographic Information System (NHGIS) database Manson et al. (2023) to collect the data.

U.S. Bureau of Labor Statistics (BLS).

$$saving_{i,t} = \beta_0 + \beta_1 Reg2_{i,t} + \beta_2 Reg3_{i,t} + \alpha X_{i,t} + \delta_t + \sigma_{i,t} \tag{2}$$

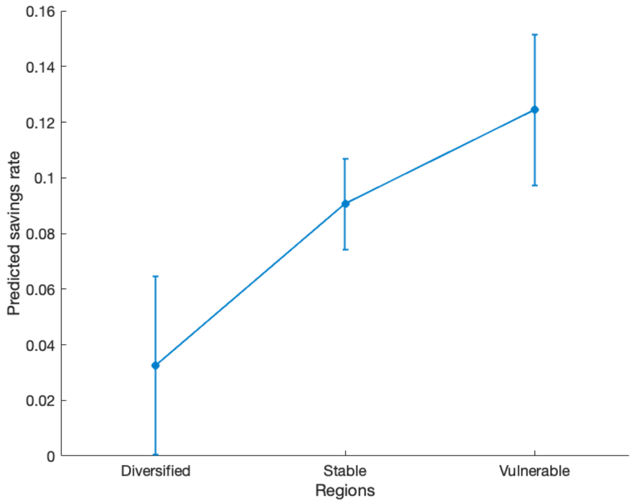
After controlling for state-level characteristics and year fixed effects, the savings rate in the diversified region is 9.19% lower, and that in the stable region is 3.38% lower than that in the vulnerable region (as shown in Table 2). Both coefficients are statistically significant. This implies that higher exposures to job separation risks is correlated with higher savings rates in the U.S. states. The correlations across regions are more different when the industry share differences are more salient (for instance, the marginal effects difference between the vulnerable region and diversified region is the largest as shown in the Figure 4).

Table 2: *Savings rate by defined regions*

VARIABLES	(1) Coefficients	(2) Robust S.E.	(3) Coefficients	(4) Robust S.E.
Stable region	-0.0338*	(0.0177)	-0.0365**	(0.0181)
Diversified region	-0.0919***	(0.0270)	-0.0917***	(0.0274)
Percentage male	2.585***	(0.900)	2.764***	(0.904)
Percentage high school	-0.875***	(0.259)	-0.811***	(0.259)
Percentage some college	-0.296	(0.280)	-0.207	(0.294)
Percentage bachelor's degree	-0.521	(0.342)	-0.523	(0.337)
Percentage master's or more	0.171	(0.275)	0.299	(0.288)
Percentage age 25_34	0.669	(0.445)	0.606	(0.440)
Percentage age 35_44	1.228***	(0.444)	1.217***	(0.430)
Percentage age 45_64	1.006**	(0.505)	0.929*	(0.503)
Percentage age 65 and above	1.655**	(0.646)	1.706***	(0.642)
Unemployment rate	-0.667***	(0.141)	-0.633***	(0.139)
Disposable income			2.18e-08	(2.11e-08)
Year fixed effect	Yes		Yes	
Constant	-1.635***	(0.602)	-1.755***	(0.610)
Observations	510		510	
Number of states	51		51	

Heteroskedasticity-robust standard errors are reported in the parantheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Notes: Each observation in the regression is a state. So the demographic characteristics, such as gender group, age group or education groups, are calculated as the ratio of the group to the total population in a state. The reference region is the vulnerable region. The reference age group is from 18-24. The reference education group is less than high school. Regression is run on data from 2010-2019. (The Census data starts from 2010. Also, I exclude the post-COVID period since the savings behaviors have changed significantly.)

Figure 4: *Marginal effects on savings rate by region*



Based on the empirical analysis, it is shown that there are significant differences in job loss probabilities across industries. Moreover, the geographical coincidence of the labor market risk and the savings behaviors indicates that this labor-market-related risk might be an important channel to affect households' savings motives when looking at the disaggregated subgroup of people. Inspired by the empirical evidence, I construct a theoretical model below with both sector heterogeneity and region heterogeneity to study the general dynamics in the system.

3 Model

3.1 Model Environment

3.1.1 Setting

The structural framework extends the canonical incomplete markets environment with heterogeneous agents developed by Huggett (1993). To align the model with the stylized facts identified in Section 2, I introduce four critical modifications from the standard setup. First, the idiosyncratic shock process is expanded to a four-state Markov chain. The four states are unemployment, employment in high-risk sectors, employment in medium-risk sectors, and employment in low-risk sectors. The risk is measured by the probability of job loss if employed in that industry. Second, to account for spatial heterogeneity, I construct different employment-based transition matrices to capture region-specific labor dynamics. The regions are classified based on the share of high-risk sectors, allowing for a granular mapping of sectoral composition to local employment volatility. Third, the paper incorporates an exogenous migration process, permitting inter-regional labor mobility. This is essential because it prevents the mismeasurement of long-term risk. Without migration, the model would overstate the hardship in high-risk regions and understate the risk in low-risk regions by assuming households stay there forever. Allowing agents to move through different regions creates a more realistic lifetime risk profile, highlighting how regional heterogeneity actually impacts households as they transition across the national economy. Fourth, households in each region make their own saving decisions based on the region-specific labor market risk exposures with the asset market clearing at the national level. Last but not least, the paper introduces y_{min}, which measures the value of home production or leisure.

3.1.2 Households' problem

Consider an economy with a continuum of infinitely-lived and risk-averse agents with total mass equal to one. The households want to maximize their lifetime utility function [11]:

$$\max_{c_t, a_{t+1}} E_0 \left[\sum_{t=1}^{\infty} \beta^t u(c_t) \right] \tag{3}$$

subject to budget constraints:

$$c_t + q_t a_{t+1} \leq a_t + y_t$$

[11] Utility function: $U(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$, where $\sigma > 1$.

$$c_t \geq 0; q_t > 0$$

$$a_{t+1} \geq -\underline{a}, \text{ given } \underline{a} \geq 0,$$

where $\underline{a}$ sets the credit limit of an indebted agent. In an incomplete market, there is only one risk-free asset and q_t is the price. y_t represents households' income in each period and income is state-contingent. Specifically, $y = \xi W + (1-\xi) y_{min}$, where W is an economy-wide constant wage income, ξ is the dummy for employment, and y_{min} is the value of home production or leisure.

$$\xi = \begin{cases} 0, & \text{if unemployed} \\ 1, & \text{if employed in any industry} \end{cases} \tag{4}$$

So, if unemployed, households only receive the value of leisure, y_{min}. If employed, households only receive a wage income of W no matter which industry they are in.

