Substitutability Between Prime-Age and Marginal-Retirement-Age Workers

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Abstract

This study examines the substitutability between prime-age (ages 25–54) and marginal-retirement-age (ages 55–64) workers by investigating the impact of internal migration of prime-age workers across 320 U.S. Metropolitan Statistical Areas from 2002 to 2019. A 1% increase in prime-age worker inflows boosts the relative employment of prime- to marginal-retirement-age workers by 1.39%. The inflow shock reduces relative earnings by 0.18%, indicating a substitution elasticity of 7.7. Interpreted via an overlapping generations model, the inflow of prime-age workers, coupled with low substitutability, enhances the welfare of workers nearing retirement. Therefore, I emphasize that policymakers should consider not just relocating people to high-inflow areas but also reducing worker substitutability to improve the welfare of the marginal-retirement-age population.

Keywords— Young-old elasticity of substitution, Internal migration
JEL: C26, E24, J21, R23

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1 Introduction

The demographic landscape of the United States is increasingly skewing older, as the proportion of prime-age workers declines and marginal-retirement-age workers becomes more prevalent.[1] Figure 1 presents the ratio of the civilian non-institutionalized population of prime-age (25–54 years old) to near-retirement-age (55–64 years old) over the past 30 years. Between 2002 and 2019, it decreased from 4.6 to 2.99,[2] and, at the same time, the relative employment between these age groups has nearly halved, decreasing from 6.8 to 3.8. Along with the national decline in relative employment, regional variance in this trend is also notable. Figure 2 shows the percentage change in relative employment at the regional level during the same period. The areas shaded in darker blue represent regions where the decline in relative employment was less pronounced. New York, Florida, Portland, and some western regions experienced a milder decline. This variation exceeds what can be attributed solely to birth or death rates; therefore, this study explores migration as a plausible explanation for this discrepancy. The migration of prime-age workers to these regions could mitigate the decline in relative employment.

Understanding the extent of inflow is crucial for evaluating an individual's welfare nearing retirement. Prime-age workers approaching the age of 55 may choose to relocate to areas where it is more beneficial for their welfare. For instance, would a person nearing retirement be better off in Florida, known for its significant inflow of prime-age workers, or in the Midwest, where this inflow is less evident? The inflow of prime-age workers stimulates the local economy, leading to increased consumption, leisure, and wage growth, thereby enhancing the welfare of workers approaching retirement. Thus, at first glance, Florida may seem more appealing to those nearing retirement.

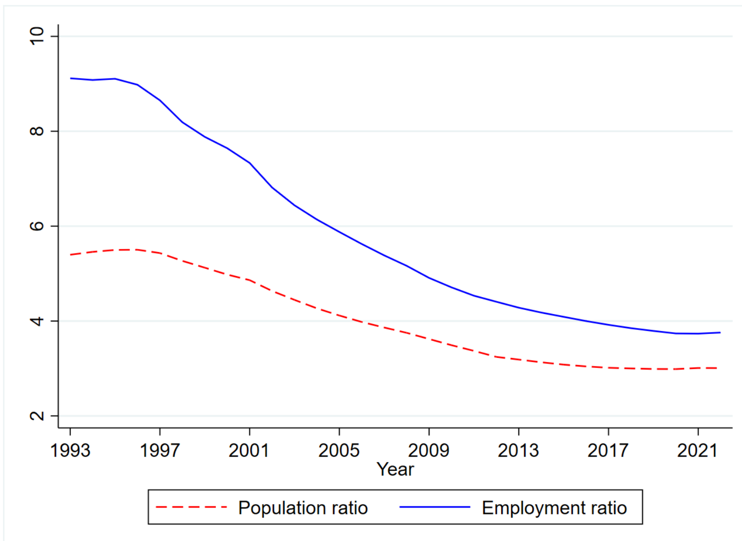
However, this positive impact might diminish in local economies with high substitutability between prime-age and marginal-retirement-age workers. High substitutability could decrease employment opportunities for the near-retirement demographic, resulting in reduced consumption levels. If Florida has a high substitutability, moving to this area to improve welfare might not be

[1] According to a report by the Congressional Budget Office (CBO) (*The Demographic Outlook: 2023 to 2053* (2023)), projections for population dynamics indicate that the demographic group aged 65 and older is expected to grow at a rate that outpaces younger cohorts over the next three decades.

[2] This reduction is attributed to the rapid increase in the 55- to 64-year-old population, from 26 million to 42 million. In contrast, there has been a modest increase among 25- to 54-year-olds, from about 122 million in 2002 to 126 million in 2019.

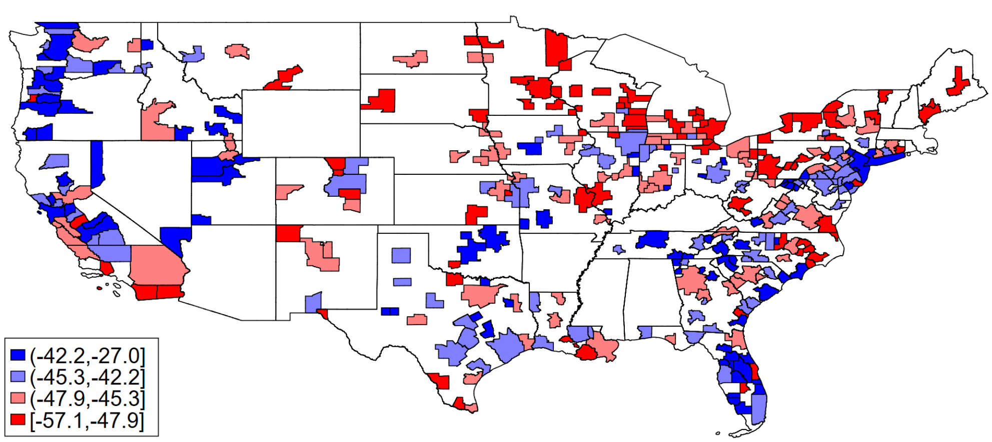
a good idea. Conversely, despite the lower inflow of prime-age workers, the Midwest could offer better prospects if it has significantly lower substitutability. At the same time, policymakers should consider not just relocating people to high-inflow areas but also reducing worker substitutability to improve the welfare of the marginal-retirement-age population. Therefore, considering both the regional variation in prime-age labor inflow and worker substitutability is essential when evaluating the welfare of near-retirement workers.

