Heterogeneous effects of Stay-at-home (SAH) orders on labor market outcomes over different age groups

A Thesis submitted by

Tiantian Ji

in partial fulfillment of the requirements for the degree of

Master of Science

in

Economics

Tufts University

May 2023

©2023, Tiantian Ji

Adviser: ChaeWon Baek

Abstract

I explore if the stay-at-home (SAH) orders have differential effects on labor market outcomes across different age groups. By leveraging the high-frequency, county-level variation in the implementation of SAH orders in California and Pennsylvania, I disentangle the effect of SAH orders from general economic effects due to COVID-19. I find that 20-24-year-old workers were hardest hit by SAH orders. While each week of SAH exposure leads to a 2% rise in the weekly initial unemployment insurance (UI) claims for these young workers, it has insignificant effect on other age groups. To rationalize this finding and to estimate the aggregate employment losses, I construct a currency union model with age-specific labor demand and supply.

Acknowledgement

I would like to express my sincere appreciation to my advisor, Professor ChaeWon Baek, for her exceptional guidance, mentorship, and patience. Her expertise, feedback, and unwavering support have been instrumental in the successful completion of my thesis and in my application to Ph.D. programs. I am grateful for the opportunity to work with such a dedicated and inspring mentor.

I would like to acknowledge the contributions of my second reader, Professor Federico Esposito, for his valuable insights. His attention to detail has pushed me to refine my ideas and improve the quality of my thesis.

I extend my deepest gratitude to my family for their unconditional love, encouragement and belief in my abilities. I especially thank my parents for their financial and emotional support. I also extend my heartfelt thanks to my friends for their encouragement, support, and countless hours of discussion and brainstorming.

I am deeply indebted to all those who have contributed to my research and supported me in various capacities. Their support has been invaluable and I am deeply grateful for their contributions to the completion of this thesis.

Contents

1 Introduction **1**

2 Data and Model Specification **4**

3 Empirical Results **8**

4 Model **14**

4.1 Model Specification 15

4.1.1 Households 15

4.1.2 Firms 19

4.1.3 International Risk Sharing Conditions and Market Clearing Conditions 21

4.2 Model Results 22

5 Conclusion **24**

Reference **26**

Appendix **28**

List of Tables

1 Bivariate Regression Results 8

2 Regression Results After Controlling for Population Density 9

3 Regression Results After Controlling for the Severity of COVID-19 10

4 Regression Results After Controlling for A Political Economy Factor 11

5 Regression Results After Controlling for Industrial Composition 11

6 Regression Results After Controlling for Industrial Composition and Population Density 12

7 Regression Results After Controlling for All 13

8 Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.093$) 22

9 Bivariate Regression (state level, quadratic form) 28

10 Regression (state level, quadratic form) controlling for all variables 29

11 Regression Results After Controlling for the Severity of COVID-19 (without share of population aged over 65) 30

12 Regression After Controlling for all (without the share of population aged over 65) 31

13 Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.08$) 32

14 Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.10$) 32

15 Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.35$) 32

16 Definition of Variables in the Impulse Responses 33

List of Figures

1 Impulse Responses to a Negative Preference Shock under Sticky Prices . . . 34

2 Impulse Responses to a Negative Preference Shock under Sticky Prices . . . 34

3 Impulse Responses to a Negative Labor-augmented Technology Shock under Sticky Prices . . . 35

4 Impulse Responses to a Negative Preference Shock under Flexible Prices . . 35

5 Impulse Responses to a Negative Labor-augmented Technology Shock under Flexible Prices . . . 36

1 Introduction

In December 2019, a new coronavirus (severe acute respiratory syndrome coronavirus 2, or SARS-CoV-2, which was later renamed as Coronavirus Disease-19 or COVID-19), was first identified in Wuhan, China. Given the rapid spread of COVID-19, the U.S. government, especially the state and local officials, adopted several nonpharmaceutical interventions (NPIs) attempting to mitigate the pandemic, including enacting Stay-at-Home (SAH) orders in March or April 2020. It restricted the movements of the population by ordering residents to stay home except for essential tasks or for work in essential business.

At the same time, there were substantial labor market disruptions. According to the Department of Labor, the number of initial unemployment insurance (UI) claims rose from 251,875 in the week ending March 14th, 2020 to 6,161,268 in the week ending April 4th, 2020.[1] However, it is difficult to identify to what extent SAH orders contribute to the rise of these initial UI claims, given that enormous coinstantaneous factors might have attributed to this rise as well. For example, retail sales dropped from $457.9 billion in February to $375.92 billion in April.[2] Manufacturing output declined by about 14% from the fourth quarter of 2019 to the second quarter of 2020.[3] The sales uncertainty rapidly rose after January 2020 as well.[4]

To disentangle the labor market effect of SAH orders from other economic disruptions due to the COVID-19 pandemic, I follow the approach of Baek et al. (2021). Specifically, I exploit the fact that the implementation of SAH orders was determined at the county level. This generated the county-level variation in the length of time that counties were

[1] https://oui.doleta.gov/unemploy/claims.asp provides state-level Unemployment Insurance Weekly Claims Data. For reference, in 2020, the largest number of initial UI claims prior to March 14th is 337,883 on January 11th, 2020.The numbers of UI claims are 2,914,268 in the week ending March 21st and 5,981,838 in the week ending March 28th.

[2] https://fred.stlouisfed.org/series/RSXFS FRED provides a graph for the Retail Trade, and the data source is the U.S. Census Bureau.

[3] https://www.bls.gov/opub/ted/2022/u-s-manufacturing-output-hours-worked-and-productivity-recover-from-covid-19.htm The BLS documents the indexes of output in manufacturing.

[4] https://www.atlantafed.org/research/surveys/business-uncertainty The Federal Reserve Bank of Atlanta provides the survey-based monthly data of the business uncertainty.

under SAH orders. By leveraging this, I estimate its effect on the initial UI claims, another high-frequency and county-level data indicating the degree of labor market disruptions.

Moreover, the cost of SAH orders does not seem to be equally borne by all workers. For example, in California, the initial UI claims for workers aged 20-24 increased 25.9 times from the week ending on March 14th to the week ending on April 4th.[5] In contrast to this, the initial UI claims of workers aged 35-54 only increased 14.4 times. This suggests that SAH orders might have heterogenous effects on labor market outcomes over different age groups.

Examining these heterogeneous effects has important implications for policy designs. If SAH orders have differential effects on workers across different age groups, then the government should target the most affected age group when designing a policy that could offset the negative effects of SAH orders. Moreover, if young workers are more severely affected by this policy than older workers, then the costs of SAH orders can be considerably larger. This is because the effect of frequent unemployment at a young age could last for a long time. Being unemployed early in life would increase the probability of future joblessness (O'Higgins, 2001) and decrease lifetime earnings (Mroz and Savage, 2006).

In this paper, I explore the heterogeneous labor market effects of SAH orders across different age groups. To that end, I estimate the effect of SAH orders on different age groups' initial UI claims by using high-frequency, county-level data in California and Pennsylvania. From this, I find that workers aged 20-24 are the most affected by SAH orders. My result suggests that one additional week of exposure to SAH orders increases the UI claims by around 2% of the exposed county's employment level for workers aged 20-24, relative to unexposed counties. In contrast to this, other age groups are hardly affected. This finding is robust to a set of control variables, such as population density, the severity of COVID-19, a political economy factor, and industrial composition. The relative-implied aggregate effect from the back-of-the-envelope calculation based on the regression estimates indicates that around 29% of UI claims of workers aged 20-24 are due to the implementation of SAH orders.

[5] https://edd.ca.gov/en/newsroom/facts-and-stats/dashboard/ provides California weekly initial claims by demographics.

The relative-implied aggregate effect from the cross-sectional analysis, however, can be different from the aggregate effect. This is because the cross-sectional analyses hold the general equilibrium effects and other aggregate factors constant. Moreover, the Stable Unit Treatment Value Assumption (SUTVA) might be violated due to the frequent trade between counties with SAH orders and those without SAH orders. Therefore, I construct a currency union model featuring age-specific labor demand and supply (young and old workers) to map the local relative effect from the empirical analysis to the aggregate effect. According to my model, when SAH orders are modeled as a negative local labor-augmented technology shock under fully flexible prices, my empirical estimate provides a lower bound for the aggregate effect. That is, the relative-implied aggregate estimate, in this case, might overrate the aggregate employment losses only by a factor of 0.99. When SAH orders are modeled as a negative local preference shock with sticky prices, my estimate represents an upper bound. In this case, the relative-implied aggregate estimate might underrate the aggregate employment losses by a factor of 2.24. Combining all, the relative-implied job losses of young workers could understate aggregate employment losses by 0%-13%. In total, SAH orders account for 29% - 42% of job losses for workers aged 20-24.

This paper makes two contributions to the literature. First, I contribute to the literature examining the effect of COVID-19-related NPIs on economic activities (Baker et al., 2020; Bartik et al., 2020; Binder, 2020; Chetty et al., 2020; Coibion et al., 2020; Goolsbee and Syverson, 2020), especially on labor market outcomes (Baek et al., 2021; Beland et al., 2020; Crucini and O'Flaherty, 2021; Gupta et al., 2023; Kong and Prinz, 2020; Lin and Meissner, 2020; Rojas et al., 2020). Following the approach of Baek et al. (2021), I take advantage of the county-level variation in the length of time that counties are exposed to SAH orders in California and Pennsylvania, and study the effect of SAH orders on the initial UI claims for workers. While Kong and Prinz (2020) and Lin and Meissner (2020) find no evidence that SAH orders have a significant impact on unemployment, my county-level empirical estimate provides some evidence that initial UI claims for workers aged 16 years and over rise as

the weeks of exposure to SAH orders increase in California and Pennsylvania. Although the statistical significance of its coefficient is sensitive to some control variables, this conclusion is more aligned with studies that demonstrate a positive effect of SAH orders on unemployment (Baek et al., 2021; Beland et al., 2020; Gupta et al., 2023). Second, I contribute to the literature on the age differences in the employment volatilities (Clark and Summers, 1981; Foote, 2007; Jaimovich et al., 2013; Jaimovich and Siu, 2009; Kim et al., 2019; Mitra and Xu, 2020; Shimer, 2001). I embody the feature of capital-experience complementarity from Jaimovich et al. (2013) in my model. In order to study possible general equilibrium forces, I use a currency union model with age-specific labor demand and supply to incorporate the effect of trade. In particular, my model replicates my empirical findings that the job losses of younger workers are larger than older workers in both home and foreign regions, consistent with the previous finding that young workers bear a larger share of cyclical employment variation (Jaimovich et al., 2013; Jaimovich and Siu, 2009; Kim et al., 2019; Mitra and Xu, 2020).