3.1.3 Government

In the model, the government can impose policies to change credit conditions or directly affect asset prices. In the baseline economy, the government determines the credit limit but does not influence asset prices, which are endogenously determined by households' saving decisions. In Section 5.1, I examine a policy where the government tightens the credit limit. In Section 5.2, the government sets the price of assets.

3.1.4 Transition matrices

Employment status. Each agent's employment status follows a Markov process that is independent of other agents. There are four employment states in the economy: unemployed (u), employed in high-risk sectors (e_h), employed in medium-risk sectors (e_m), and employed in low-risk sectors (e_l). The state variable to indicate their employment status is, $\epsilon = \{u, e_h, e_m, e_l\}$. Thereby, the unemployment risk for people in region i is described by a transition matrix π, which has the below presentation:

$$\begin{bmatrix} \pi_{u,u} & \pi_{u,e_h} & \pi_{u,e_m} & \pi_{u,e_l} \\ \pi_{e_h,u} & \pi_{e_h,e_h} & 0 & 0 \\ \pi_{e_m,u} & 0 & \pi_{e_m,e_m} & 0 \\ \pi_{e_l,u} & 0 & 0 & \pi_{e_l,e_l} \end{bmatrix}_i \tag{5}$$

Earning risk in this model comes from the chance of job loss. Transition probability $\pi(\epsilon_{t+1}|\epsilon_t)$ captures the stochastic process. This model does not allow on-the-job search, so the job-to-job transition probabilities are zeros. Each region i has a separate transition matrix.

Mobility. There are three types of region in the economy, which are vulnerable, stable, and diversified, ranking by the share of employment in high-risk industries. The vulnerable regions have the largest share of high-risk industries, thus households living in those regions have a larger probability of working in the high-risk sectors. In each period, households face an exogenous probability, $m(i, i')$, of moving to another region. I assume the moving probability to be exogenous instead of an endogenous decision for the following reasons. On the one hand, inter-region migration is not the main focus of this paper. The purpose of incorporating regional mobility is to avoid overestimating or underestimating the risk faced in any given region, and the exogenous moving probability is sufficient to achieve this. On the other hand, empirical evidence suggests that only 1.15% of the population moves out of their current region. For those who move, fewer than half do so for work-related reasons. Details on the empirical evidence are in the Appendix E.

3.2 Equilibrium

3.2.1 Probability measure

The individual state is defined by (a, ϵ, i), which are households' asset holdings, employment status, and current region. Define the compact set $A \in [-\underline{a}, a_{max}]$ for asset holdings and the countable set E and R for all possible idiosyncratic employment shocks, which are u, e_h, e_m, e_l and current regions, which are r_v, r_s, r_d. Define the Cartesian product as the state space, $S \equiv A \times E \times R$ with Borel σ algebra $\mathcal{B}$. Individuals, in each region i, transit across states following the transition function, $Q_i((a, \epsilon, i), A \times E \times R)$, which gives the transition probabilities. Formally, Q: $S \times \mathcal{B} \to [0, 1]$ and

$$Q((a, \epsilon, i), A \times E \times R) = \sum_{\epsilon' \in E, i' \in R} I\{a'(a, \epsilon', i') \in A\} m(i, i') \pi_{i'}(\epsilon, \epsilon')$$

where I is the indicator function. $a'(a, \epsilon', i')$ is the optimal saving policy function. $m(i, i')$ is the moving probability from region i to i'. $\pi_{i'}(\epsilon, \epsilon')$ is the transition probability from the current employment status ϵ to another in the new region i'.

3.2.2 Recursive competitive equilibrium

The households' problem in recursive form can be written as:

$$v(a, \epsilon, i; q) = \max_{a'} \{u(c) + \beta \sum_{\epsilon' \in E; i' \in R} m(i, i') \pi_{i'}(\epsilon, \epsilon') v(a', \epsilon', i'; q)\}$$

$$s.t. \qquad c + qa' = a + y(\epsilon)$$

$$a' \geq -\underline{a}$$

Let s summarize the possible states$(a,\ \epsilon,\ i)$. The recursive competitive equilibrium can then be defined by a value function v, policy functions for asset holdings a' and consumption

c, a constant asset price q, and a stationary probability measure λ^*, such that the following conditions hold:

- Households optimization: given asset price q, households make the optimal decisions on a' and c to maximize their value function v.
- λ^* is a stationary probability measure. It is the sum of stationary probability measures for each region weighted by the share of employment in each region with a moving probability across regions.
- Market clearing conditions: (1) Goods market clearing: $\int_s c(s)d\lambda^*(s) = \int_s y(s)d\lambda^*(s)$; (2)Asset market clearing: $\int_s a'(s)d\lambda^*(s) = 0$.

4 Model Quantification

4.1 Calibration

To solve the model outlined in the previous section, parameters are assigned or estimated from data as reported in Table 3 and Table 4. The frequency of the model in the numerical simulation part is a quarter. The discount factor is set to be 0.99, corresponding with the annual discount rate of 0.96. Utility function parameters, the value of leisure[12], and borrowing constraint is selected as other literature normally do. Wage income is normalized to 1 without the loss of generality.

[12]I use this value for the value of leisure also because the average U.S. replacement rate between 2000-2019 is 0.4 according to the UI Replacement Rate Report by the U.S. Department of Labor.