Figure 1: Ratio of population and employment between prime- and marginal-retirement-age



Note: The ratio of the population and employment of prime-age (25-54 years old) to marginal-retirement-age (55-64 years old) has dropped over the past 30 years.
Data sources: Congressional Budget Office (2023), Quarterly Workforce Indicator

Figure 2: Changes in relative employment (2002-2019)



Note: Substantial regional variation is evident in the decline of relative employment.
Data sources: Quarterly Workforce Indicator

This study explores the impact on internal migration of prime-age workers across 320 Metropolitan Statistical Areas (MSAs) in the United States from 2002 to 2019.[3] Specifically, this research investigates the impact of inflow shock on the relative employment and earnings to measure the substitutability between prime- and marginal-retirement-age workers. I find that a 1% increase in prime-age worker inflows increases the relative employment of prime-age to marginal-retirement-age workers by 1.39% and decreases the relative earnings by 0.18%, which indicates an elasticity of substitution of around 7.7 between these two labor cohorts. Thus, prime- and marginal-retirement-age workers function as strong substitutes in the labor market.

Extensive research has been conducted on the impact of different age groups of workers on each other, particularly focusing on how delayed retirement and the consequent increased labor supply of older workers affect younger individuals in the labor market. Some studies report negative impacts on younger workers (Bertoni and Brunello (2021); Bianchi et al. (2021); Bianchi and Paradisi (2022); Mohnen (2022)), while others report contrasting findings (Gruber et al. (2009); Munnell and Wu (2012)). Another strand of research examines the degree of substitutability between different age groups (Welch (1979); Katz and Murphy (1992); Card and Lemieux (2001); Borjas (2003); Ottaviano and Peri (2012)).[4] Given the varied age definitions and samples across these studies, their estimates are not directly comparable. However, in broad terms, substitutability estimates fall within the 3–5 range, with several studies finding a complementarity between age cohorts (Mitchell and Levine (1988); Gruber and Milligan (2010); Lim (2011)).

My research, however, diverges from previous studies by focusing on the regional variation across Metropolitan Statistical Areas (MSAs) and age-related labor substitutability. At the regional level, the labor market outcomes for marginal-retirement-age individuals can be affected by the inflow of prime-age workers. During such an inflow, coupled with the declining relative wages of prime-age workers, marginal-retirement-age workers may encounter increased pressure for involuntary early retirement or reduced working hours. On the other hand, marginal-retirement-age workers may also

[3]Due to the incorporation of three lags for the inflow shock in a regression equation, the first three years are excluded from the primary analysis. As a result, the main findings pertain to the economic phenomena observed between 2005 and 2019.

[4]Since the late 1970s, the canonical model that compares relative employment and wages has become a cornerstone for understanding a range of labor market issues, including the college wage premium, capital-skill complementarity, and elasticity of substitution between heterogeneous people.

benefit from increased employment opportunities due to economic growth in the region. Considering these contrasting potential scenarios, it is imperative to assess the impact of prime-age workers' internal migration on the marginal-retirement-age labor force at the regional level.

This research introduces a novel methodological approach. To mitigate potential biases from reverse causation, this study utilizes a shift-share instrumental variable approach for identifying the inflow shocks. Additionally, I use the local projection method, which helps reduce the effects of unobservable endogenous variables and traces the dynamic response of relative employment and earnings between prime- and marginal-retirement-age workers.

Furthermore, this study constructs a theoretical framework using an overlapping generations (OLG) model to examine the welfare impact on workers nearing retirement. My model reveals that the inflow of prime-age workers enhances the welfare of the marginal-retirement-age population. However, if the local economy has a high elasticity of substitution, the positive impact of the inflow on the welfare of marginal retirement people may be less pronounced than when it has a low elasticity of substitution. The United States has exhibited a high elasticity of substitution since 2002, which could potentially exacerbate the welfare of workers nearing retirement.

My research offers a critical analysis of the effect of labor migration and the degree of substitutability and how these factors influence the welfare of relevant demographics. Consequently, this study offers valuable insights for aging societies, including the United States, with high elasticity of substitution and may inform the formulation of welfare policies tailored to the needs of near-retirement workers.

The rest of the paper is organized as follows. Section 2 lays out the instrument construction, and Section 3 introduces the empirical strategy. Section 4 presents the impacts of inflow shocks on labor market outcomes for workers and estimates the elasticity of substitution between the prime- and marginal-retirement-age workers. Section 5 employs the OLG model and conducts a welfare analysis. Section 6 concludes.

2 Internal Migration Shock

This paper focuses on the internal migration between Metropolitan Statistical Areas (MSAs) within the United States, rather than on international migration. Therefore, it is possible to predict the inflows of workers into a specific MSA by checking the outflows from other metropolitan regions within the United States. Put simply, the total in-migration to a particular MSA is composed of the aggregated flows from all other MSAs towards it. For example, people moving to the Chicago MSA often originate from nearby MSAs, such as Michigan City (IN), Racine (WI), and Niles (IL). There is also an inflow from distant MSAs, such as Miami (FL), Los Angeles (CA), and Seattle (WA). From the perspective of origination MSAs, it can be observed that 40% of the outflows from Michigan City, 30% from Racine, 16% from Niles, 3% from Miami, 2% from Los Angeles, and 2% from Seattle, among others, migrate to Chicago annually. The total annual inflow to the Chicago MSA is derived from the weighted sum of out-migrations from other MSAs. In this study, I employ this principle to construct the instrumental variables. The inflow change for the metro area is quantified as the sum of changes in outflows from other metros times the share that historically moved to the MSA of interest, which is used to define the inflow shock. Thus, the inflow shock represents the difference between the calculated inflow of the preceding year and that of the current year.

This approach is intended to mitigate the pull factors of migration in the receiving metropolitan areas, thereby reducing the bias attributed to reverse causality. Consequently, factors such as Chicago's high employment rates or attractive wage levels, which may draw individuals, are ruled out. Admittedly, reverse causality may still occur if sending metros are geographically proximate to receiving metros or share similar industry structures. Thus, such metros are dropped in the calculation of the inflow shock, which will be elaborated upon in subsequent section 2.3. The supply-push instrumental variable has been widely used in studies (Altonji and Card (1991); Card (2001); Saiz (2007); Boustan et al. (2010); Burstein et al. (2017); Aksu et al. (2022)), and the identification strategy used in this study is similar to Howard (2020) applying the domestic migration setting.

2.1 Data

I employ two primary datasets from the Longitudinal Employer-Household Dynamics (LEHD). The first is the Job-to-Job Flows (J2J). The J2J statistics provides the job-to-job transition rate and characteristics of origin and destination jobs for the transitions, like the industries with which migrant workers are associated, in the United States. The data is accessible at the national, state, and metropolitan area levels, and this research primarily utilizes data segmented at the metro level. Although it is not possible to observe detailed individual worker characteristics through publicly accessible data, the J2J dataset provides total counts categorized by age group and sex. By leveraging J2J statistics, this research comprehensively covers an extensive array of minor MSAs, thereby enabling precise quantification of changes in flows. In numerous publicly available survey data, geographic information is limited to the state level if individuals reside in a sparsely populated MSAs. This results in a high sample attrition rate at the MSA level. However, in my research, the number of metros absent from the sample is minimal, and it is possible to construct a strongly balanced panel dataset from the J2J dataset, spanning 18 years and encompassing 19 industries across 320 MSAs.