2 Data and Model Specification

To estimate the effect of SAH orders on initial UI claims across different age groups, I run the following regression for each age group:

$$UI_i^j = \beta_0^j + \beta_1^j weeks_i + X_i'\gamma + \alpha_s^j + \epsilon_i^j, \tag{1}$$

where i stands for the different counties and j represents different age groups (16-19, 20-24, 25-34, 35-44, 45-54, 55-64, more than 65, and all workers above 16). X_i' is a vector of controls with an associated vector of coefficients γ, α_s^j denotes the state fixed effects, and ϵ_i^j represents the error term.

Here, $weeks_i$, is the number of weeks for a county i to be exposed to SAH orders, and it is the main regressor of interest. It is constructed as the total number of days between the

start date of the policy to April 4th, 2020, divided by 7. UI_i^j is the main dependent variable of interest. It indicates the cumulative change of weekly UI claims from March 14th, 2020 to April 4th, 2020 for county i's age group j, normalized by its employment size. To be more specific, it is defined as follows:

$$UI_i^j = \frac{UI_{i,Mar21}^j + UI_{i,Mar28}^j + UI_{i,Apr4}^j - 3 * UI_{i,Mar14}^j}{Emp_i^j}, \tag{2}$$

$UI_{i,Mar21}^j + UI_{i,Mar28}^j + UI_{i,Apr4}^j$ is the cumulative weekly unemployment insurance claims by county i's age group j from March 14th, 2020 to April 4th, 2020. $UI_{i,Mar14}^j$ is the weekly unemployment insurance claims by county i's age group j from March 7th, 2020 to March 14th, 2020, before SAH orders were implemented. Emp_i^j is the size of employment for county i's age group j.[6]

In this county-level regression, I focus on the weekly initial UI claims of two states, California and Pennsylvania.[7] Not only do these two states have weekly county-level data of UI claims for each age group, but there is within-state variation in the timing of implementation of SAH orders.[8] For example, in Pennsylvania, on March 23rd, 2020, the state governor, Tom Wolf signed an order enforcing the SAH policy for all residents in Allegheny and six other counties. One week later, on March 30th, the governor added Carbon, Cumberland, Dauphin and Schuylkill counties to the list of SAH orders, commencing on April 1st, bringing all 26 counties in the state under a SAH order. The various timing of policy and the availability of initial UI claims data by age groups at the county level enables me to

[6] https://data.census.gov/table?q=labor+force+by+county&tid=ACSST5Y2019.S2301 The Census Bureau releases 5-year averages estimates for all geographic area, and these estimates are based on data collected over a 5-year period of time, describing the average characteristics for that 5-year time period. According to the Census Bureau, the primary advantage of using 5-year estimates is the increased statistical reliability of the data for less populated areas and small population subgroups.

[7] The empirical analysis requires both available data for initial UI claims of different age groups and variations in the timing of the implementation of SAH orders. Only counties in California and Pennsylvania satisfy both conditions.

[8] https://calmatters.org/health/coronavirus/2021/03/timeline-california-pandemic-year-key-points/ documents the timing of the implementation of SAH orders in every county in California. https://www.abc27.com/timeline-of-a-year-of-covid-19-in-pennsylvania/ documents the timing of the implementation of SAH orders in every county in Pennsylvania.

discuss the effect of SAH orders on different age groups. In the Appendix, I also examine the effect of SAH orders with monthly state-level continued UI claim data for each age group. This monthly data is of poor quality for three reasons: first, the first two age groups, 16-21 and 22-24, are incompatible with the age groups in the BLS labor force data of 16-19 and 20-24; second, this data is not available at weekly frequency, and therefore it is more likely that factors other than SAH orders might affect the number of continued UI claims; third, in contrast to initial claims, continued claims exclude the cases of those who are unemployed but ineligible for UI benefits, thereby underestimating the number of the unemployed.

For a vector of control variables, I focus on the following four groups: population density, the severity of COVID-19, a political economy factor, and the industrial composition.

First, I control for population density. On the one hand, this measures a county's prosperity. For example, dense counties like San Francisco have more job opportunities and higher employment rates. On the other hand, with a denser population, the possibility of exposure to COVID-19 increases, which could have a negative impact on employment. In addition, the government might implement SAH orders earlier due to a higher possibility of being infected with COVID-19.

Second, the severity of COVID-19 is highly correlated with the timing of the enforcement of SAH orders. If one county was more exposed to this pandemic, it is more likely for this county to enforce this order early than late. The severity of COVID-19 is measured by the cases per thousand population, excessive deaths per thousand population, and the share of the population aged over 65, which is the most susceptible population according to the Centers for Disease Control and Prevention (CDC). With the data from the CDC, I track the cumulative cases of COVID-19 on March 14th, 2020, and the share of the population over 65 for every county.[9] Since there is no data on excessive deaths at the county level, I built this variable with the total number of deaths in March 2020, minus the number of

[9] https://covid.cdc.gov/covid-data-tracker/#county-view?list_select_state=all_states&data-type=CommunityLevels CDC provides county-level data of population density, the number of COVID-19 cases and the share of the population over 65.

deaths in March 2019.[10]

The third group represents a political economy factor. To incorporate this, I include the county-level vote share for Trump in 2016 documented by New York Times.[11] If different parties disagree about the potential risks of the pandemic, i.e., one party believes that this pandemic will end quickly and the other believes it will last longer, they may differ in the policy response. Moreover, with a party offering more generous UI benefits or faster in processing the UI claims and paying for the benefits, one would be more willing to apply for UI benefits when unemployed.

Lastly, the industrial composition is highly related to the magnitude of job losses and could be potentially related to the timing of SAH orders.[12] For this reason, I construct a Bartik-predicted job loss index, with the county-level industrial composition in 2019, and the national-level job losses in the United States.[13]

$$Bartik - predicted\ job\ loss_i = \sum_k \Delta \ln Emp_{k,March} * \omega_{k,i}, \tag{3}$$

where i represents different counties and k stands for different industries. $\omega_{k,i}$ is the employment of industry k divided by the total employment in the county. $\Delta \ln Emp_{k,March}$ is the percentage change of national employment in industry k from February 2020 to March 2020. This data is based on a BLS survey that ended on March 14, before the first SAH policy was implemented. It could predict the magnitude of job losses without SAH orders, due to the industrial composition. The second control variable is the work-at-home index. I construct a county-level work-at-home index by taking a county employment-weighted average of the industry-level (two-digit NAICS) work-at-home index constructed by Dingel and

[10] https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htm#ExcessDeaths CDC provides monthly county-level deaths data.

[11] https://www.nytimes.com/elections/2016/results/president New York Times documents county-level share of votes in 2016.

[12] https://www.census.gov/library/visualizations/interactive/county-business-patterns-by-industry-2019.html documents all county-level industrial composition in 2019.

[13] https://www.bls.gov/charts/employment-situation/employment-by-industry-monthly-changes.htm The BLS provides data of monthly change in employment and the total employment by industry.

Neiman (2020), measuring the ability to accomplish their work if forced to stay at home. As the index rises, more requirements could be fulfilled at home, leading to less unemployment during the policy implementation.

3 Empirical Results

This section shows the regression results estimated from the regression model described in the previous section to study the effect of SAH orders on initial UI claims across different age groups. And in all regressions below, the state-level fixed effect is included.

Table 1 shows the results from the bivariate regression of SAH orders on the initial UI claims across different age groups. The estimates imply that SAH orders have a differential impact on workers in different age groups. As the week of exposure to SAH orders increases, the initial UI claim significantly increases by 1.3% of its unemployment level, relative to unexposed counties, for workers aged 20-24. In contrast to this, other age groups are hardly affected. The coefficient in the last column suggests that the rise in the weeks of exposure to SAH orders positively impacts total unemployment for workers aged above 16.

Table 1: Bivariate Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.002	0.013**	-0.005	-0.008	-0.011**	-0.008	0.0004	0.013*
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
Constant	0.095***	0.107***	0.133***	0.105***	0.100***	0.088***	0.069***	0.059***
	(0.014)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)
Observations	125	125	125	125	125	125	125	125
R-squared	0.052	0.035	0.022	0.229	0.242	0.299	0.334	0.119

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In the Bivariate Regression, I only control for the state-fixed effect. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^*p < 0.10$;$^{**}p < 0.05$;$^{***}p < 0.01$.

This result for workers aged 20-24 is robust to other model specifications. Specifically, controlling for a set of control variables such as population density, the severity of COVID-19, a political factor, and industry composition generates the same result. First, Table 2 shows

the estimation results when I add population density as a control variable. After controlling for population density, the weeks of implementation of the Stay-At-Home orders still have a significant positive effect on the initial UI claims by the second age group (20-24) and all workers above 16 with little change in the absolute value of the coefficient.

Table 2: Regression Results After Controlling for Population Density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.002	0.013**	-0.001	-0.007	-0.013**	-0.010*	0.001	0.012*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)
population density	0.119	0.422	-2.556***	-0.506	0.853	1.438	-0.430	0.162
	(0.607)	(0.802)	(0.571)	(0.556)	(0.680)	(1.153)	(1.034)	(0.572)
Constant	0.096***	0.108***	0.124***	0.103***	0.103***	0.093***	0.068***	0.060***
	(0.014)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)
Observations	125	125	125	125	125	125	125	125
R-squared	0.0517	0.0353	0.0387	0.2300	0.2448	0.3071	0.3344	0.119

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the population density and the state-fixed effect. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$.

In Table 3, I add another set of control variables (the severity of COVID-19), including cumulative COVID-19 cases per thousand population, excess death per thousand population, and the share of the population aged over 65.[14] When the week of implementing SAH increases, the initial UI claims of workers aged 20-24 increase by 1.7% of its employment level, on average, relative to other counties without SAH orders. The estimate for this age group has slightly increased with the COVID-19-related controls. Besides, the coefficients for other age groups are statistically insignificant, leaving the age group from 20-24 the only group severely influenced by SAH orders. In particular, the effect of SAH orders on workers aged above 16 is not persistent, and its statistical significance is sensitive to the severity of COVID-19.