Table 3: *Assigned Parameters*

Parameter	Description	Value	Source
β	Discount factor	0.99	
σ	Utility function parameter	1.5	Huggett (1993)
W	Earnings if employed	1	Huggett (1993)
$\underline{a}$	Borrowing constraint	8	Huggett (1993)
y_{min}	Value of leisure	0.4	Shimer (2005)

Parameters in Table 4 are estimated from survey data. The quarterly UU rate and separation rate are estimated using the monthly CPS dataset. The advantage of using the database instead of the ASEC data as in the empirical section is that it has a higher frequency. The ASEC data might overestimate the quarterly separation probability since even one-day unemployment is marked as 1 in the dataset. With the monthly CPS data, I can calculate the quarterly transition probability based on the employment status in the first month of each quarter. Estimations are done for each industry group and are adjusted by the harmonized weight "LNKFWMIS14WT1" for the first four months of the panel rotation. Industry share data comes from QCEW database. Industry codes in the QCEW follow NAICS and the matching between NAICS and the Census industrial classification is explained in the Appendix C. Industry shares in each region are calculated by the average share of employment from 1990 to 2022 for each state. National average moving probabilities between regions are estimated from the "migrate1" in the ASEC from 2010 to 2019. The annual moving probabilities from the data are transformed into quarterly frequency.

Table 4: *Parameters estimated from the data*

Parameters		High-risk industries	Medium-risk industries	Low-risk industries	Data sources
Industry share, $share_{i,j}$	Vulnerable region	0.338	0.287	0.375	
	Stable region	0.207	0.34	0.453	
	Diversified region	0.088	0.289	0.623	QCEW
Separation rate, $l_{i,j}$	Vulnerable region	0.032	0.032	0.022	
	Stable region	0.033	0.03	0.023	
	Diversified region	0.033	0.028	0.02	CPS
UU rates, uu_i	Vulnerable region		0.508		
	Stable region		0.492		
	Diversified region		0.453		CPS
Moving probabilities, $m(i, i')$	Stay in the same region		0.9970		
	Move to another region		0.0015		ASEC

4.1.1 Transition matrices

Employment status. With the estimated UU rates and separation rates, the transition matrix for each region can be constructed respectively. Suppose each region has subscript i, and each industry has subscript j. Indicators estimated for calibration are the region-specific UU rate, uu_i, the region-specific job-losing rate for each industry, $l_{i,j}$, and region-specific industry share, $s_{i,j}$.

There are four employment-related states in the economy: unemployed, employed in high-risk industry, in medium-risk industry, and in low-risk industry.

$$\begin{bmatrix} uu_i & (1-uu_i)*s_{i,1} & (1-uu_i)*s_{i,2} & (1-uu_i)*s_{i,3} \\ l_{i,1} & (1-l_{i,1}) & 0 & 0 \\ l_{i,2} & 0 & (1-l_{i,2}) & 0 \\ l_{i,3} & 0 & 0 & (1-l_{i,3}) \end{bmatrix} \tag{6}$$

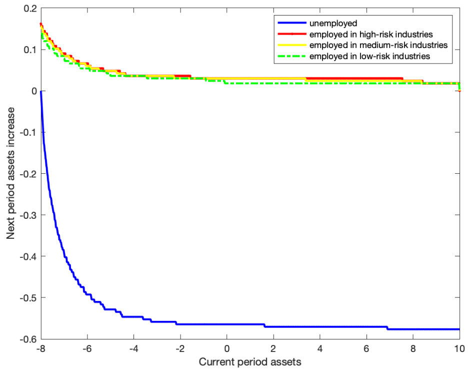
Mobility. I assume the exogenous moving probabilities are homogeneous across regions. Specifically, the probability of staying in the same region is 0.9970. With that, I assume it is equally likely to move to either of the regions. I could estimate the region-specific moving probabilities among the three regions, which also has the same feature that the probability of staying in a region is pretty high, being 0.992 or more. However, if I calibrate the model with the actual region-specific data, it is less computationally feasible. Given that this is not the main focus of the paper and the moving probabilities are pretty small numbers, I simplify this assumption by applying homogeneous moving probabilities across regions.

$$\begin{bmatrix} 0.9970 & 0.0015 & 0.0015 \\ 0.0015 & 0.9970 & 0.0015 \\ 0.0015 & 0.0015 & 0.9970 \end{bmatrix} \tag{7}$$

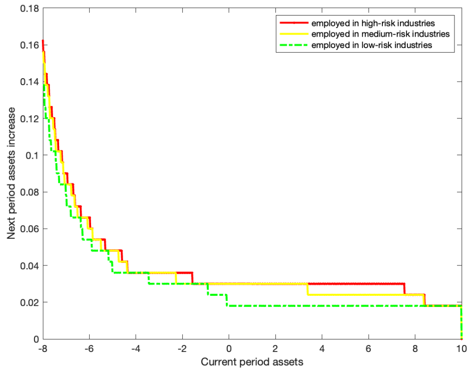
4.2 Model dynamics

Figure 5a plots the policy functions for households across different employment states in the baseline model. The unemployed do not earn wage income and always borrow in the next period until they hit the borrowing limit. In addition, for the unemployed, the wealthier they are, the more they tend to borrow in the next period as they are less constrained by the borrowing limit. In the extreme case where the unemployed hit the borrowing constraint, they cannot borrow further. Similar to the patterns for the unemployed workers, the wealthier the employed households are, the less they save. Different from the unemployed, the employed households are net savers, as they accumulate assets to insure against potential unemployment risk and smooth consumption. Within the employed (shown in Figure 5b), people working in high-risk industries, who face the highest job separation risks, save no less than those working in lower-risk industries across all wealth levels. That means that when households are poorer, the different job loss probabilities across regions has a more sizable impact on the precautionary savings behavior. This also implies the importance of checking the across-sector differences in job loss probabilities.