The second dataset utilized in this study is the Quarterly Workforce Indicators (QWI). The QWI encompasses data on employment, job creation, earnings, and various other aspects of employment dynamics. This dataset parallels the Quarterly Census of Employment and Wages but offers additional advantage of enabling the measurement of employment numbers disaggregated by worker's sex and age group.

As a supplementary data source, local population data were obtained from the U.S. Census Bureau. To assign states to MSAs, the crosswalk provided by the Missouri Census Data Center was employed. For MSAs spanning multiple states, each was designated to the state where the majority of its population resided, based on the 2010 Census data.

2.2 Historical migration networks and the identification of inflows

The initial step involves constructing historical outflow patterns. Utilizing the 1940 full Census data from the Integrated Public Use Microdata Series (IPUMS), I compute the shares of outflows from each metro area j to another metro i, excluding within-MSA movements. The share represents the historical migration networks in 1940, which are similar to contemporary patterns.[5] The outflows from each sending MSA were normalized such that the sum of their shares equals 1.[6] While this exposure might be deemed sufficiently exogenous due to its temporal distance from the current analysis period, the potential for endogeneity cannot be ruled out due to its high correlation with contemporary exposures. Thus, the exogeneity of the instrument variable is primarily anchored in its shift component, the specifics of which are elaborated upon later in this study.

Table 1 presents the top ten and bottom ten sending MSAs along with their respective exposures, forming the inflow shock for the Chicago MSA. For MSAs in proximity to Chicago, a substantial share of workers migrated there, whereas for those farther away, the exposure notably decreases.

Table 1: Exposure to the Chicago MSA ($s_{Chicago,j}$)

	Sending MSA	Share	Sending MSA	Share
Top 10 MSAs	Kankakee-Bradley (IL)	.469	Danville (IL)	.191
	Michigan City-La Porte (IN)	.364	Carbondale (IL)	.176
	Racine (WI)	.252	Milwaukee-Waukesha (WI)	.157
	Rockford (IL)	.251	Champaign-Urbana (IL)	.153
	Davenport-Moline (IA-IL)	.207	Peoria (IL)	.146
Bottom 10 MSAs	New Bern (NC)	.0002	Rocky Mount (NC)	.0006
	Dover (DE)	.0004	Napa (CA)	.0006
	Mount Vernon-Anacortes (WA)	.0005	Midland (TX)	.0007
	Chico (CA)	.0005	Myrtle Beach-North Myrtle Beach (SC)	.0009
	Merced (CA)	.0006	St. George (UT)	.0010

Note: This table represent the exposure of sending MSAs with respect to the inflow of workers to Chicago, prior to normalization and without any distinction across industries. If the official name of the MSA includes two or more counties, only the first two county names are listed for brevity.

$$IV_{k,i,t} = \sum_{j \neq i} s^k_{i,j} \Delta m^y_{k,j \to j^-,t} = \sum_{j \neq i} s^k_{i,j} (m^y_{k,j \to j^-,t} - m^y_{k,j \to j^-,t-1}) \tag{1}$$

Next, the historical outflow shares are multiplied by the changes in the current gross outflows of prime-age workers in each metropolitan area. The changes in outflows are calculated using the

[5]The migration patterns of 1940 may diverge from recent trends. Historically, there was a prevalent westward migration, while recent patterns show a stronger southward drift. However, Table A1 demonstrates that the historical migration patterns in 1940 still can explain current patterns well.

[6]The migration patterns sourced from the 1940 Census data were not distinguished by industry; however, in the normalization process, the weights vary across industries, resulting in differentiated shares by industry.

J2J statistics. The multiplied figure denotes the annual change in flows from each other MSA into the specified MSA, indicating an acceleration in inflows. $\Delta m^{y}_{k,j\rightarrow j^{-},t}$ represents the changes in the current gross outflow of prime-age workers in industry k in metro j at the year t to all other MSAs.[7] Then, the weighted sum of the changes in current outflow from all other MSAs directed toward MSA i constitutes the in-migration shock for MSA i.[8] Based on this logic, for example, the inflow shock for Chicago is gauged by the weighted sum of total outflow changes from Kankakee, Michigan City, New Bern, Dover, and others. The shift-share instrument is formulated for each industry ($k \in [1, \cdots, 19]$),[9] MSA (i), and year (t) and is normalized by the metropolitan area's population from the preceding year. Overall, the instrumental variable covers 19 industries across 320 MSAs, from 2002 to 2019.

2.3 Exclusion of highly correlated regions

This study employs an instrumental variable consisting of the sum of the expected inflow changes to mitigate reverse causality. However, including cities that are geographically close can generate reverse causation. For example, neighboring MSAs to Chicago, such as Milwaukee, might face elevated worker outflows due to Chicago's rising productivity. Consequently, the projected worker inflow to Chicago is influenced by pulling factors, potentially giving rise to a reverse causality concern. Therefore, when constructing the instrument, this study excludes some sending MSAs that are geographically close to a receiving MSA. The presumption here is that the proximity of physical distance tends to positively correlate with shared characteristics that influence internal migration. I calculate the geographical distance,[10] denoted as $D_{1,(i,j)}$, by using each MSA's latitude and longitude coordinates. Then, the sending MSAs that fall within the lowest 1% percentile for the $D_{1,(i,j)}$ index are excluded. Excluding geographically adjacent sending MSAs from the instrumental

[7] $m^{y}_{k,j\rightarrow j^{-},t}$ is the total number of prime-age workers (y) who moved out from MSA j in industry k and year t. Thus, $\sum_{j\neq i} s_{i,j} m^{y}_{k,j\rightarrow j^{-},t}$ represents expected current inflows at MSA i.

[8] The main analysis of this research did not isolate the impacts stemming from the inflow of individuals who relocated to another MSA while maintaining employment in the same industry versus those who transitioned to a different industry upon moving to another MSA. In other words, $m^{y}_{k,j\rightarrow j^{-},t}$ signifies the total outflow from industry k of MSA j, irrespective of the industry in which people are employed in the destination MSA.

[9] I use the 2-digit NAICS sectors. This study is confined to employment within privately owned firms, and the NAICS 92 (public administration sector) is excluded.

[10] I used the *geodist* module in Stata (StataCorp), version 17.

variable calculation alleviates the reverse causality issue.