This result is robust to adding another set of control variables: a political economy factor, industrial composition. Table 4 shows the results after controlling for the share of

[14]I thank Professor Federico Esposito for his helpful comments. He points out that one reason that the coefficient of workers aged 45-54 and 55-64 become insignificant is a high correlation between these three variables. According to my data, the correlation between these three variables are relative small (less than 0.3) and more details are in the Appendix.

Table 3: Regression Results After Controlling for the Severity of COVID-19

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	-0.001	0.017*	-0.0004	-0.001	-0.010	-0.006	0.005	0.015
	(0.008)	(0.009)	(0.011)	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)
cases	-0.002	-0.004	0.001	-0.005	-0.002	-0.003	-0.007	-0.003
	(0.005)	(0.007)	(0.010)	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
excess death	-0.001	0.019	0.004	0.016	0.0004	0.012	-0.018	0.007
	(0.025)	(0.034)	(0.033)	(0.025)	(0.026)	(0.024)	(0.022)	(0.021)
share of population aged over 65	-0.159	-0.021	0.048	0.064	0.049	0.041	-0.025	-0.028
	(0.102)	(0.135)	(0.121)	(0.082)	(0.073)	(0.070)	(0.079)	(0.077)
population density	-0.438	0.472	-2.400***	-0.120	1.114	1.676	-0.328	0.147
	(0.536)	(0.826)	(0.791)	(0.561)	(0.720)	(1.127)	(1.043)	(0.676)
Constant	0.138***	0.103***	0.111***	0.073***	0.084***	0.074***	0.067***	0.060**
	(0.030)	(0.036)	(0.040)	(0.024)	(0.024)	(0.020)	(0.025)	(0.027)
Observations	125	125	125	125	125	125	125	125
R-squared	0.100	0.042	0.042	0.250	0.252	0.316	0.351	0.125

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect, the severity of COVID-19 (cases per thousand population, excess deaths per thousand population and share of population aged over 65), and population density. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^*p < 0.10$;$^{**}p < 0.05$;$^{***}p < 0.01$.

votes for Trump in 2016. It again suggests that the age group of 20-24 is severely harmed by SAH orders. In Table 5 (without population density) and Table 6 (with population density), the Bartik-predicted job loss and the work-at-home index are constructed and utilized to control for the industrial composition. SAH orders still have a significantly positive effect on the initial UI claims of the second age group (20-24).

Table 4: Regression Results After Controlling for A Political Economy Factor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	-0.002	0.015*	-0.003	-0.008	-0.013*	-0.008	-0.003	0.011
	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)
Share of vote	-0.019	0.008	0.009	0.003	-0.007	-0.002	-0.015	-0.009
	(0.030)	(0.030)	(0.030)	(0.024)	(0.021)	(0.023)	(0.024)	(0.022)
Constant	0.114**	0.099***	0.124***	0.103***	0.107***	0.090***	0.084***	0.068**
	(0.031)	(0.033)	(0.034)	(0.028)	(0.027)	(0.026)	(0.025)	(0.029)
Observations	125	125	125	125	125	125	125	125
R-squared	0.056	0.036	0.0224	0.229	0.242	0.299	0.336	0.121

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect and a political factor, the share of votes for Trump in 2016. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^*p < 0.10;^{**} p < 0.05;^{***} p < 0.01$.

Table 5: Regression Results After Controlling for Industrial Composition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.004	0.016**	0.006	-0.003	-0.007	-0.007	0.001	0.013**
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
Bartik-Predicted job loss	-3.284***	-3.193*	-3.127	-1.816	-2.063*	-1.484	-1.754*	-1.968
	(0.983)	(1.791)	(1.953)	(1.284)	(1.081)	(1.093)	(0.962)	(1.361)
work-at-home index	-0.069	-0.066	-0.217**	-0.100*	-0.095	-0.022	-0.028	-0.041
	(0.052)	(0.068)	(0.107)	(0.055)	(0.069)	(0.056)	(0.050)	(0.065)
Constant	0.152***	0.162***	0.208***	0.145***	0.143***	0.113***	0.099***	0.095***
	(0.022)	(0.032)	(0.046)	(0.028)	(0.030)	(0.027)	(0.024)	(0.033)
Observations	125	125	125	125	125	125	125	125
R-squared	0.144	0.098	0.118	0.269	0.289	0.320	0.362	0.181

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect and the industrial composition, including Bartik-Predicted job loss and the work-at-home index. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^*p < 0.10;^{**} p < 0.05;^{***} p < 0.01$.

Table 6: Regression Results After Controlling for Industrial Composition and Population Density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.004	0.015**	0.006	-0.003	-0.008	-0.008	0.002	0.013*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
population density	0.484	0.843	-0.603	0.491	2.098**	1.843	-0.510	0.327
	(0.802)	(1.033)	(1.180)	(0.802)	(1.015)	(1.348)	(1.180)	(0.847)
Bartik-Predicted job loss	-3.308***	-3.235*	-3.097	-1.841	-2.168**	-1.577	-1.728*	-1.980
	(0.980)	(1.786)	(2.007)	(1.296)	(1.069)	(1.076)	(0.978)	(1.374)
work-at-home index	-0.078	-0.082	-0.206	-0.109	-0.134*	-0.056	-0.018	-0.047
	(0.063)	(0.081)	(0.128)	(0.066)	(0.080)	(0.062)	(0.059)	(0.078)
Constant	0.155***	0.168***	0.203***	0.148***	0.157***	0.125***	0.095***	0.104*
	(0.024)	(0.035)	(0.052)	(0.032)	(0.033)	(0.028)	(0.026)	(0.062)
Observations	125	125	125	125	125	125	125	125
R-squared	0.145	0.100	0.118	0.270	0.303	0.331	0.363	0.181

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect, the industrial composition (Bartik-Predicted job loss and the work-at-home index), and population density. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$.

Lastly, Table 7 shows the estimation results with all the control variables mentioned above: population density, the severity of COVID-19, a political factor, and the industrial composition. It shows that the influence of SAH orders on the initial UI claims by the second age group, from 20 to 24, is still statistically significant, demonstrating the robustness of the result even after controlling for all these variables together. In contrast, the effects of SAH orders on other age groups' UI claims, as well as the UI claims for workers aged above 16, are not statistically different from zero, suggesting heterogeneous impacts of SAH orders on labor market outcomes across different age groups. The age group of 20-24 is the most influenced. Part of the reason might be that, compared to older workers, they are more inexperienced (Brussevich, 2020), and therefore the cost of firing them might be lower for employers.[15]

Based on the estimate above, I calculate a back-of-the-envelope calculation from the

[15]It is possible that younger workers aged 16-19 are similarly affected by SAH orders. However, they are more likely to have part-time jobs without being adequately insured or with wages lower than the requirement to obtain the benefits. For this reason, their job losses might not be captured by the initial UI claims.

Table 7: Regression Results After Controlling for All

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.001	0.020*	0.001	-0.001	-0.009	-0.005	0.003	0.013
	(0.009)	(0.011)	(0.012)	(0.009)	(0.009)	(0.008)	(0.010)	(0.010)
cases	-0.002	-0.003	0.001	-0.004	-0.003	-0.002	-0.006	-0.003
	(0.005)	(0.007)	(0.008)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
excess death	0.005	0.025	0.014	0.023	0.008	0.016	-0.012	0.009
	(0.028)	(0.038)	(0.037)	(0.028)	(0.029)	(0.026)	(0.023)	(0.025)
share of population aged over 65	-0.075	0.104	0.167*	0.158*	0.137*	0.119*	0.053	0.066
	(0.106)	(0.109)	(0.099)	(0.073)	(0.070)	(0.068)	(0.072)	(0.069)
population density	0.208	0.944	-1.111	0.374	1.933**	1.890	-0.494	0.219
	(0.892)	(1.228)	(1.079)	(0.799)	(0.970)	(1.277)	(1.227)	(0.816)
share of vote	-0.022	-0.008	-0.058	-0.039	-0.037	-0.013	-0.028	-0.024
	(0.038)	(0.037)	(0.047)	(0.037)	(0.034)	(0.030)	(0.029)	(0.032)
Bartik-Predicted job loss	-2.904**	-4.011**	-4.328**	-2.997**	-3.115**	-2.413**	-2.018*	-2.500
	(1.184)	(1.758)	(2.131)	(1.331)	(1.266)	(1.157)	(1.115)	(1.461)
work-at-home index	-0.108	-0.075	-0.231	-0.122	-0.148	-0.051	-0.041	-0.047
	(0.069)	(0.091)	(0.143)	(0.077)	(0.092)	(0.0671)	(0.069)	(0.078)
Constant	0.193***	0.144***	0.228**	0.144***	0.160***	0.106**	0.105**	0.097***
	(0.049)	(0.053)	(0.091)	(0.052)	(0.056)	(0.042)	(0.046)	(0.036)
Observations	125	125	125	125	125	125	125	125
R-squared	0.160	0.119	0.157	0.325	0.338	0.359	0.382	0.181

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect, the population density, the severity of COVID-19, a political economy factor, and county industrial composition. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^*p < 0.10;^{**} p < 0.05;^{***} p < 0.01$.

equation below:

$$\text{Relative-Implied-Aggregate-Claims} = \sum_i \hat{\beta} * weeks_{i,Apr,4} * Emp_i. \tag{4}$$

It suggests that about 29% of the initial UI claims by workers aged 20-24 are due to SAH orders. Here i represents different counties, and $\hat{\beta}$ is the coefficient from the empirical result when controlling for all control variables.

With the cross-sectional regression above, I investigate the heterogeneous effects of the SAH orders on initial UI claims across different age groups. The results show that, compared with counties without this policy, one additional week in the SAH orders yields about a 2% increase in the initial UI claims for workers aged 20-24, adjusted by the county's employment size for the same age group. This, however, only represents the local relative effect of SAH orders. The constant term absorbs general equilibrium effects and other aggregate factors in the regression, which is not incorporated by the back-of-the-envelope estimate. One of

the concerns is that, the interdependence of firms and households in the entire economy creates a non-ignorable general equilibrium effect. Even if one county did not implement the SAH orders, this policy in other regions could still affect its labor market outcome via trade, causing the empirical analysis to be a biased estimate of aggregate employment. Therefore, in the next section, I use a currency union model to examine how the relative-implied estimate could differ from the aggregate effect with the general equilibrium forces.