Figure 5: *Policy functions in the baseline model*



(a)



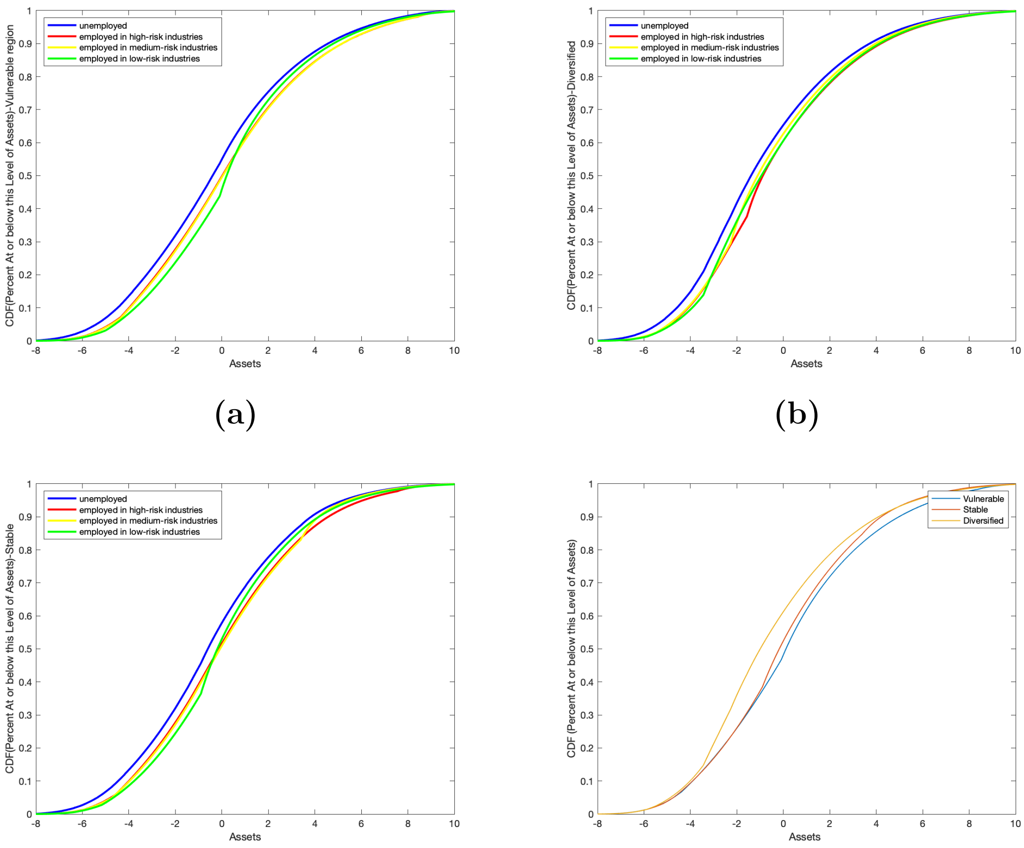
(b)

Notes: The above chart shows the baseline estimations for the average of three regions. Taking the average does not change the patterns if looking at each region separately.

Figure 6 depicts the cumulative asset distribution comparisons across employment states as well as across regions. The subfigures 6a, 6b, and 6c plot the cumulative asset holdings across different employment states in all three regions separately. In all regions, the unemployed household saves the least (borrows the most) since they do not earn wage income, and the income effects dominate. The cumulative distribution function (CDF) comparisons for the employed are more subtle. For the indebted group of people, there are slightly more people working in the high-risk or medium-risk industries than those in the low-risk industries. That is because people working in high-risk industries have higher risks of losing jobs, and when the income effect dominates, more households borrow. For the wealthier group, people tend to save more when they face higher job risks due to precautionary saving motives.

In addition to the common patterns mentioned above regarding the subplots 6a, 6b, and 6c, the distributions across employment states are a little bit different for each region. The heterogeneity in the gaps can be jointly explained by variations in the separation rates across industries and the industry shares across regions. For instance, in the vulnerable region (Figure 6a), the estimated separation rates of the high-risk industries and medium-risk industries are the same, so the differences in CDF only come from industry share differences. That is why the asset CDFs are quite similar for high-risk and low-risk industries.

Figure 6: *Asset CDF comparisons across industries and regions*

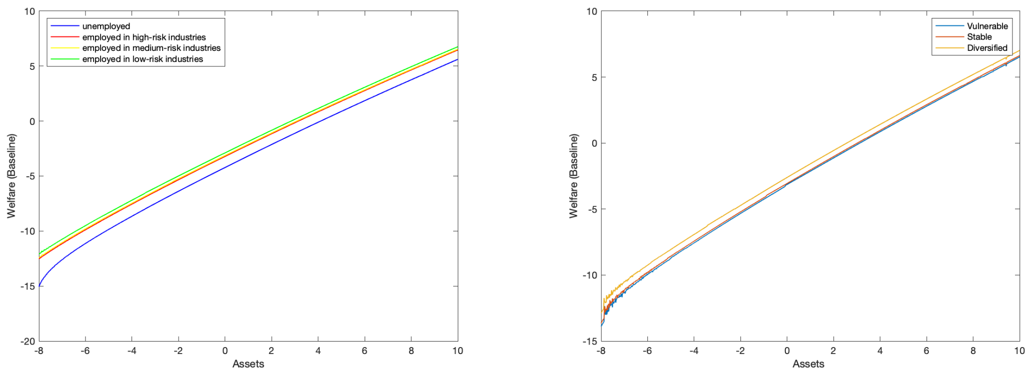


(a) **(b)** **(c)** **(d)**

The subplot 6d compares asset CDFs across regions. As the share of high-risk industries increases, households tend to save more since they have a higher probability of working in high-risk industries and face a higher probability of losing their jobs. So, the precautionary saving motives are the strongest in the vulnerable region and the least in the diversified region.

Plots in Figure 7 compare the average present discounted values for people with particular asset levels across employment status and regions, respectively. In Figure 7a, households with the same level of assets will have relatively higher values as the unemployment risk goes down. Similarly, in Figure 7b, people living in the diversified region have much higher values for any given level of current assets. This is because the diversified region has the least share of high-risk industries, where agents face the lowest probability of working in a high-risk sector thus facing a lower probability of job loss.

Figure 7: *Present discounted value comparisons*



(a) (b)

To sum up, the baseline model successfully shows the existence of precautionary saving motives due to heterogeneous job separation risks. The heterogeneity in the labor market risk comes from both the industries households are working in and the region they reside in. When households are employed, in the absence of wage differences as assumed in the model, households save more with higher labor market risks. The differences are larger for the poor group. This can only be seen from a model with a multi-sector feature. Higher unemployment risk is worsening the welfare (calculated by the present discounted value) given the same level of initial wealth. Geographically, people living in the vulnerable region tend to save more to insure against future job uncertainties and have lower present discounted value. The model dynamics confirm that industry-specific and region-specific labor market risks can have noteworthy impacts on households' consumption and savings behaviors.