The reverse causality problem also arises when the industrial structures of receiving and the sending MSAs are similar. For example, suppose two cities have similar industrial structures. Under these circumstances, a surge in manufacturing productivity in one city could attract manufacturing workers from the other, drawn by the prospect of higher wages in the city with increasing productivity. This effect intensifies as the industrial congruence of the two cities grows more pronounced. As a result, it is the change in wages that affects the inflow of workers rather than the inflow of workers affecting wages. To address the reverse shift issue, excluding sending MSAs with similar industry structures from the instrumental variable calculation is advisable. To measure industrial similarities between metropolitan areas, I first calculate the employment share in each North American Industry Classification System (NAICS) 3-digit subsector k for each MSA i in 2001 ($s_{k,i,2001}$). Then, I compute the Euclidean distance in the shares of two distinct MSAs, i and j, denoted as $D_{2,(i,j)}$. Lower values of the index indicate greater similarity between the MSAs. Subsequently, the sending MSAs that rank within the bottom 1% percentile for the $D_{2,(i,j)}$ index are dropped.

$$D_{2,(i,j)} = \sqrt{\sum_{K}(s_{k,i,2001} - s_{k,j,2001})^2} \tag{2}$$

Table 2 shows the list of sending MSAs that were excluded when calculating the inflow shock of the Chicago MSA. The $D_{1,(i,j)}$ index is computed by logarithmically transforming the distance in miles between two metropolitan areas. If either of the $D_{1,(i,j)}$ or $D_{2,(i,j)}$ indices fall within the lowest 1% among all 320 sending MSAs, those MSAs are excluded from the construction of the instrumental variable. Consequently, out of the 320 total MSAs, 6 are excluded – 3 due to the $D_{1,(i,j)}$ and 3 owing to the $D_{2,(i,j)}$ criteria.

Table 3 presents basic summary statistics, comparing the actual inflow changes of prime- and marginal-retirement-age workers to the estimates from shift-shares.[11] The shift-share for marginal-retirement-age workers is computed similarly to Equation 1, with the sole difference being the substitution of the change in the total outflow of marginal-retirement-age workers in place of that

[11] In the regression analysis, the instrument is normalized relative to the local population. However, since meaningful comparisons are only possible at the third and fourth decimal places, this table presents values before normalization for clearer distinction.

for prime-age workers. On average, each MSA sees a yearly inflow change of about 192 prime-age workers, with large variations across industries and regions. The shift-share values are lower than the actual inflow changes.

Table 2: Sending MSAs dropped by the 1% exclusion rule in the Chicago MSA case

	Sending MSA	Index
Lowest 1% in $D_{1,(i,j)}$ Index	Kankakee-Bradley (IL)	3.679
	Niles-Benton Harbor (MI)	4.110
	Michigan City-La Porte (IN)	4.123
Lowest 1% in $D_{2,(i,j)}$ Index	Philadelphia-Camden (PA-NJ-DE-MD)	0.040
	Baltimore-Towson (MD)	0.043
	Cleveland-Elyria (OH)	0.048

Note: This table shows the sending MSAs that are dropped when calculating the inflow shock of the Chicago MSA. When either the $D_{1,(i,j)}$ or $D_{2,(i,j)}$ indices fall within the lowest 1% among all sending MSAs, those MSAs are excluded from the construction of the instrumental variable. Out of the 320 total MSAs, 6 are excluded - 3 due to the $D_{1,(i,j)}$ criteria and 3 owing to the $D_{2,(i,j)}$ criteria. No MSAs concurrently met both exclusion criteria. If the official name of the MSA includes two or more counties, only the names of the first two counties are included for the sake of brevity.

Table 3: Comparison between the instrumental variable and the actual changes in inflow

	MSA-level	MSA-industry level
Actual changes:	191.66	11.38
inflow of prime-age workers	(1,517.89)	(146.08)
Shift-shares:	111.22	6.24
inflow of prime-age workers (IV)	(1,307.36)	(101.37)
Actual changes:	49.98	2.99
inflow of marginal-retirement-age workers	(172.20)	(20.25)
Shift-shares:	39.48	2.21
inflow of marginal-retirement-age workers	(146.18)	(11.88)
The number of MSAs	320	320
The number of industries		19
The number of years	18	18
Observations	5,760	102,690

Note: This table compares the shift-shares with the actual changes in the number of incoming workers before normalization by the total local population of the MSA. Shift-share for marginal-retirement-age workers is computed similarly to Equation 1, with the only difference being the substitution of the change in total outflow of marginal-retirement-age workers for that of prime-age workers. Standard deviations are reported in parentheses. In the second column, the number of pairs (MSA, industry) is 5,705, which is primarily due to data attrition in Agriculture (NAICS 11), Mining (NAICS 12), and Construction (NAICS 23) industries.

This occurs due to two reasons. First, workers flow into a region from other metros beyond the 320 analyzed in this study. Out of the 384 MSAs identifiable in the complete QWI dataset, around 64 MSAs were excluded. Consequently, this approach likely underestimates the inflow, as the inflow shock in this study was constructed using flows only among these 320 MSAs. However, the MSAs included in this study encompass a population of 209.4 million as of 2019. The dropped MSAs account for only 34.6 million people, meaning the study covers approximately 86% of the total MSA population. Furthermore, my instrumental variables statistically significantly explain the actual inflow changes, suggesting that this identification strategy is less prone to compromising the integrity of causal relationships. A detailed explanation is provided in the following section.

Secondly, I exclude the flows from certain sending MSAs with similar industrial structures or proximate geographical locations to the receiving MSA. Since workers typically migrate between such cities, this exclusion results in a lower estimation of inflow changes. Without the exclusions, the shift-share for prime-age workers increases to 135.50, and that for marginal-retirement-age workers rises to 47.86, which is closer to the actual value. Despite the potential underestimation, this approach is advantageous as it helps minimize bias arising from potential reverse causality.

To sum up, the pull factor from a receiving MSA can indirectly impact the outflows in sending MSAs. This leads to reverse causality if a sending MSA exhibits a similar industrial composition to a receiving MSA or is geographically proximate to the receiving MSA. Therefore, excluding MSAs that are geographically close or have similar industrial structures can secure stricter exogeneity in the inflow and reduce bias. Therefore, while constructing the shift-shares, MSAs falling within the lowest 1% percentile for either the $D_{1,(i,j)}$ or $D_{2,(i,j)}$ index are excluded.[12] These exclusions further ensure that the instrumental variable effectively minimizes reverse causality.

[12] Statistically significant empirical results are obtained even when excluding MSAs with the lowest 5% or 10% percentile of the similarity index. The magnitude of these effects varied with the exclusion level, which is further elaborated in the Table A2.