Another concern is that the enforcement of SAH orders in one county due to the outbreak of COVID-19 could lead to the neighboring counties expecting this policy to be implemented soon. Therefore, they might respond to the SAH orders in the neighboring regions, implying that the relative effect could underrate the aggregate effect. Although I could not embody this characteristic in the model, the effects of this spillover could be negligible due to my focus on a relatively short horizon (a three-week horizon).

4 Model

In this section, I use a model to map the local relative effect, differences in the change in employment of young workers between the home and foreign regions, to the aggregate effect, the total change in employment of young workers in two regions.

To be more specific, I use a currency-union model with age-specific labor supply and demand to capture the effects of SAH orders in home and foreign regions and the entire economy. To that end, I incorporate the age-dependent labor demand and supply of Jaimovich et al. (2013) into a currency-union model of Baek et al. (2021). Following Baek et al. (2021), I consider an economy characterized by either sticky or flexible prices, with SAH orders modeled as either a pure local demand shock or a pure local supply shock (labor-augmented technology shock).

To generate heterogeneous labor market outcomes across different age groups, I incorporate capital, "young" labor, and "old labor" into the production function, featuring different

elasticity of substitution between capital and labor for young and old. Following Jaimovich et al. (2013), I assume complementarities in production between experienced (old) labor and capital, i.e., skilled operational knowledge (capital) requires experienced (old) labor. This embodies the phenomenon of capital-experience complementarity (Krusell et al., 2000) in production as a channel to rationalize more severe employment losses of young workers. Because capital is difficult to adjust in the short run, the employment of young workers would be more volatile compared to old workers.[16]

4.1 Model Specification

4.1.1 Households

Following Jaimovich et al. (2013), I assume that households consist of young and old workers. Let s_Y be the size of young workers and $1 - s_Y$ be the size of old workers in a household. Specifically, s_Y is the share of young workers (aged 20-24) to the overall employment (20 and above) in the United States. In order to calibrate some parameters in the model, I set s_Y equals 0.093 based on the BLS data in 2019. This number fluctuated between 0.091 and 0.095, so 0.08 and 0.1 are used to test whether the result is insensitive to the value of this essential parameter.[17]

In home and foreign regions, there is a continuum of identical households with the same initial wealth. Household $j \in (0, n]$ in a home region where n is the relative size of a home

[16]There are two possible channels that SAH orders lead to heterogeneous labor market outcomes: First, young workers tend to work in industries that are hard hit by SAH orders; Second, young workers are more likely to have fewer skills and firms can easily shed young workers than old workers. In unreported regressions, I reconstruct the Bartik-predicted job losses and work-at-home index with the national-level data where the Bartik-predicted job losses is defined as $\sum_k \Delta \ln Emp_{k,March} * \omega_{k,i} * \delta_{k,j}$ with $\delta_{k,j}$ being the number of workers in age group j working in industry k adjusted by the total employment size of the same age group. Since there is no county-level data on the employment size of workers in different age groups in different industries, $\delta_{k,j}$ is based on the national-level data. Similarly, I construct the work-at-home index. There is no substantial change compared with the previous regression. The regression results provide some evidence that the first channel cannot account for the significant coefficient in the regression. Therefore, I choose the second rather than the first channel in my model.

[17]I include $s_Y = 0.35$ which is the proportion of workers aged 16-34 based on the BLS data in 2019 to provide a higher ceiling of this parameter. Still, the result is insensitive to the change.

region solves the following problem:

$$\max_{C^j_{Y,t},C^j_{O,t},N^j_{Y,t},N^j_{O,t},K^j_{t+1}} E_0 \sum_{t=0}^{\infty} \beta^t \left[s_Y * U^j_{Y,t} + (1 - s_Y) * U^j_{O,t} \right] \tag{5}$$

where

$$U^j_{Y,t} = \delta_t \frac{\left(C^j_{Y,t}\right)^{1-\sigma_Y}}{1-\sigma_Y} - \chi_Y \frac{\left(N^j_{Y,t}\right)^{1+\psi_Y}}{1+\psi_Y}, \quad U^j_{O,t} = \delta_t \frac{\left(C^j_{O,t}\right)^{1-\sigma_O}}{1-\sigma_O} - \chi_O \frac{\left(N^j_{O,t}\right)^{1+\psi_O}}{1+\psi_O}, \tag{6}$$

$C^j_{Y,t}$ and $C^j_{O,t}$ are the consumption of young and old workers. $N^j_{Y,t}$ and $N^j_{O,t}$ are the labor supply of young and old workers, respectively. β is the rate of time discounting, σ_Y and σ_O are the inverse intertemporal elasticity of substitution, ψ_Y and ψ_O are the inverse Frisch elasticity of labor supply, and χ_Y and χ_O are the terms related to labor supply disutility for young and old workers.[18] δ_t denotes a preference shock that evolves according to the following law of motion:

$$\log \delta_t = \rho^\delta \log \delta_{t-1} + \epsilon^\delta_t. \tag{7}$$

The total consumption of household j in a home region is a CES aggregator of a bundle of home goods, $C^j_{H,t}$ and a bundle of foreign goods, $C^j_{F,t}$:

$$C^j_t = \left[\phi_H^{\frac{1}{\eta}} \left(C^j_{H,t}\right)^{\frac{\eta-1}{\eta}} + \phi_F^{\frac{1}{\eta}} \left(C^j_{F,t}\right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{8}$$

$$C^j_{H,t} = \left(\int_0^n \left(\frac{1}{n}\right)^{\frac{1}{\epsilon}} c^j_{h,t}(i)^{\frac{\epsilon-1}{\epsilon}} \, di \right)^{\frac{\epsilon}{\epsilon-1}}, \quad C^j_{F,t} = \left(\int_0^n \left(\frac{1}{n}\right)^{\frac{1}{\epsilon}} c^j_{f,t}(i)^{\frac{\epsilon-1}{\epsilon}} \, di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{9}$$

[18] Here, $\beta = 0.99$, $\sigma_Y = \sigma_O = 1$, $\psi_Y = \psi_O = 1$, $\chi_Y = 1.8445$ and $\chi_O = 3.3736$, following Jaimovich et al. (2013). Although they consider young labor as aged 16-29 and old as aged over 30, their results are robust to five-year variation in this cut-off age. Fortuitous for me, the age threshold I use is in the five-year variation. Therefore, instead of re-calibrating all parameters, I only estimate the elasticity parameter σ and ρ in the production function with their approach with $s_Y = 0.08$, $s_Y = 0.093$, and $s_Y = 0.1$.

where ϕ_H and ϕ_F are preference parameters indicating households' choice for home and foreign goods, and $\phi_H + \phi_F = 1$. When $\phi_H = 1 - \phi_F > n$, there is a home bias. Following Nakamura and Steinsson (2014), I calibrated $n = 0.1$, while $\phi_H = 0.69$. $\eta > 0$ is the elasticity of substitution between home goods and foreign goods, and $\epsilon > 1$ denotes the elasticity of substitution across differentiated goods.

Then optimal allocations of expenditures (per household) are given by

$$C_{H,t}^j = \phi_H \left(\frac{P_{H,t}}{P_t}\right)^{-\eta} C_t^j, \quad C_{F,t}^j = \phi_F \left(\frac{P_{F,t}}{P_t}\right)^{-\eta} C_t^j, \tag{10}$$

$$c_{h,t}^j(i) = \left(\frac{p_{h,t}(i)}{P_{H,t}}\right)^{-\epsilon} C_{H,t}^j, \quad c_{f,t}^j(i) = \left(\frac{p_{f,t}(i)}{P_{F,t}}\right)^{-\epsilon} C_{F,t}^j, \tag{11}$$

where

$$P_t = \left[\phi_H P_{H,t}^{1-\eta} + \phi_F P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}, \tag{12}$$

$$P_{H,t} = \left[\frac{1}{n}\int_0^n p_{h,t}(i)^{1-\epsilon}\, di\right]^{\frac{1}{1-\epsilon}}, \quad P_{F,t} = \left[\frac{1}{1-n}\int_0^n p_{f,t}(i)^{1-\epsilon}\, di\right]^{\frac{1}{1-\epsilon}}. \tag{13}$$

P_t denotes the consumer price index (CPI) of a home region, and $P_{H,t}$ ($P_{F,t}$) is the producer price index (PPI) of home (foreign) goods.

The assumption of complete financial markets makes aggregation straightforward:

$$c_{h,t}(i) \equiv \int_0^n c_{h,t}^j(i)\, dj = \left(\frac{p_{h,t}(i)}{P_{H,t}}\right)^{-\epsilon} C_{H,t}, \quad c_{f,t}(i) \equiv \int_0^n c_{f,t}^j(i)\, dj = \left(\frac{p_{f,t}(i)}{P_{F,t}}\right)^{-\epsilon} C_{F,t}, \tag{14}$$

$$C_{H,t} = \int_0^n C_{H,t}^j\, dj = \phi_H \left(\frac{P_{H,t}}{P_t}\right)^{-\eta} C_t, \quad C_{F,t} = \int_0^n C_{F,t}^j\, dj = \phi_F \left(\frac{P_{F,t}}{P_t}\right)^{-\eta} C_t, \tag{15}$$

$$C_t = \int_0^n C_t^j \, dj = nC_t^j, \tag{16}$$

where variables without j superscript are aggregate variables in a home region.

With the optimal allocations, household j's budget constraint becomes as follows:

$$C_t^j + K_{t+1}^j = \left(1 - \gamma^K\right) K_t^j + r_t K_t^j + s_Y \frac{W_{Y,t}}{P_t} + \left(1 - s_Y\right) \frac{W_{O,t}}{P_t} N_{O,t}^j + \frac{\Pi_t^j}{P_t}, \tag{17}$$

where $C_t^j \equiv s_Y C_{Y,t}^j + \left(1 - s_Y\right) C_{O,t}^j$ is total consumption of household j in a home region, $W_{Y,t}$ and $W_{O,t}$ are the home region's nominal wages of young and old workers, r_t is the real interest rate for capital, and γ^K is the loss of capital in each period.[19] Here, I assume perfect immobility across the regions, meaning wages will be determined at the regional level. K_{t+1}^j is the capital provided by household j and is predetermined in period t. Π_t^j is the firm profit that household j owns. Here P_t denotes the price index that gives the minimum price of one unit of consumption good, $C_{Y,t}$ ($C_{O,t}$).