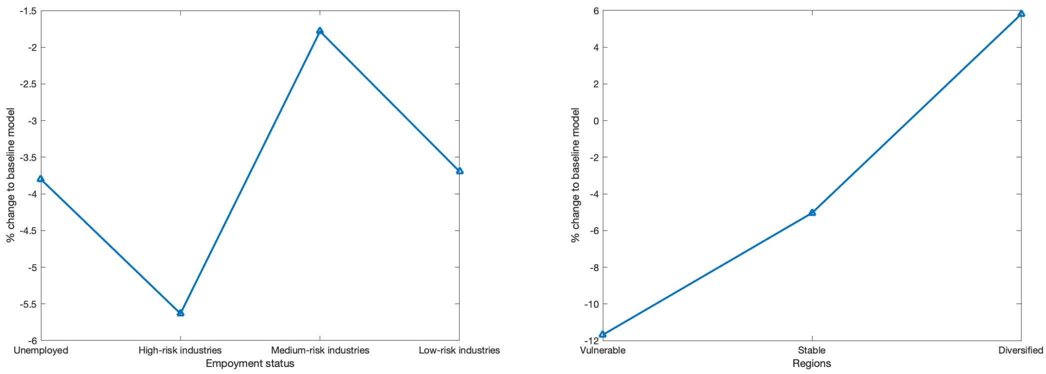
5 Policy Experiment

5.1 Credit crunch

This section analyzes the transitional dynamics following a sudden and permanent contraction of the borrowing limit. Consistent with the findings of Guerrieri and Lorenzoni (2017), this credit shock forces indebted households to deleverage while prompting unconstrained agents to increase their precautionary savings. However, my framework extends this analysis by exploiting the model's granular structure to investigate the distributional consequences across distinct sub-populations. While existing studies typically rely on generic income shocks, this paper explicitly distinguishes between sectoral and regional labor risks. By modeling the transition between employment states (unemployment vs. high-, medium-, and low-risk sectors) across heterogeneous regions, I can isolate how credit tightening interacts with specific job-separation risks. This allows for a more nuanced understanding of how credit crises propagate through different segments of the labor market.

I arbitrarily shrink the borrowing limit from 8 to 2 to study the impact of a credit crunch. Figure 8 presents the aggregated welfare percentage changes to the baseline case across employment status or regions. Figure 8a infers that households in all employment states suffer welfare losses. Surprisingly, workers in high-risk industries experience larger welfare losses than the unemployed. Because the high-risk industry workers are net savers, whereas unemployed households are net borrowers (as shown in Figure 5a), the decrease in the endogenous interest rate following credit tightening makes high-risk industry workers worse off. Figure 8b shows that aggregate welfare increases for people in the diversified region as the policy shock motivates them to save more. The welfare decreases in vulnerable region since the endogenous interest rate decreases with bigger saving motives. The various welfare changes confirm the value of considering region-specific and industry-specific heterogeneity in this paper.

Figure 8: *Welfare comparisons with credit crunch*



(a) **(b)**

This model setup allows for a detailed examination of impacts by industry and region. As illustrated in Figure 9a, which plots region- and sector-specific welfare changes, the variation across regions is more pronounced than the heterogeneity across industries. Furthermore, the sectoral impact is conditional on the regional context. For instance, in the stable region, where the share of three industries is more balanced, welfare decreases in all sectors but the magnitude is small and similar across industries. By contrast, the welfare consequences in the other two regions are more imbalanced. In the vulnerable region, the high concentration of high-risk sectors initially drives a stronger motive for precautionary savings. Following the credit crunch, the general equilibrium effect leads to a lower risk-free interest rate to discourage excessive saving. This decline in the rate of return on assets disproportionately penalizes households in these high-risk areas, driving the observed welfare losses.

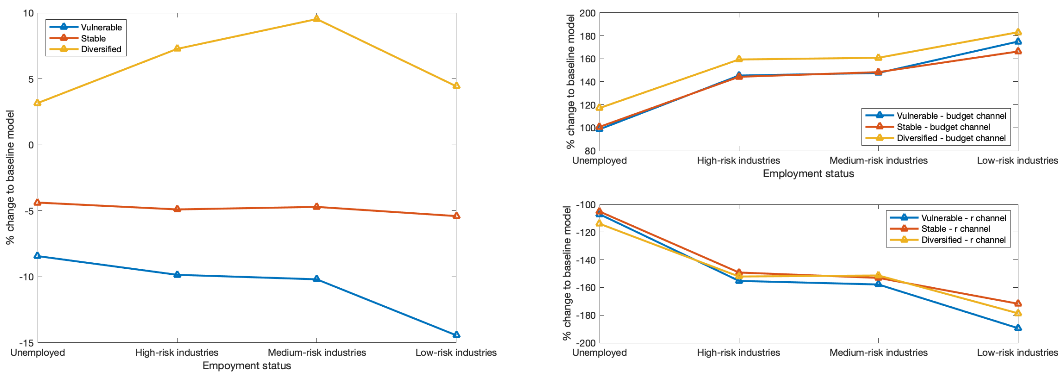
Another way of decomposition is to separate the effect of the credit crunch policy into two channels: the exogenous tightening of credit limit[13] and the endogenous decrease in the risk-free rate [14]. Figure 9b attempts to show the two results. In the top plot, I keep the risk-free rate at the baseline level and only allow the budget constraint to shrink. The exogenous budget channel increases the welfare of all regions since all households are forced to save more either due to

[13]From -8 to -2 based on the model assumption on the credit crunch case.

[14]The equilibrium risk-free rate decreases from 4.07% in the baseline model to 3.37% in the credit crunch case.

binding credit limits or precautionary motives. This process is costly as the interest rate is kept exogenously high as in the baseline level with effective extra pay from the fed to the economy. The diversified region has the largest increase in welfare across all employment states since they did not save as much in the baseline case. In the bottom plot of Figure 9b, I am showing the effect of the second channel, which is calculated by taking the difference between the total welfare effects of the credit crunch policy and the first channel's effects. The endogenous risk-free rate will decrease the welfare of all three regions since it aims to prevent excessive savings. Across regions, since the vulnerable region has the strongest saving motives, the welfare decrease is the most. Across employment states, the unemployed, who tend to be more credit-constrained, benefit from the decline in the interest rate, as it reduces their financing rate. Consequently, the reduction in their borrowing costs mitigates their overall welfare loss relative to other groups. Similarly, people working in the low-risk industries have the largest welfare loss as they are net savers.