3 Empirical Analysis

3.1 Analysis using the local projection method

The dynamics of worker flow and employment demonstrate considerable inertia. Historical values serve as robust predictors of contemporary and prospective trajectories. The local projection method can address this potential concerns by including lags of the endogenous variable (Jordà (2005)). This approach gauges the evolutionary trajectory of the dependent variable over time following an exogenous shock. I assess the impacts of the inflow of prime-age workers using Equation (3).

$$\log(\frac{N_{1,k,i,t+s}}{N_{2,k,i,t+s}}) - \log(\frac{N_{1,k,i,t-1}}{N_{2,k,i,t-1}}) = \beta_{1,s} IV_{k,i,t} + \gamma X_{k,i,t} + \rho_{k,i} + \tau_{i,t} + \epsilon_{k,i,t} \quad (3)$$

Each observation is the Industry(k)-MSA(i)-year(t) aggregated cell. The main outcome variable is relative employment between prime-age and marginal retirement-age workers. The time span, s, ranges from -4 to 10, marking the period from 4 years prior to the in-migration shock to 10 years past the shock. Consequently, I estimate the cumulative effect of the inflow shock conditional on the preceding responses for a given industry and MSA. The instrumental variable measures the changes in the annual inflow of prime-age workers.[13]

A set of control variables ($X_{k,i,t}$) incorporates three lags of the instrument variable and shift-shares for marginal retirement-age workers.[14] Analogous to the method employed in constructing the shift-share for prime-age workers, a corresponding shift-share has been constructed for workers approaching retirement age. This calculates the changes in the inflow of marginal-retirement-age workers and is incorporated to control the unobservable factors affecting workers' labor market outcomes. Industry by MSA (k, i) and MSA by year (i, t) fixed effects are added. Borusyak et al. (2022) found that year fixed effects interacted with the sum of exposure shares need to be included in a regression if the sum of shares varies across observations. In my study, the shares change across MSAs and industries, and I added the interaction terms as controls. The shift-shares are normalized

[13] Autor et al. (2021) and Hanson (2023) specify the coal shock as the logarithmic change in national coal production employment over the analysis period in their shift-share instrument. In my analysis, I also employ a fixed share and shock shift, but I measure the shift on an annual basis rather than the difference over the entire analysis period. The detailed calculation is presented in Appendix A1.4.

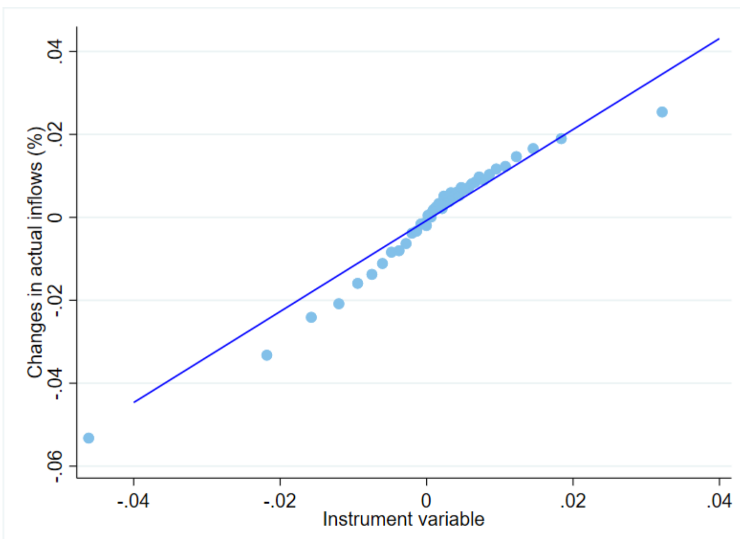
[14] Jaeger et al. (2018) highlight that including lagged instrument variables can help mitigate omitted variable bias from the dynamic adjustment of the shift-share IV.

by the metropolitan population one year ago, and standard errors are clustered at the state level.[15]

3.2 First-stage results

This research employs instruments to account for changes in worker inflow. A strong positive correlation between the instrumental variable and actual changes in inflows is evident in Figure 3. The first-stage regression results also support the relevance condition. Table 4 illustrates the extent to which the instrumented inflow shock accounts for the actual changes in worker inflow. All specifications are analogous to those in Equation (3), wherein s is equivalent to 0, and the outcome variable is the yearly changes in actual worker inflow. In response to a 1% increase in the instrument variable, the actual inflow of prime-age workers increases by approximately 0.66%.

Figure 3: Relationship between changes in actual inflows and the IV



Note: It illustrates the relationship between changes in actual inflows relative to the total local population and the IV, weighted by prime-age employment at the industry-MSA-year level, using a binscatter plot (50 bins). F-statistic is 103.4. Sources: LEHD; Job-to-Job Flows (2002-2019)

[15]The data were collected at MSA levels, but I cluster the standard errors at the state level. This is because movement between MSAs within a state was largely excluded based on the exclusion rules described earlier.

Table 4: First-stage result [Unit: %]

	$\beta_{1,0}$
IV	0.658***
	(0.065)
F-statistic	103.4
Three lags of IV	Y
Three lags of shift-shares of old	Y
Industry × MSA fixed effect	Y
MSA × Year fixed effect	Y
Observations	85,575

Note: The table illustrates the result of regressing the log changes in the actual inflow of younger workers on the instrument variable. Each observation is the Industry-MSA-year aggregated cell. A set of control variables incorporates three lags of the instrument variable and shift-shares for marginal retirement-age workers. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3 Causal identification

Recent studies have examined the causal identification of shift-share instruments, and this subsection explores the characteristics of my instrumental variables. Shift-share instruments combine observed shocks with shock exposure. In this study, the observed shocks are changes in the outflows of workers from other MSAs, and the shock exposure is the share of flows that measures to what extent inflows in the MSA are affected by outflows from other MSAs.

To establish a causal inference through an instrumental variable, the instrument variable needs to be orthogonal to unobserved shocks (ϵ_i). Borusyak et al. (2022) formulated sufficient conditions for achieving causal identification in empirical analysis when using the shift-share IV. The orthogonality condition is satisfied if either the out-migration patterns are exogenous and uncorrelated with unobserved shocks or if the variation in the underlying shock is quasi-random, and their framework focuses on the latter condition. That is, the orthogonality between the underlying shocks ($\Delta m_{k,j}$; the changes in outflow) and the exposure-weighted average of unobserved shocks for the sending MSA j ($\bar{\epsilon_j} = \sum_i s_{i,j}\epsilon_i / \sum_i s_{i,j}$) is utilized.

$$\mathbb{E}[\sum_i IV_{k,i}\epsilon_i] = \mathbb{E}[\sum_i \sum_j s_{i,j}\Delta m_{k,j}\epsilon_i] = \mathbb{E}[\sum_j s_j \Delta m_{k,j}\bar{\epsilon_j}] = 0 \tag{4}$$

For a different approach to shift-share instruments, see Goldsmith-Pinkham et al. (2020). This alternative view on shift-share instruments relies on the exogeneity of exposure with could-be endogenous shock. However, this assumption is likely violated in my case due to the potentially endogenous share. Even if lagged by many years, the migration patterns from 1940 could still be endogenous. Thus, orthogonality is defined for the outflow shocks in this study, and the identifying assumption is that the shock is orthogonal to the unobserved residual.