The optimality conditions of household $j \in (0, n]$ are:

$$\left(C_{Y,t}^j\right)^{-\sigma_Y} = \left(C_{O,t}^j\right)^{-\sigma_O}, \tag{18}$$

$$\chi_Y \left(N_{Y,t}^j\right)^{\psi_Y} = \frac{W_{Y,t}}{P_t} \delta_t \left(C_{Y,t}^j\right)^{-\sigma_Y}, \quad \chi_O \left(N_{O,t}^j\right)^{\psi_O} = \frac{W_{O,t}}{P_t} \delta_t \left(C_{O,t}^j\right)^{-\sigma_O}, \tag{19}$$

$$E_t \beta \delta_{t+1} \left(C_{Y,t+1}^j\right)^{-\sigma_Y} \left[1 + r_{t+1} - \gamma^K\right] = \delta_t \left(C_{Y,t}^j\right)^{-\sigma_Y}. \tag{20}$$

Households in a foreign region are symmetric to those in a home region with asterisks to

[19] $\gamma^K = 0.025$. Same for the capital loss γ^{*K} in the foreign region.

denote foreign variables.

$$\left(C_{Y,t}^{*j}\right)^{-\sigma_Y} = \left(C_{O,t}^{*j}\right)^{-\sigma_O}, \tag{21}$$

$$\chi_Y \left(N_{Y,t}^{*j}\right)^{\psi_Y} = \frac{W_{Y,t}^*}{P_t^*}\delta_t^* \left(C_{Y,t}^{*j}\right)^{-\sigma_Y}, \quad \chi_O \left(N_{O,t}^{*j}\right)^{\psi_O} = \frac{W_{O,t}^*}{P_t^*}\delta_t^* \left(C_{O,t}^{*j}\right)^{-\sigma_O}, \tag{22}$$

$$E_t \beta \delta_{t+1}^* \left(C_{Y,t+1}^{*j}\right)^{-\sigma_Y} \left[1 + r_{t+1}^* - \gamma^{*K}\right] = \delta_t^* \left(C_{Y,t}^{*j}\right)^{-\sigma_Y}. \tag{23}$$

4.1.2 Firms

There is a representative, perfectly competitive firm producing final goods in a home region, $Y_{H,t}$, which is the CES aggregator of intermediate goods, $y_{h,t}(i)$ for $i \in [0,1]$:

$$Y_{H,t} = \left[\int_0^1 y_{h,t}(i)^{\frac{\epsilon-1}{\epsilon}} \, di\right]^{\frac{\epsilon}{\epsilon-1}}. \tag{24}$$

A representative final-goods-producing firm in a foreign region is similarly defined.

I assume that there is a continuum of intermediate-goods-producing firms in each region, producing differentiated intermediate goods using labor and capital as input. The production technology of each intermediate-goods-producing firm is given by

$$Y_{H,t} = \left\{\mu \left(A_t H_{Y,t}\right)^{\sigma} + (1-\mu)\left[\lambda K_t^{\rho} + (1-\lambda)\left(A_t H_{O,t}\right)^{\rho}\right]^{\frac{\sigma}{\rho}}\right\}^{\frac{1}{\sigma}}, \tag{25}$$

$$Y_{F,t} = \left\{\mu \left(A_t^* H_{Y,t}^*\right)^{\sigma} + (1-\mu)\left[\lambda \left(K_t^*\right)^{\rho} + (1-\lambda)\left(A_t^* H_{O,t}^*\right)^{\rho}\right]^{\frac{\sigma}{\rho}}\right\}^{\frac{1}{\sigma}}, \tag{26}$$

where $Y_{H,t}$ ($Y_{F,t}$) is the total production in a home (foreign) region, A_t (A_t^*) is a region-wide

labor-augmented technology in a home (foreign) region. $H_{Y,t}$, $H_{O,t}$, $H^*_{Y,t}$, $H^*_{O,t}$ are defined as

$$H_{Y,t} \equiv s_Y * N_{Y,t}, \quad H_{O,t} \equiv (1 - s_Y) * N_{O,t}, \tag{27}$$

$$H^*_{Y,t} \equiv s_Y * N^*_{Y,t}, \quad H^*_{O,t} \equiv (1 - s_Y) * N^*_{O,t}. \tag{28}$$

μ represents the allocation between young and old workers, and λ represents the proportion between capital and the labor supply of old workers. The elasticity of substitution between old workers and capital is given by $(1-\rho)^{-1}$, while the elasticity of substitution between young workers and the combination of $H_{O,t}$ and K_t is $(1-\sigma)^{-1}$. I calibrate μ and λ based on Jaimovich et al. (2013). Here, the calibration of μ and λ is associated with the value of s_Y and the steady state values of output $\left(\bar{Y}\right)$, young and old workers' employment $\left(\bar{N}_Y\right), \left(\bar{N}_O\right)$, and capital $\left(\bar{K}\right)$:

$$\mu = Q_Y * \left(1 - \frac{\bar{Y}}{s_Y * \bar{N}_Y}\right)^{\sigma}, \quad \lambda = \left(1 + \frac{\bar{K}^{\rho} * Q_O}{Q_K * \left(s_Y * \bar{N}_O\right)^{\rho} * e^{\rho}}\right)^{-1}, \tag{29}$$

where Q_K is the income share of capital, Q_O is the income share of old and $Q_Y \equiv 1 - Q_K - Q_O$ is the income share of old.[20] Here, I use a bar to denote the steady state. e is the Euler number. The labor-augmented technology shock, A_t, evolves according to the following process:

$$\log A_t = \rho^A \log A_{t-1} + \epsilon^A_t. \tag{30}$$

Following Baek et al. (2021), I consider both sticky and fully flexible price cases. In the case of sticky prices, I assume that firms are subject to Calvo (1983)-type pricing frictions with the associated price-reset parameter of θ. When working with the sticky price model, I set

[20] Following Jaimovich et al. (2013), $Q_K = 0.37$, $Q_O = 0.50$. These are the 1964-2010 national income shares.

the Calvo parameter $\theta = 0.75$; with flexible price, $\theta = 0$.

4.1.3 International Risk Sharing Conditions and Market Clearing Conditions

To describe the optimal risk-sharing in two regions, I combine the home and foreign consumption Euler equations following Backus and Smith (1993),

$$\frac{\delta_t^* \left(C_{Y,t}^{*j}\right)^{-\sigma_Y}}{\delta_t \left(C_{Y,t}^{j}\right)^{-\sigma_Y}} = \frac{P_t^*}{P_t}. \tag{31}$$

Goods market clearing conditions in each region are:

$$Y_{H,t} = C_{H,t} + C_{H,t}^* + I_t, \tag{32}$$

$$Y_{F,t} = C_{F,t} + C_{F,t}^* + I_t^*. \tag{33}$$

Finally, I close the model by imposing the following monetary policy rule:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left(\phi_\pi \pi_t^{agg} + \phi_y \hat{y}_t^{agg}\right), \tag{34}$$

where π_t^{agg} is a union-wide inflation rate and $\hat{y}_t^{agg}$ is the union-wide output gap defined as follows:

$$\pi_t^{agg} = n * \pi_{H,t} + (1-n) * \pi_{F,t}, \tag{35}$$

$$\hat{y}_t^{agg} = n * \left(Y_{H,t} - \bar{Y}_H\right) + (1-n) * \left(Y_{F,t} - \bar{Y}_F\right) \tag{36}$$

where $\pi_{H,t}$ and $\pi_{F,t}$ are CPI in home and foreign regions; $\bar{Y}_H$ and $\bar{Y}_F$ are the steady-state output in home and foreign regions.

4.2 Model Results

Based on Baek et al. (2021), this model is calibrated to a quarterly frequency. Therefore, the relative horizon for mapping the model to the empirical specification is the on-impact relative effect. I model the implementation of SAH orders as either a one-time negative local demand shock (preference shock) with $\epsilon_t^{\delta} = -1$ or a one-time negative local labor-augmented technology shock with $\epsilon_t^{A} = -1$. Each shock is separated under either sticky prices or flexible prices. In each scenario, I calculate the differences in the on-impact employment of young workers between the shocked home regions and non-shocked foreign regions and the on-impact employment changes of young and old workers in the entire economy.

Table 8: Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.093$)

		Flexible Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^{\delta} = 0$	-0.0056	-0.0049	-0.0085	-0.0078	1.5149	1.5882
Technology Shock	$\rho^{A} = 0$	-0.0603	-0.0396	-0.0596	-0.0403	0.9889	1.0168
		Sticky Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^{\delta} = 0.9$	-0.3485	-0.1791	-0.7239	-0.3846	2.0771	2.1471
Preference Shock	$\rho^{\delta} = 0$	-0.0671	-0.0570	-0.1508	-0.1294	2.2481	2.2705
Technology Shock	$\rho^{A} = 0$	0.0375	0.0539	0.0541	0.0665	1.4420	1.2338

Note: This table shows the on-impact response of the relative employment (Implied) and the aggregate employment (Total). Implied young (old) are the differences in the on-impact employment of young workers between the home and foreign regions, multiplied by the home region's size. Total young (old) is a population-weighted average of the employment change of young (old) workers in both home and foreign regions. Factor young (old) is Total young (old) divided by Implied young (old), a mapping between relative effect and aggregate effect.

Among the four scenarios, three of them are consistent with the empirical findings: When SAH orders are modeled as a preference shock in both sticky and flexible price settings and they are modeled as a technology shock with flexible prices, the employment of young workers drops more in a home region than that in a foreign region, and the relative effect of young workers is greater than old workers. In contrast to this, when SAH orders are modeled as a technology shock under the sticky prices, the model is inconsistent with the empirical findings. The employment of young workers in a home region rises compared to that in a foreign region.

If SAH orders are modeled as a negative local labor-augmented technology shock and

prices are flexible, the on-impact relative effect provides an upper bound on the aggregate effect over the same horizon. In this case, while employment in a home region decreases, part of it is offset by the increase in employment in a foreign region. This is because, in response to a negative supply shock in a home region, the foreign region's terms of trade improve, increasing demand for foreign goods. This increases production and labor demand in a foreign region.

When SAH orders are modeled as a transitory local preference shock and prices are sticky, the relative effect generates a lower bound on the aggregate effect. In this case, employment in both home and foreign regions decreases. In response to a negative home-region demand shock, the foreign region's terms of trade deteriorate, making foreign goods relatively more expensive. As a result, demand for foreign goods decreases, leading to a decline in employment in a foreign region. The other relevant cases lie between the previous two cases.