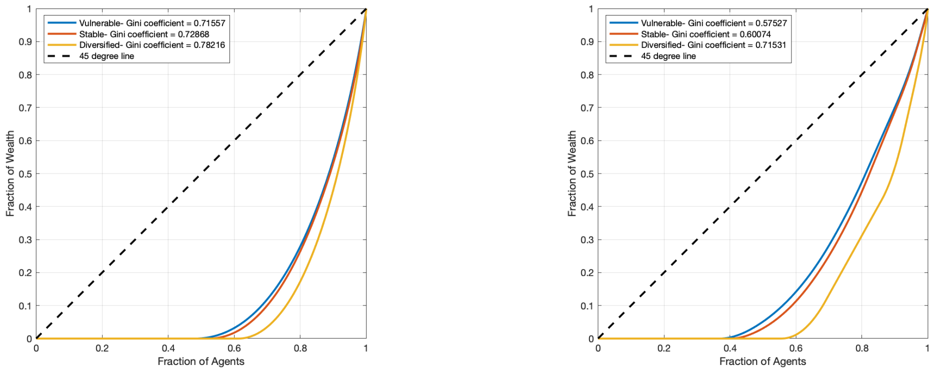
Figure 9: *Welfare comparisons with credit crunch - details*



(a) **(b)**

Wealth inequality is improved with credit crunch at the aggregate level as well as in each region. However, the gaps across regions have been enlarged. Figure 10 reports the Gini coefficient comparison between the baseline case (Figure 10a) and the policy change case (Figure 10b). Figure 10 illustrates that the region with the least share of high-risk industries, the diversified region, has the largest wealth inequality compared to the other two regions. Meanwhile, wealth inequality is improved with the credit crunch policy for all three regions. However, the inequality across regions is enlarged with a tighter credit constraint since the gaps between lines in Figure 10b become larger than those in Figure 10a.

Figure 10: *Gini coefficient across regions*



(a) **(b)**

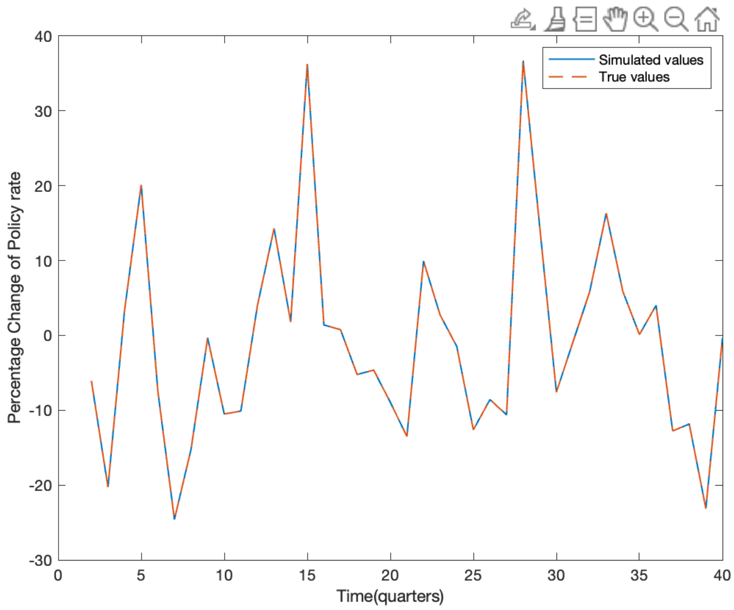
5.2 Simulation with risk-free rate during 2010-2019

All previous sections considered a fully endogenous risk-free rate. This section simulates the savings behavior when the government changes rates. I assume the government can impose certain risk-free rates by compensating the net asset gap to achieve asset market clearing. As a result, the risk-free rate is exogenous when solving the model in this policy experiment.

In the baseline model, the annualized risk-free rate is about 4.07%. I use this as the starting point and simulate the model according to the rate changes of 10-year U.S. treasury securities from 2010q1 to 2019q4[15]. At period zero, the economy is assumed to be in baseline equilibrium. The policy rate patterns are shown in Figure 11.

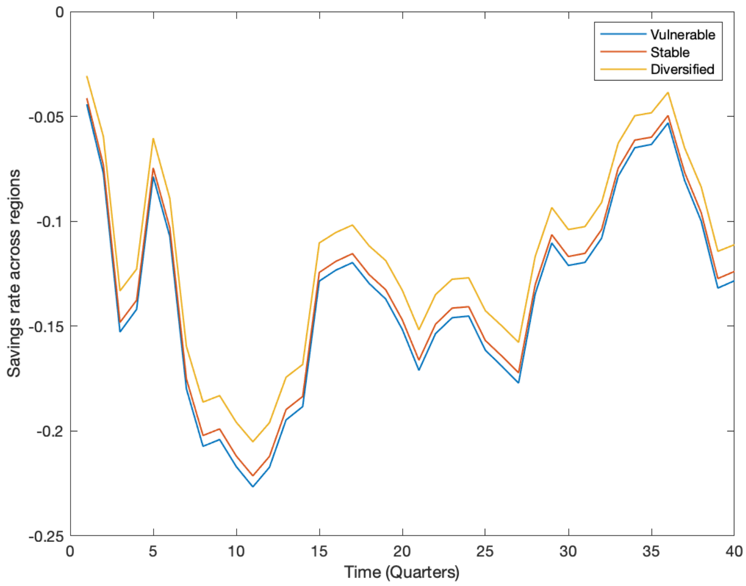
[15]Board of Governors of the Federal Reserve System (U.S.), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis [DGS10], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10, April 2024.