To check the orthogonality between the underlying shock and the residuals, two assumptions need to be met. First, shocks should be as good as randomly assigned, as if arising from a natural experiment. Borusyak et al. (2022) suggested regressing current shocks on past outcomes. However, as previously stated, the lagged variables of the instrumental variable are already included as controls. Thus, instead, I focus on examining pre-trends for the other outcome variables. Figure 4(a) reveals that, conditional on control variables, there was little pre-trend pattern in the inflow shocks. The effect of the inflow shock on the residual is analyzed by the local projection method.

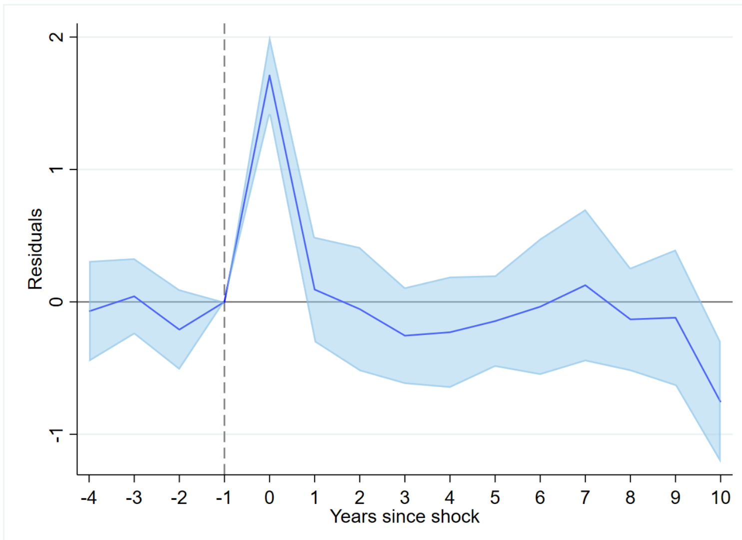
The second assumption is that the instrument should incorporate many independent shocks with sufficiently small average exposure. Figure 4(b) illustrates that each outflow shock has a sufficiently small average exposure. Therefore, Figure 4 shows that my causal identification framework satisfies Borusyak et al. (2022)'s two assumptions and is sufficient to indicate causality.

Furthermore, two types of exclusions further reinforce the exogenous nature of the shocks. If sending MSAs that are similar to receiving MSAs are not excluded, the inflow shock explains the changes in relative employment prior to the shock at the 90% significance level, which might indicate a reverse causal relationship. Therefore, excluding similar regions when constructing the instrument can remove the pre-trend and help to reduce the reverse causality problem effectively.

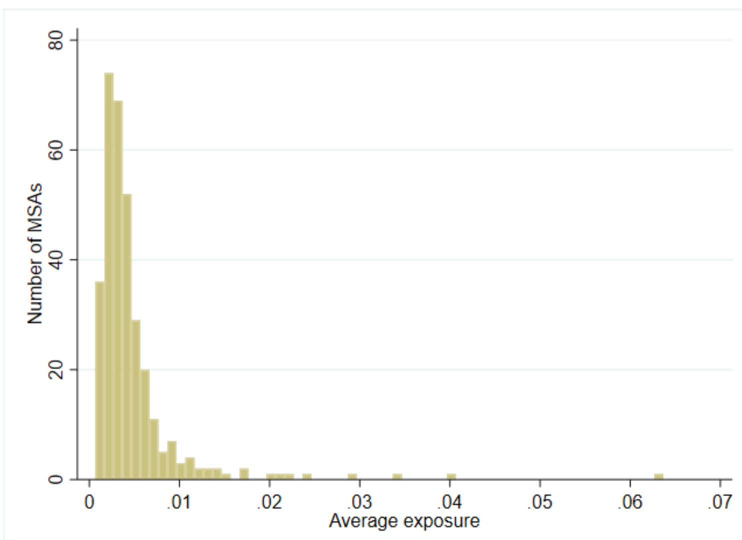
Additionally, using the *ssaggregate* module in Stata, developed by Borusyak et al. (2022), I conduct a shock level analysis. I find that the estimates and standard errors obtained using this approach are statistically significant and comparable to those derived from the instrument level analysis. Appendix 1.5 discusses this finding in detail. Consequently, the empirical specification using the instrumental variables in this study suggests causal relationships.

Figure 4: Satisfying two assumptions (Borusyak et al. (2022))

(a) No pre-trends in the inflow shock conditional on observables



(b) Small average exposure



Note: Panel (a) shows that conditional on controls, shocks are as-good-as-randomly assigned without the pre-trends. Panel (b) represents that outflow shocks have a sufficiently small average exposure.

4 Elasticity of Substitution

The elasticity of substitution is estimated by how much relative employment changes in response to changes in relative earnings between prime-age and marginal-retirement-age workers induced by internal migration. The elasticity of substitution is assessed by comparing relative earnings and relative employment changes in response to the inflow shock. The impact on relative employment and relative earnings is examined in this section. Then, the outcome of estimating the elasticity of substitution is presented.

4.1 Impacts on relative employment

This section illustrates the impact of the inflow shock of prime-age workers on relative employment. Table 5 shows three results: OLS without the use of the instrument, the reduced form employing the instrument, and the two-stage least squares (2SLS). The reduced form result is the same as the result from the local projection with s equal to 0 in Equation (3). That is, the outcome variable equates to the one-year logarithmic change in relative employment.