In addition to this, my model successfully generates that young workers are more negatively impacted by SAH orders than old workers. This is due to both the age-specific labor supply and the complementarity of old with capital in production. Capital is fixed in the short run. Therefore, labor demand for young workers, inexperienced labor that is less tied to capital, fluctuates relatively more than that for old workers. Note, however, that the mapping of the relative effect to the aggregate employment effect of young workers is identical to old workers, indicating that the general equilibrium effect is the same for these two groups.

With the trade between regions, the interdependence of firms and households in the entire economy creates the general equilibrium effects. It implies that the potential outcomes for each region i are related to the treatment status of other regions, indicating a violation of SUTVA (Chodorow-Reich, 2020). SAH-induced negative shocks in a home region effects non-shocked foreign regions through trade and interdependency between regions. In the empirical analysis, the back-of-the-envelope calculation suggests that in the early period of the crisis, approximately 29% of initial UI claims of young workers aged 20-24 were due

to SAH orders. My model suggests that this relative-implied aggregate estimate might underrate the aggregate employment losses by a factor of 2.25 (in the case of sticky prices and a transitory local demand shock) or overrate it by a factor of 0.99 (in the case of fully flexible prices and a local supply shock). In summary, the relative-implied job losses of young workers based on the empirical estimate could understate aggregate employment losses by 0%-13%.

5 Conclusion

In this paper, I examine how stay-at-home orders influence the labor market. Prior research focuses on the impact of SAH orders on job losses for all workers aged over 16, while I highlight the heterogeneous effects of SAH orders on workers in different age groups. Understanding the heterogeneous impacts of SAH orders is of great importance since the government needs to target the most affected groups to offset its negative effects. Additionally, although young workers only constitute a relatively small proportion of the entire labor force, being unemployed early in life could have a severe long-lasting effect on their future.

I find that SAH orders contributed to the increase in unemployment. In particular, workers aged 20-24 are the ones most affected by the implementation of SAH orders. Specifically, as the week of exposure to SAH orders increases, unemployment claims for workers aged 20-24 increase by 2% of the employment size of that age group. A back-of-the-envelope calculation indicates that 29% of the initial UI claims of workers aged 20-24 are due to SAH orders. I then use a currency union model with age-specific labor demand and supply. Consistent with the empirical finding, the job losses of young workers are larger than old workers in both home and foreign regions. The model results indicate that the empirical estimate might underestimate the aggregate employment losses by a factor of 2.24 or overestimate it by a factor of 0.99. Based on the empirical analysis, the relative-implied estimate could understate the aggregate job losses by 0%-13%. In total, SAH orders account for 29% - 42%

of job losses for workers aged 20-24.

My results shed some light on the heterogeneous effect of NPIs on labor market outcomes and provide evidence for the age differences in employment volatilities. This implies that targeting the most affected age group (20-24) might be the appropriate approach in order to offset the negative effects of SAH orders. Mroz and Savage (2006) demonstrate that despite the catch-up response, there are longer-term adverse impacts on earnings from unemployment experienced early in the employment life cycle. Their results indicate that six-month unemployment at age 22 would result in a 5% decrease in wages at age 26, compared with their undisturbed level, and 2-3 percent lower wages at ages 30 and 31. However, based on my model and their findings, policies regarding job training, as well as other human capital enhancing activities will effectively lessen the long-lasting adverse consequences of youth unemployment.

References

Backus, D. K. and Smith, G. W. (1993). Consumption and real exchange rates in dynamic economies with non-traded goods. *Journal of international economics*, 35(3):297–316.

Baek, C., McCrory, P. B., Messer, T., and Mui, P. (2021). Unemployment effects of stay-at-home orders: Evidence from high-frequency claims data. *The review of economics and statistics*, 103(5):979–993.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How Does Household Spending Respond to an Epidemic? Consumption during the 2020 COVID-19 Pandemic. *The Review of Asset Pricing Studies*, 10(4):834–862.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020). The impact of covid-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences - PNAS*, 117(30):17656–17666.

Beland, L.-P., Brodeur, A., and Wright, T. (2020). Covid-19, stay-at-home orders and employment: Evidence from cps data. *IDEAS Working Paper Series from RePEc*.

Binder, C. (2020). Coronavirus fears and macroeconomic expectations. *The review of economics and statistics*, 102(4):721–730.

Brussevich, M. (2020). *Who will Bear the Brunt of Lockdown Policies? Evidence from Teleworkability Measures Across Countries*. IMF Working Papers. International Monetary Fund, Washington, D.C.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of monetary economics*, 12(3):383–398.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and Team, T. O. I. (2020). The economic impacts of covid-19: Evidence from a new public database built using private sector data. *NBER Working Paper Series*.

Chodorow-Reich, G. (2020). Regional data in macroeconomics: Some advice for practitioners. *Journal of economic dynamics control*, 115:103875–.

Clark, K. B. and Summers, L. H. (1981). Demographic differences in cyclical employment variation. *The Journal of human resources*, 16(1):61–79.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. *NBER Working Paper Series*.

Crucini, M. J. and O'Flaherty, O. (2021). Stay-at-home orders in a fiscal union. *IDEAS Working Paper Series from RePEc*.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of public economics*, 189:104235–104235.

Foote, C. L. (2007). Space and time in macroeconomic panel data: young workers and state-level unemployment revisited. *IDEAS Working Paper Series from RePEc*.

Goolsbee, A. and Syverson, C. (2020). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *NBER Working Paper Series*.

Gupta, S., Montenovo, L., Nguyen, T., Lozano-Rojas, F., Schmutte, I., Simon, K., Weinberg, B. A., and Wing, C. (2023). Effects of social distancing policy on labor market outcomes. *Contemporary economic policy*, 41(1):166–193.

Jaimovich, N., Pruitt, S., and Siu, H. E. (2013). The demand for youth: Explaining age differences in the volatility of hours. *The American economic review*, 103(7):3022–3044.

Jaimovich, N. and Siu, H. E. (2009). The young, the old, and the restless: Demographics and business cycle volatility. *The American economic review*, 99(3):804–826.

Kim, W. H., Lee, S., Shim, M., and Yang, H.-S. (2019). Technological progress and youth employment in south korea. *Global economic review*, 48(3):320–333.

Kong, E. and Prinz, D. (2020). Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the covid-19 pandemic? *Journal of public economics*, 189:104257–.

Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., and Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–1053.

Lin, Z. and Meissner, C. M. (2020). Health vs. wealth? public health policies and the economy during covid-19. *NBER Working Paper Series*.

Mitra, I. and Xu, Y. (2020). Time-varying risk premium and unemployment risk across age groups. *The Review of financial studies*, 33(8):3624–3673.

Mroz, T. A. and Savage, T. H. (2006). The long-term effects of youth unemployment. *The Journal of human resources*, XLI(2):259–293.

Nakamura, E. and Steinsson, J. (2014). Fiscal stimulus in a monetary union: Evidence from us regions. *The American economic review*, 104(3):753–792.

O'Higgins, N. (2001). Youth unemployment and employment policy: a global perspective. *IDEAS Working Paper Series from RePEc*.

Rojas, F. L., Jiang, X., Montenovo, L., Simon, K. I., Weinberg, B. A., and Wing, C. (2020). Is the cure worse than the problem itself? immediate labor market effects of covid-19 case rates and school closures in the u.s. *NBER Working Paper Series*.

Shimer, R. (2001). The impact of young workers on the aggregate labor market. *The Quarterly journal of economics*, 116(3):969–1007.

Appendix to Heterogeneous effects of Stay-at-home (SAH) orders on labor market outcomes over different age groups

Tiantian Ji

May 2023

A.1 State-level Regression Results

In the state-level regression, because the data is incompatible, I merge the first two age groups in the county-level regression and combine them into one age group (16-24). Here, I fail to find evidence in the linear form proving that the age group (16-24) is most impacted by the SAH orders. But in the regression of quadratic form, the SAH orders led to an increase in the unemployment of workers aged 16-24 in 2.3 weeks. This result is consistent with Chetty et al. (2020), suggesting that high-wage workers experienced a "V-shaped" recession. Since there is a minimum wage requirement for workers to file continued UI claims, the state-level regression result might be more aligned with the unemployment of high-wage workers. Below is the results of the regression.

Table 9: Bivariate Regression (state level, quadratic form)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age group	16-24	25-34	35-44	45-54	55-64	65+	All
week	0.056**	0.019	0.018	0.027**	0.032**	0.016	0.013
	(0.021)	(0.014)	(0.013)	(0.012)	(0.014)	(0.013)	(0.012)
week2	-0.012**	-0.002	-0.002	-0.005	-0.005	-0.0003	-0.0001
	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Constant	0.043**	0.064***	0.037**	0.016	0.004	0.032***	0.059***
	(0.021)	(0.010)	(0.014)	(0.012)	(0.015)	(0.010)	(0.008)
Observations	51	51	51	51	51	51	51
R-squared	0.243	0.212	0.247	0.308	0.315	0.200	0.182

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**} p < 0.05;^{***} p < 0.01$.

Here, from the original county level regression, I add several variables:

$$uirate_i = \frac{continued\ UI\ claim_i}{Unemp_i}, \tag{37}$$

where i represents different age groups. $continued\ UI\ claim_i$ is the total continued UI claims in 2019. $Unemp_i$ is the total unemployment in 2019. This variable is age-specific and highly correlated with the UI replacement rate. *first payment timeliness* is the percentage of UI claims getting first payment within 14 days. *minimum UI payment* is the state-level minimum UI payment per week. It also represents the minimum wage required to get UI benefit.