Figure 11: *Rate changes during the period*



The savings rate is calculated by the change of asset holdings in each period as a fraction of the income in that period. Consistent with the actual data, the vulnerable and stable regions' savings rates are very close to each other and quite different from those in the vulnerable region as in Section 2.3 Figure 3. This might be closely related to the fact that the actual job separation rates are very close in the two regions. So this could provide evidence of the importance of job separation rates as a channel to affect savings behavior. However, the simulated savings rates are all negative (shown in Figure 12) which does not match the real data. The model economy exhibits aggregate borrowing because the interest rate is exogenously set by the government. As a result, the government must provide additional transfers to clear the asset market.

Figure 12: *Simulated savings rates over time*



6 Conclusion

This paper investigates how the heterogeneity in job loss risk across industries and regions shapes households' savings behavior, welfare, and wealth inequality. Using micro-level data and an extended heterogeneous-agent model, the paper shows that precautionary savings are significantly driven by geographic and sectoral exposure to labor market risks. Furthermore, the analysis reveals that the welfare consequences of credit shocks vary substantially across population subgroups.

The empirical analysis quantifies substantial differences in job separation rate across industries, the uneven concentration of these industries across the U.S. states, and variations in saving rate across regions with distinct risk profiles. Motivated by the empirical evidence, I construct a heterogeneous-agent equilibrium model to study the impact of labor market risks on households' saving behaviors and wealth distributions. With the model parameters estimated from U.S. data, the model proves that the heterogeneity in job separation risks are large enough to affect households' savings behavior and welfare. Notably, the saving differences across industries are more salient for the low-wealth households.

Furthermore, the model's endogenous interest rate setup proves to be an important channel for the transmission of credit shocks. While a credit crunch reduces aggregate welfare, the resulting decline in the endogenous risk-free rate acts as a partial buffer for the most vulnerable households. This highlights a channel commonly overlooked in models with exogenous interest rates. In addition, although the aggregate inequality is improved with the credit shocks, the inequality gaps among population subgroups are widened. These results confirm the significance of a sectoral and regional approach when studying the distributional consequences of labor market risk.

The developed framework provides a way to view the long-term structural shifts. For instance, with technology development and structural reforms, industry shares in each region keep changing over time (as shown in Figure D.1). This proposed model can help to evaluate how this change can affect the endogenous risk-free rate and imply the heterogeneous distributional effect of the policies. Further research could extend this analysis by homogenizing job search behavior or exploring feedback loops between firm dynamics and regional labor supply.

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A Computation procedures

There are 1000 grid points for assets. Steps to compute equilibrium to the calibration model are described below.

1. Given price q, compute policy function $a'(a, \epsilon', i')$ and iterated value function v for each region.

2. Given $a'(a, \epsilon', i')$, iterate on the probability measure, λ, until it converges.

3. Given $a'(a, \epsilon', i')$ and λ^*, check for the national-level asset market clearing.

4. Update q and repeat previous steps until the asset market is cleared at the national level.

B Detailed industry codes based on the 1990 Census Bureau industrial classification system

The 1990 basis industry codes are developed to enhance the comparability of industry data in historical U.S. census samples in IPUMS-USA. The re-coded classification system also provides a consistent set of industry codes for IPUMS-CPS from 1968 onward. Detailed industries are shown in the left column in Table B.1 and more can be found on the IPUMS website.

Table B.1: *List of industries and defined industry groups*

Agriculture, Forestry, and Fisheries Personal Services Professional and Related Services Public Administration Active Duty Military	Agriculture, some Services, and Public sectors (Low-risk industries)
Mining Transportation, Communications, and Other Public Utilities Wholesale Trade Retail Trade Finance, Insurance, and Real Estate Business and Repair Services Entertainment and Recreation Services	Transportation, Trade, and main Business sectors (Medium-risk industries)
Construction Manufacturing	Manufacturing and Construction (High-risk industries)

Note: Based on the 1990 Census Bureau industrial classification system by IPUMS and author's calculations.

To define the industry group, I first run a similar logistic regression as in the equation 1, where I include sector dummies as independent variables for all industries other than a default industry. I run this regression multiple times having each industry as the default industry, and get the coefficients βs. With regression results, industries are classified in the same group if the difference in job loss probability between two industries is not statistically significant. Details on the defined industry groups and their member sectors are shown in Table B.1.

C Detailed NAICS codes

Industry shares of each region are determined by the share of employment in each industry group. The Quarterly Census of Employment and Wages (QCEW) program provides county-level employment data from 1990 to 2022 at quarterly frequency. The industry codes in the QCEW follow NAICS, so industries in QCEW are matched with the constructed industry group in Table C.1.

Table C.1: *List of industries*

Defined industry groups	NAICS codes	NAICS names
Agriculture, some Services, and Public sectors	11	Agriculture, Forestry, Fishing and Hunting
	54	Professional and Technical Services
	56	Administrative and Waste Services
	61	Education Services
	62	Health Care and Social Assistance
	72	Accommodation and Food Services
	81	Other Services, Except Public Administration
	92	Public Administration
Transportation, Trade, and main Business sectors	21	Mining, Quarrying, and Oil and Gas Extraction
	22	Utilities
	42	Wholesale Trade
	44_45	Retail Trade
	48_49	Transportation and Warehousing
	51	Information
	52	Finance and Insurance
	53	Real Estate and Rental and Leasing
	55	Management of Companies and Enterprise
	71	Arts, Entertainment, and Recreation
Manufacturing and Construction	23	Construction
	31_33	Manufacturing

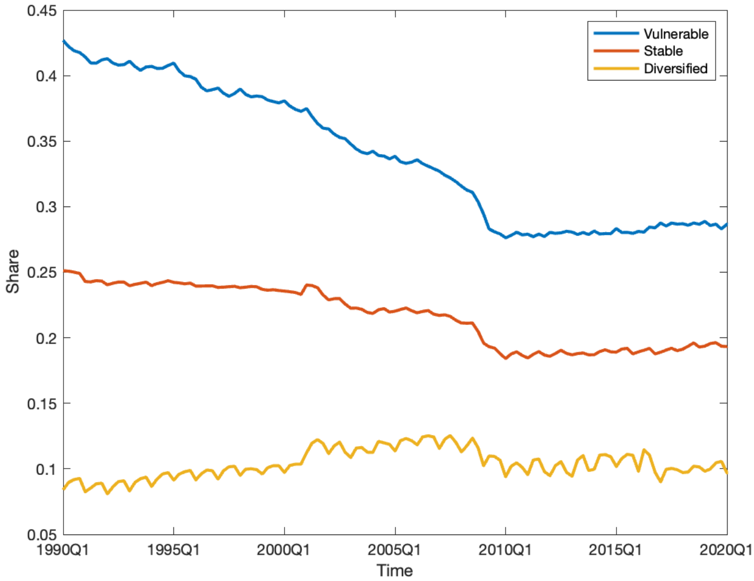
Note: Based on the QCEW program's industry classifications and author's calculations.