Table 5: Effects on the changes in relative employment [Unit: %]

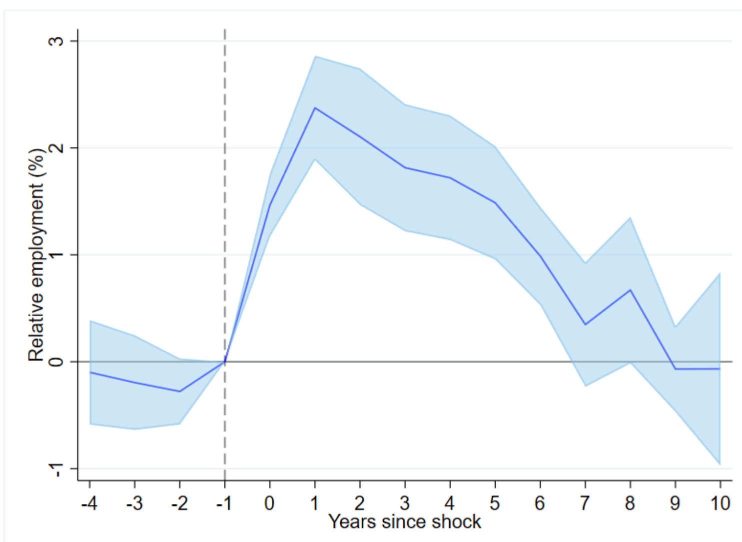
	OLS	RF	2SLS
Changes in actual inflows	1.082***		2.114***
	(0.117)		(0.182)
IV		1.391***	
		(0.144)	
Observations	85,575	85,575	85,575
Kleibergen-Paap F			103.4

Note: The first column illustrates the result of regressing the log changes in the relative employment between young and old workers on the changes in the actual inflow of young workers. The second column illustrates the result of regressing the log changes in the relative employment between young and old workers on the instrument in the reduced form. The third column illustrates estimates in the two stage least squares. A set of control variables incorporates three lags of the instrument and shift-shares for marginal retirement-age workers. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A 1% increase in the inflow of prime-age workers elevates the relative employment between prime- and marginal-retirement-age workers by 1.39%, and the F-statistic is 103.4. I mainly use the reduced-form results in the second column when estimating the elasticity of substitution between the two labor cohorts later in this paper.

Figure 5 presents the outcomes of the local projection regression Equation (3). The impact of the shock in year 0 aligns with the result from the reduced-form analysis in the second column of Table 5. The blue lines plot the $\beta_{1,s}$ coefficients from Equation (3) and the blue-shaded areas are 95% confidence intervals for the estimates. In each year, the dependent variable represents the log change in relative employment from the base year to the year prior- or post-shock. Since the impact of the instrument on the employment of prime-age workers significantly outweighs that of marginal-retirement-age workers, a surge in relative employment is observed.[16] The effect of inflow shock persists for up to six years.

Figure 5: Impacts on relative employment



Note: The figure illustrates the local projection results of regressing the log changes in the relative employment between young and old workers on the instrument variable. The blue-shaded area shows 95% confidence intervals for the estimates.

[16] Refer to Appendix 1.3 for further details.

4.2 Effects on changes in relative net employment

The results in the preceding section combine the direct employment augmentation attributed to the inflow of workers with the additionally increased employment. Here, I disentangle these two effects. If the employment, minus the number of directly inflowing workers, exceeds the employment level prior to the shock, then there is an additional employment effect attributable to the inflow of workers. This outcome might result from a decrease in worker outflow due to the inflow or other reasons, or it could stem from an employment multiplier effect. While this study cannot distinctly differentiate between these causes, the analysis enables us to gauge the magnitude of the net employment increase in relation to the inflow. The same analyses are conducted utilizing Equation (3), but the outcome variable now is relative employment excluding the actual number of inflow workers.

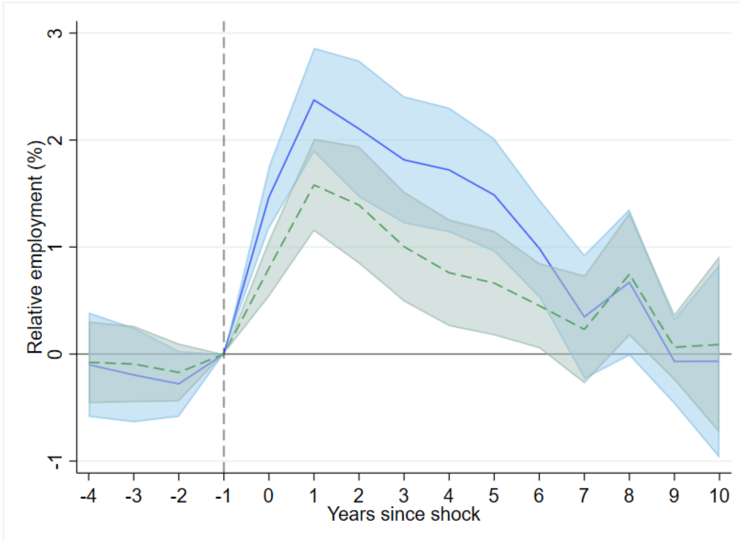
Table 6: Effects on the changes in relative net employment [Unit: %]

	OLS	RF	2SLS
Changes in actual inflows	0.117		1.144***
	(0.117)		(0.183)
IV		0.753***	
		(0.116)	
Observations	85,575	85,575	85,575
Kleibergen-Paap F			103.4

Note: All descriptions are the same as in Table 3. The only difference is that in this table, net relative employment that excludes mechanical impact on employment from the inflow of young workers is used as the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As presented in the second column in Table 6, when inflow increases by 1%, an additional increase of 0.75% manifests as a spillover effect. Figure 6 illustrates the local projection results. The blue solid line illustrates the results from regressing logarithmic changes in relative employment, while the green dotted line indicates the outcomes for relative net employment, calculated by subtracting the mechanical increase from the blue line. According to these results, around 54% of the total effect comes from the spillover effect of the inflow of prime-age workers.

Figure 6: Effects on the changes in relative net employment



Note: The figure compares the local projection results of regressing the log changes in the relative employment and that in the relative net employment. The blue solid line represents the former, and the green dotted line is the latter. The shaded areas show 95% confidence intervals for these estimates.

Table 7: Impulse responses of relative employment to the inflow shock

	0	1	2	3	4	5	6	7	8
Net effects	0.753	1.490	1.306	0.929	0.695	0.579	0.405	0.223	0.773
Total effects	1.391	2.234	1.968	1.685	1.593	1.324	0.902	0.328	0.699
Share (%)	54.1	66.7	66.4	55.1	43.6	43.8	44.9	68.0	110.5
Observations	85,575	79,870	74,165	68,460	62,755	57,050	51,345	45,640	39,935