Table 10: Regression (state level, quadratic form) controlling for all variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age group	16-24	25-34	35-44	45-54	55-64	65+	All
week	0.060***	0.026*	0.027**	0.031***	0.036***	0.018	0.028**
	(0.021)	(0.014)	(0.012)	(0.011)	(0.012)	(0.013)	(0.012)
week2	-0.014**	-0.005	-0.005	-0.007**	-0.008**	-0.003	-0.006*
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
uirate (1-6)	0.064*	0.003	0.006**	0.006***	0.007***	0.002	0.008*
	(0.032)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)
case	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.0004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0009)
excess death	0.075**	0.056**	0.053**	0.062***	0.068***	0.061**	0.056**
	(0.033)	(0.022)	(0.021)	(0.020)	(0.020)	(0.027)	(0.019)
share of population aged over 65	0.140	0.170	0.277	0.212	0.092	0.265	0.108
	(0.565)	(0.388)	(0.326)	(0.269)	(0.291)	(0.338)	(0.311)
Share of vote	-0.096	-0.156	-0.161**	-0.168**	-0.184**	-0.166**	-0.132*
	(0.126)	(0.097)	(0.077)	(0.066)	(0.077)	(0.066)	(0.077)
minimum UI payment	-0.368**	-0.087	-0.078	-0.120	-0.102	-0.187	-0.094
	(0.175)	(0.128)	(0.131)	(0.107)	(0.127)	(0.137)	(0.115)
first payment timeliness	-0.062	-0.039	-0.002	-0.020	-0.060	-0.014	-0.031
	(0.112)	(0.086)	(0.067)	(0.055)	(0.059)	(0.072)	(0.068)
Bartik-predicted job loss	-4.315	-12.306	-14.095*	-6.152	-5.019	-10.582	-9.158
	(11.337)	(8.396)	(7.306)	(6.344)	(6.841)	(8.396)	(6.987)
work-at-home index	-0.703	-1.232**	-1.324***	-0.881***	-0.894**	-0.710*	-0.978***
	(0.682)	(0.476)	(0.402)	(0.316)	(0.337)	(0.410)	(0.357)
Constant	0.467	0.803**	0.787***	0.514**	0.552**	0.537*	0.622**
	(0.478)	(0.347)	(0.281)	(0.224)	(0.243)	(0.293)	(0.262)
Observations	51	51	51	51	51	51	51
R-squared	0.389	0.372	0.432	0.518	0.525	0.333	0.318

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the the severity of COVID-19, political economy factors, and industrial composition. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$.

A.2 Correlation between Control Variables

Another essential problem that requires to be examined is the correlation between control variables in the second group – the severity of COVID-19, since the strong correlation between three variables within this group might lead to the insignificance of the coefficients for the age groups 45-54 and 55-64. However, my data demonstrates a relatively weak correlation between the cases per thousand population, excessive deaths per thousand population and the share of population aged over 65. Based on the data from CDC, in the early stage of COVID-19, the case fatality rate was not stable.[21]

Without any additional solid evidence on the relationship between the share of population aged over 65 and the cases or excessive deaths per thousand population, I run regressions excluding the share of population aged over 65 in Table 11 and Table 12. The change in results is immaterial compared with Table 3 and Table 7. This indicates that the significance of coefficients of age group 45-54 and 55-64 is not robust to this group of control variables.

Table 11: Regression Results After Controlling for the Severity of COVID-19 (without share of population aged over 65)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.002	0.018*	-0.004	-0.002	-0.009	-0.005	0.005	0.012
	(0.008)	(0.009)	(0.011)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
cases	-0.001	-0.004	-0.0004	-0.005	-0.002	-0.002	-0.007	-0.002
	(0.006)	(0.006)	(0.010)	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)
excess death	-0.013	0.017	0.007	0.021	0.004	0.015	-0.019	0.004
	(0.023)	(0.031)	(0.031)	(0.024)	(0.024)	(0.022)	(0.020)	(0.020)
Constant	0.095***	0.096***	0.131***	0.091***	0.095***	0.081***	0.061***	0.062***
	(0.020)	(0.024)	(0.030)	(0.019)	(0.020)	(0.017)	(0.020)	(0.020)
Observations	125	125	125	125	125	125	125	125
R-squared	0.054	0.040	0.022	0.241	0.243	0.303	0.349	0.098

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect, the severity of COVID-19 (without the share of population aged over 65). The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$.

[21] https://ourworldindata.org/mortality-risk-covid Data from the CDC show that in the early stage, the case fatality rate is similar to an inverted-U shape, especially before March 14th, 2020.

Table 12: Regression After Controlling for all (without the share of population aged over 65)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	16-19	20-24	25-34	35-44	45-54	55-64	65+	All
weeks	0.001	0.020*	0.001	-0.001	-0.008	-0.005	0.003	0.011
	(0.010)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
cases	-0.001	-0.004	-0.0004	-0.005	-0.003	-0.003	-0.007	-0.002
	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)
excess death	0.002	0.028	0.020	0.029	0.012	0.020	-0.010	0.012
	(0.028)	(0.037)	(0.034)	(0.027)	(0.027)	(0.025)	(0.022)	(0.024)
population density	0.201	0.954	-1.095	0.389	1.946*	1.901	-0.489	0.244
	(0.906)	(1.181)	(1.065)	(0.825)	(1.019)	(1.353)	(1.254)	(0.721)
share of vote	-0.030	0.002	-0.042	-0.023	-0.023	-0.001	-0.023	-0.024
	(0.038)	(0.037)	(0.046)	(0.034)	(0.032)	(0.028)	(0.030)	(0.030)
Bartik-predicted job loss	-3.374***	-3.365*	-3.285	-2.014	-2.263**	-1.673*	-1.690*	-2.133
	(1.010)	(1.705)	(2.026)	(1.216)	(1.064)	(0.981)	(1.010)	(1.359)
work-at-home index	-0.104	-0.080	-0.240*	-0.130*	-0.155*	-0.057	-0.044	-0.091
	(0.070)	(0.090)	(0.141)	(0.075)	(0.091)	(0.068)	(0.068)	(0.092)
Constant	0.185***	0.155***	0.246***	0.160***	0.174***	0.119***	0.110**	0.128**
	(0.047)	(0.052)	(0.089)	(0.052)	(0.057)	(0.043)	(0.044)	(0.058)
Observations	125	125	125	125	125	125	125	125
R-squared	0.153	0.109	0.131	0.290	0.311	0.339	0.378	0.221

Note: This table reports results from estimating the equation: $UI_i^j = \beta_0^j + \beta_1^j weeks_i + \alpha_s^j + \epsilon_i^j$, where each column considers a different age group, and the last column considers all workers above 16. In this table, I control for the state-fixed effect, the population density, the severity of COVID-19, a political economy factor, and county industrial composition. The dependent variable in the column is my measure of cumulative initial UI claims for the corresponding age group, normalized by the county employment of this group. Robust standard errors in parentheses. Significant at $^{*}p < 0.10;^{**}p < 0.05;^{***}p < 0.01$.

A.3 Robustness Check for Model

To test the robustness of the results in 4.2 to the change of the essential parameter s_Y, I include the model results for $s_Y = 0.08$, $s_Y = 0.10$,[22] and $s_Y = 0.35$.[23] Table 13, 14, 15 show that the result is not sensitive to the percentage of young workers in the labor force. These models suggest that this relative-implied aggregate estimate might underestimate the aggregate employment losses by a factor of 2.24 (in the case of sticky prices and a transitory local demand shock) or overestimate it by a factor of 0.85 (in the case of fully flexible prices and a local supply shock when $s_Y = 0.10$).

[22]This range is based on the size of workers aged 20-24

[23]This range is based on the proportion of workers aged 16-34 to further explore the robustness of the model.

Table 13: Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.08$)

		Flexible Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0$	-0.0056	-0.0049	-0.0088	-0.0078	1.5777	1.5882
Technology Shock	$\rho^A = 0$	-0.0602	-0.0397	-0.0599	-0.0395	0.9945	0.9944
		Sticky Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0.9$	-0.3386	-0.1754	-0.7483	-0.3946	2.2098	2.2497
Preference Shock	$\rho^\delta = 0$	-0.0672	-0.0572	-0.1503	-0.1286	2.2364	2.2493
Technology Shock	$\rho^A = 0$	0.0378	0.0541	0.0537	0.0661	1.4189	1.2218

Note: This table shows the on-impact response of the relative employment (Implied) and the aggregate employment (Total) when $s_Y = 0.08$. Implied young (old) are the differences in the on-impact employment of young workers between the home and foreign regions, multiplied by the home region's size. Total young (old) is a population-weighted average of the employment change of young (old) workers in both home and foreign regions. Factor young (old) is Total young (old) divided by Implied young (old), a mapping between relative effect and aggregate effect.

Table 14: Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.10$)

		Flexible Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0$	-0.0056	-0.0048	-0.0082	-0.0078	1.4528	1.5760
Technology Shock	$\rho^A = 0$	-0.0612	-0.0399	-0.0523	-0.0378	0.8547	0.9471
		Sticky Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0.9$	-0.3700	-0.1873	-0.8171	-0.4213	2.2084	2.2496
Preference Shock	$\rho^\delta = 0$	-0.0672	-0.0566	-0.1502	-0.1274	2.2353	2.2495
Technology Shock	$\rho^A = 0$	0.0371	0.0537	0.0524	0.0653	1.4140	1.2155

Note: This table shows the on-impact response of the relative employment (Implied) and the aggregate employment (Total) when $s_Y = 0.10$. Implied young (old) are the differences in the on-impact employment of young workers between the home and foreign regions, multiplied by the home region's size. Total young (old) is a population-weighted average of the employment change of young (old) workers in both home and foreign regions. Factor young (old) is Total young (old) divided by Implied young (old), a mapping between relative effect and aggregate effect.

Table 15: Relative Change of Young and Old Workers' Employment Between the Shocked home Region and the Non-shocked Foreign Region ($s_Y = 0.35$)

		Flexible Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0$	-0.0029	-0.0025	-0.0044	-0.0038	1.51111	1.5110
Technology Shock	$\rho^A = 0$	-0.0575	-0.0379	-0.0605	-0.0381	1.0530	1.0007
		Sticky Price					
		Implied young	Implied old	Total young	Total old	Factor young	Factor old
Preference Shock	$\rho^\delta = 0.9$	-0.2470	-0.1404	-0.5468	-0.3160	2.2136	2.2500
Preference Shock	$\rho^\delta = 0$	-0.0726	-0.0621	-0.1623	-0.1395	2.2353	2.2489
Technology Shock	$\rho^A = 0$	0.0651	0.0644	0.1613	0.1447	2/4788	2.2483

This table shows the on-impact response of the relative employment (Implied) and the aggregate employment (Total). Implied young (old) are the differences in the on-impact employment of young workers between the home and foreign regions, multiplied by the home region's size. Total young (old) is a population-weighted average of the employment change of young (old) workers in both home and foreign regions. Factor young (old) is Total young (old) divided by Implied young (old), a mapping between relative effect and aggregate effect.