D Region classifications

Table D.1: *Region classifications*

Regions	States included
Vulnerable region	Arkansas; Ohio; Indiana; South Carolina; Tennessee; Alabama
Stable region	Arizona; Nevada; Alaska; South; Dakota; California; New Jersey; Florida; Nebraska; Texas; Rhode Island; Massachusetts; Wyoming; Oklahoma; Maryland; Washington; Kansas; Utah; Idaho; West Virginia; Oregon; New York; Connecticut; New Hampshire; Maine; Vermont; Louisiana; Illinois; Missouri; Virginia; Minnesota; Delaware; Pennsylvania; Kentucky; Michigan; Georgia; Iowa; Wisconsin; North Carolina; Mississippi
Diversified region	District of Columbia; Hawaii; Montana; New Mexico; North Dakota; Colorado

Figure D.1: *Industry shares overtime*



E Migration due to heterogeneous unemployment risks

Figure E.1: *Only 1.15% of people moved to another region*

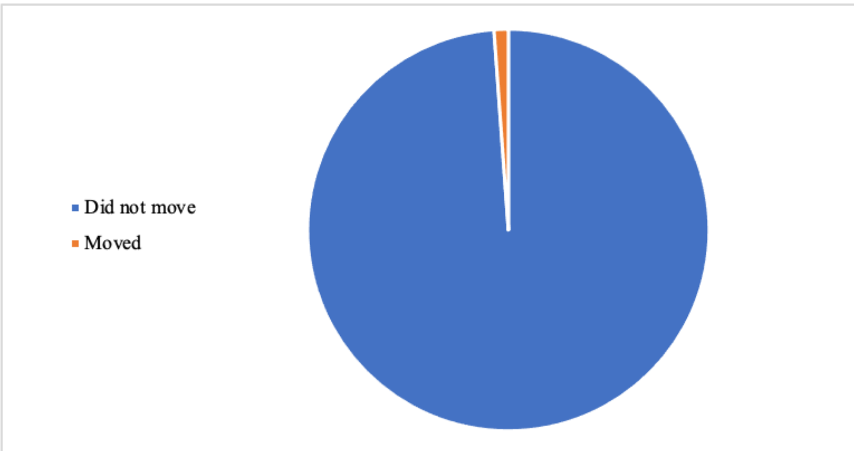
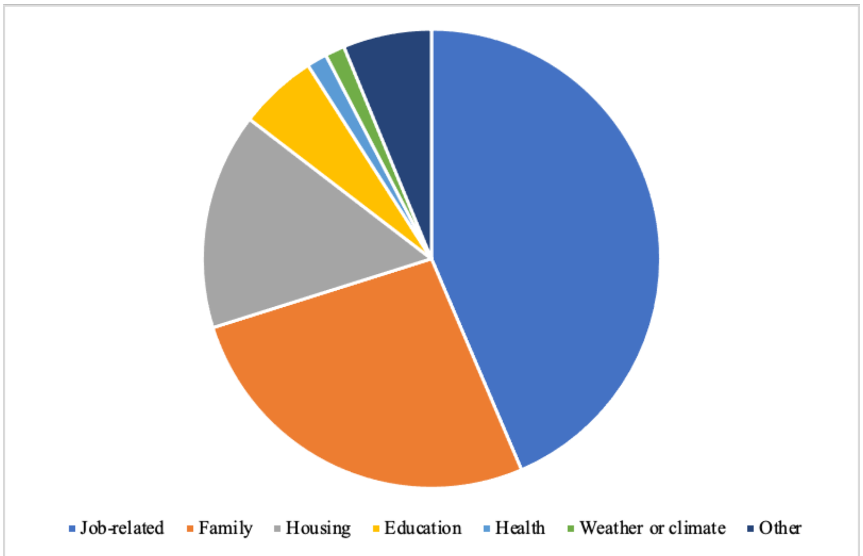
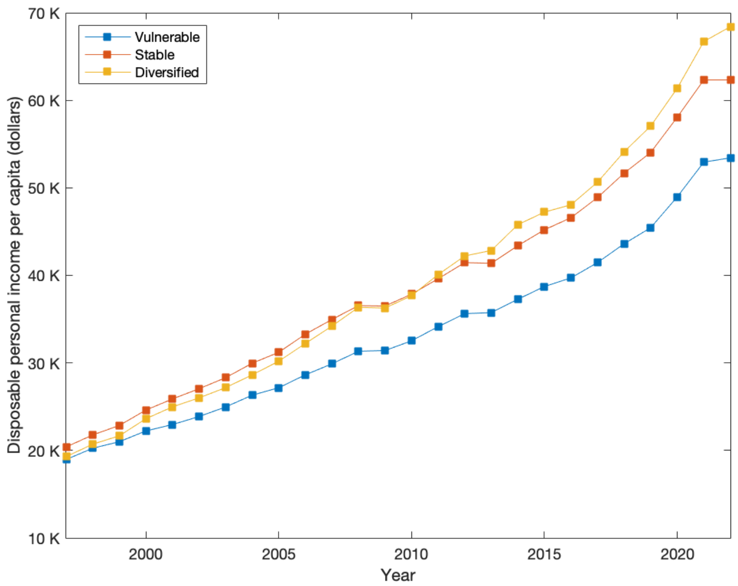


Figure E.2: *44% of the moving between regions due to work-related reasons*



F Income effects

Figure F.1: *Disposable income per capita is constantly lower in the vulnerable region*



Note: Data is from 1997 to 2022.