To further demonstrate my work in the section 4, I include the impulse responses for the model when $s_Y = 0.093$. Below is the definition of variables in the impulse responses and figures of impulse responses in five scenarios.

Table 16: Definition of Variables in the Impulse Responses

Variable	Definition
Nyh	labor of young workers in a home region
Noh	labor of old workers in a home region
Nyf	labor of young workers in a foreign region
Nof	labor of old workers in a foreign region
YH	output in a home region
YF	output in a foreign region
Y	aggregate output in home and foreign regions
N	total labor adjusted by the size of home and foreign regions and the size of young and old workers
s	terms of trade
pi	CPI inflation in a home region
pis	CPI inflation in a foreign region
pih	PPI inflation in a home region
pif	PPI inflation in a foreign region
pish	optimal PPI inflation in a home region
pisf	optimal PPI inflation in a foreign region
rh	real interest rate in a home region
rf	real interest rate in a foreign region
Kh	capital in a home region
Kf	capital in a foreign region

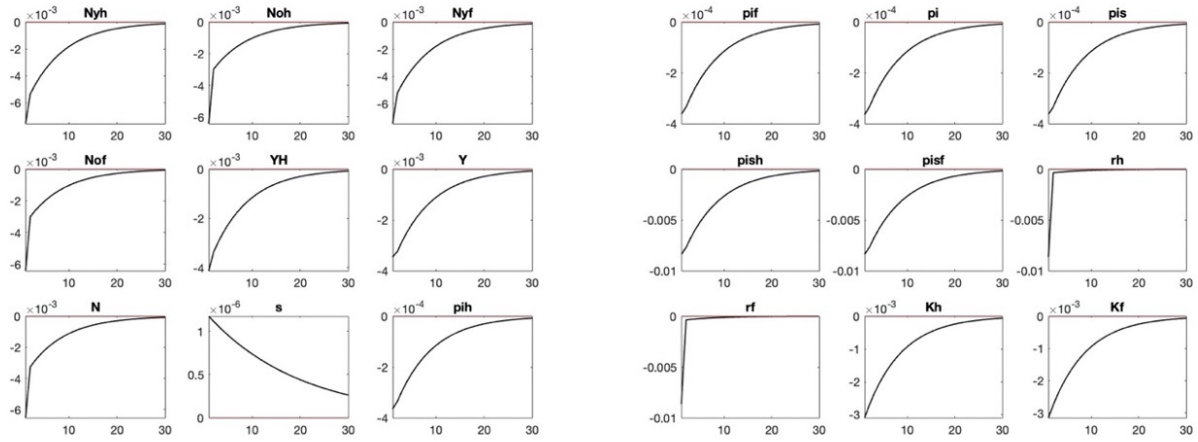

Figure 1: Impulse Responses to a Negative Preference Shock under Sticky Prices

Note: This figure shows the impulse responses of variables to a transitory negative preference shock $\left(\rho^{\delta}=0\right)$ under sticky prices $(\theta=0.75)$.

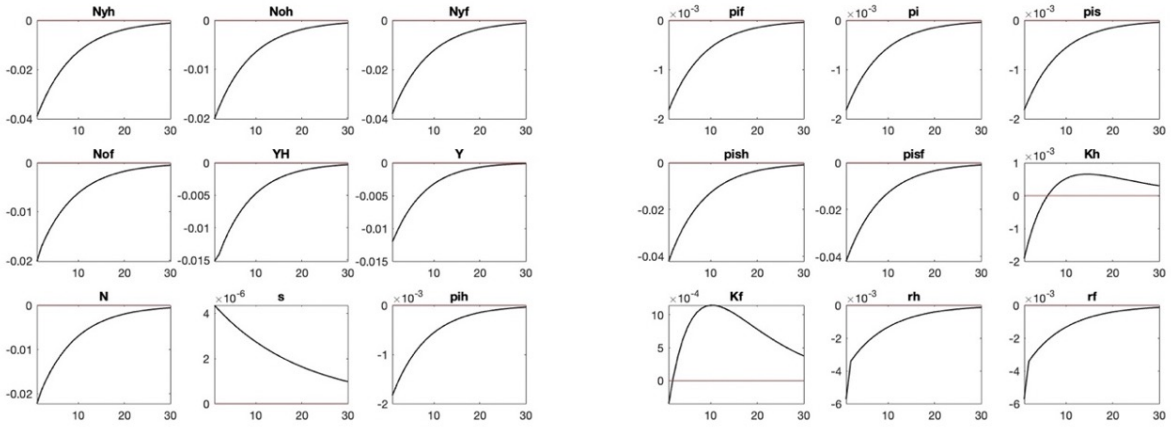

Figure 2: Impulse Responses to a Negative Preference Shock under Sticky Prices

Note: This figure shows the impulse responses of variables to a persistent negative preference shock $\left(\rho^{\delta}=0.9\right)$ under sticky prices $(\theta=0.75)$.

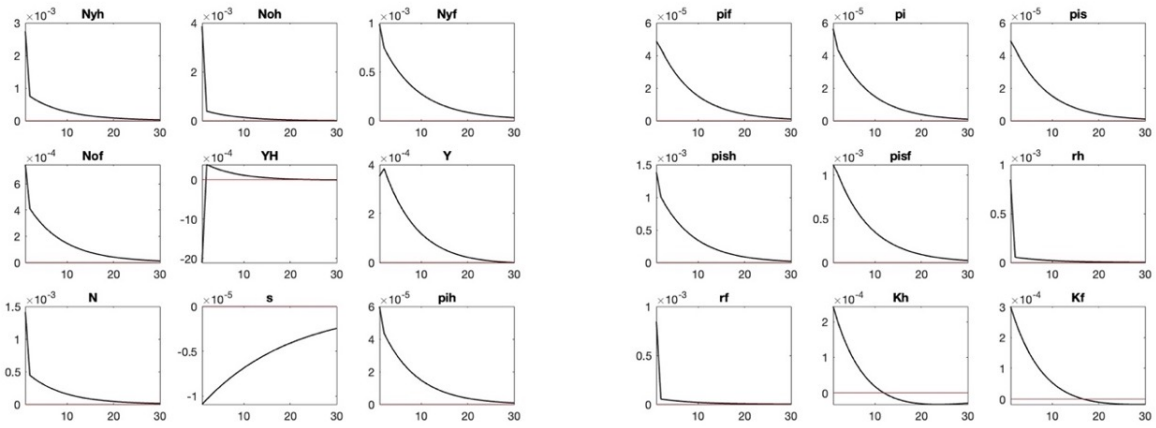

Figure 3: Impulse Responses to a Negative Labor-augmented Technology Shock under Sticky Prices

Note: This figure shows the impulse responses of variables to a transitory negative labor-augmented technology shock $\left(\rho^A = 0\right)$ under sticky prices $(\theta = 0.75)$.

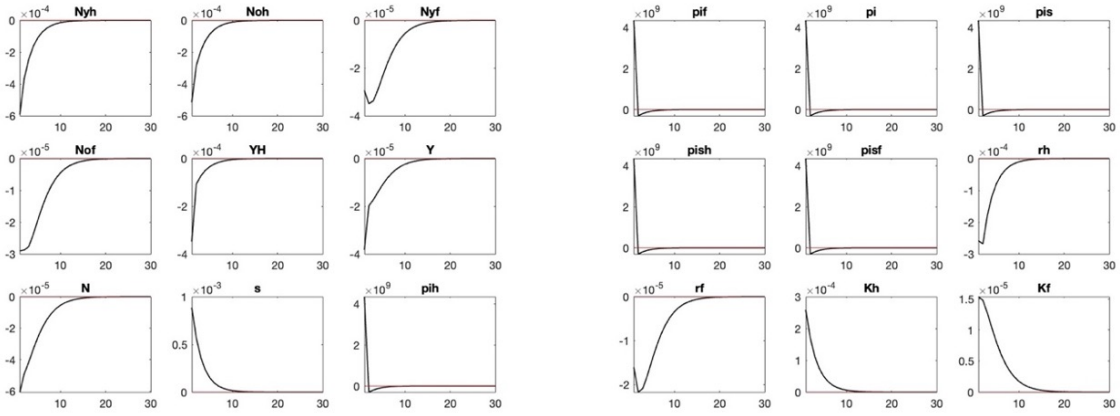

Figure 4: Impulse Responses to a Negative Preference Shock under Flexible Prices

Note: This figure shows the impulse responses of variables to a transitory negative preference shock $\left(\rho^\delta = 0\right)$ under flexible prices $(\theta = 0)$.

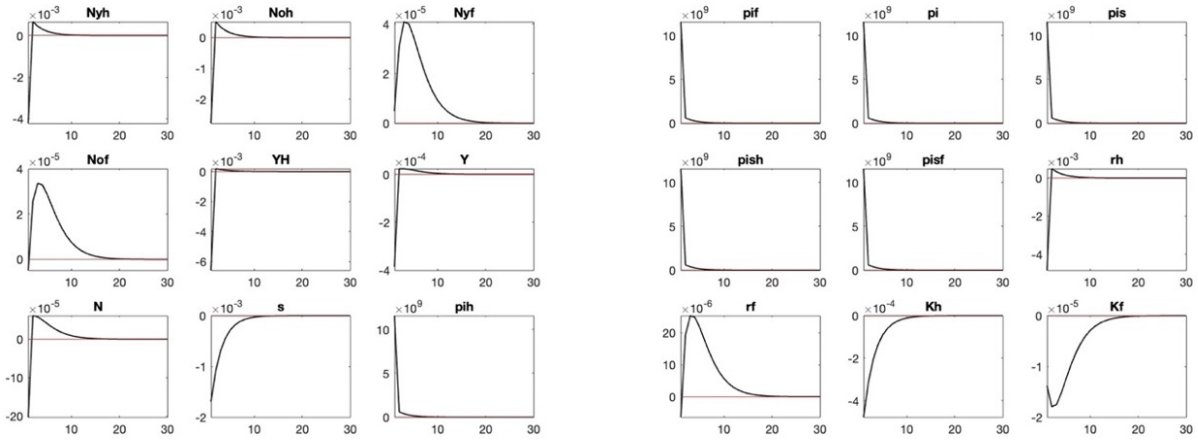

Figure 5: Impulse Responses to a Negative Labor-augmented Technology Shock under Flexible Prices

Note: This figure shows the impulse responses of variables to a transitory negative labor-augmented technology shock $\left(\rho^A = 0\right)$ under flexible prices $(\theta = 0)$.