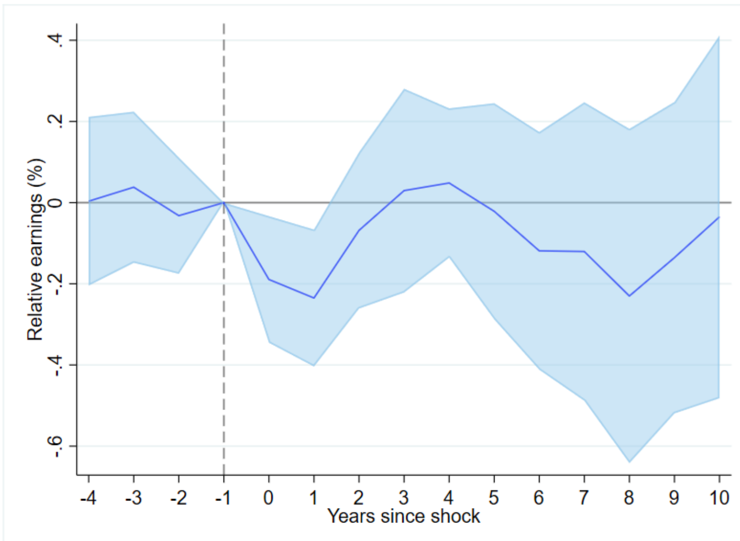
Note: Each column represents a local projection estimate of Equation (3) with the same controls. State-clustered standard errors are shown in parentheses. Share is determined by dividing the net effect coefficient by the total effect coefficient at each horizon. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Impacts on relative earnings

The average monthly earnings per worker, aggregated at each industry, MSA, and year level and sourced from the QWI, are used to assess the effects on relative earnings. The same regression equation (3) is applied, except for the outcome variable, which in this case is relative earnings.

Figure 7 depicts the impact of the inflow shock on relative earnings. With a 1% increase in the instrument, relative earnings decrease by approximately 0.18%. The effects are statistically significant but tend to dissipate one year after the shock. The second and third columns in Table 8 separately analyze the effect on the earnings of prime-age and marginal-retirement-age workers. It reveals a significant drop in the earnings of prime-age workers, while there is little effect on the wages of marginal-retirement-age workers.

Figure 7: Impacts on relative earnings



Note: The figure illustrates the local projection results of regressing the log changes in the relative earnings between young and old workers on the instrument variable. The blue-shaded area shows 95% confidence intervals for the estimates.

Table 8: Effects on relative earnings and earnings of young and old workers [Unit: %]

	Young and Old	Young	Old
IV	0.181**	-0.181***	0.000
	(0.071)	(0.056)	(0.087)
Three lags of IV	Y	Y	Y
Three lags of shift-shares of old	Y	Y	Y
Industry × MSA fixed effect	Y	Y	Y
MSA × Year fixed effect	Y	Y	Y
Observations	85,575	85,575	85,575

Note: The first column illustrates the result of regressing the log changes in the relative earnings between young and old workers on the instrument variable. The second column illustrates the result of regressing the log changes in the earnings of young workers on the instrument. The third column illustrates the result of regressing the log changes in the earnings of old workers on the instrument. A set of control variables incorporates three lags of the instrument and shift-shares for marginal retirement-age workers. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4 Estimation of the substitutability

I constructed impulse responses of relative employment and earnings to the inflow shock using local projections. The results suggest that an inflow of prime-age workers positively impacts relative employment between prime-age and marginal-retirement-age workers, while negatively affecting relative earnings. In this section, I estimate the elasticity of substitution between these two labor cohorts. The fundamental concept here is that the instrumental variable, which successfully explains changes in worker inflow, is used as an instrumental variable for relative employment. In the end, the two-step regression has the same result as the effect of the IV on relative earnings divided by the effect of the IV on relative employment.

The local projection regression equation is used as follows, with all control variables the same as shown in equation (3). The coefficients of interest are $\hat{\beta}_{2,s}$, which equates to the negative reciprocal of the elasticity of substitution. In this local projection, the time span, s, has only values of 0 or 1 because the effect of worker inflow on relative earnings dissipates two years after the shock, as shown in the previous section. As such, the value corresponding to the elasticity formula's numerator loses its statistical significance.

$$1st : \Delta_s \log(\frac{N_{1,k,i,t}}{N_{2,k,i,t}}) = \beta_{1,s} IV_{k,i,t} + \gamma X_{k,i,t} + \rho_{k,i} + \tau_{i,t} + \epsilon_{k,i,t}$$

$$2nd : \Delta_s \log(\frac{w_{1,k,i,t}}{w_{2,k,i,t}}) = \underbrace{\beta_{2,s}}_{\hat{\beta_{2,s}} = -\frac{\hat{1}}{\sigma_s}} \widehat{\Delta_s \log(\frac{N_{1,k,i,t}}{N_{2,k,i,t}})} + \gamma X_{k,i,t} + \rho_{k,i} + \tau_{i,t} + \epsilon_{k,i,t} \quad (5)$$

Table 9 shows the elasticity of substitutions using the 2SLS estimates. The coefficient equals the ratio of estimates of relative earnings to those of relative employment and is the inverse of elasticity. The estimated elasticity of substitution between prime-age and marginal-retirement-age workers is between 7 and 10. Local projections indicate that relative employment had increased by 3.63 percent during the first two years after the shock. Relative earnings had decreased by 0.41 percent, which indicates the elasticity is around 8.86. Figure 8 illustrates the negative reciprocal of the elasticity of substitution ($-\frac{1}{\hat{\sigma_s}}$). Coefficients of time spans ranging from -1 to 5 are plotted. As expected, the statistical significance of the estimate diminishes two years following the occurrence of the inflow shock.

Table 9: Elasticity of substitution

	0 year since shock ($s = 0$)	1 year since shock ($s = 1$)
FS ($\beta_{1,s}$)	1.391***	2.234***
(IV on N)	(0.144)	(0.214)
RF	-0.181**	-0.228***
(IV on W)	(0.071)	(0.078)
2SLS ($\beta_{2,s}$)	-0.130**	-0.102***
	(0.052)	(0.032)
Elasticity ($-\frac{1}{\beta_{2,s}}$)	7.676**	9.782***
	(3.063)	(3.094)
Kleibergen-Paap F	93.73	109.2
Observations	85,875	79,870

Note: The first row illustrates the result of regressing the log changes in the relative employment between young and old workers on the instrument variable. The second row illustrates the result of regressing the log changes in the relative earnings on the instrument variable. The third row illustrates the result of regressing the log changes in the relative earnings on the instrument variable in the 2SLS. The fourth row shows the elasticity of substitution, which is equal to the negative reciprocal of the 2SLS estimate. The reciprocal numbers are slightly different because of rounding. The two columns illustrate the impulse response at time 0 and 1, respectively. A set of control variables incorporates three lags of the instrument and shift-shares for marginal retirement-age workers. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 8: (-) Reciprocal of the elasticity of substitution

Note: The figure illustrates the local projection results of regressing the log changes in the relative earnings between young and old workers on the instrument variable in the two-stage least squares ($\beta_{2,s}$) and 95% confidence intervals for these estimates.

The estimated elasticity of substitution diverges slightly on the higher side relative to the extant literature, where the estimated range typically oscillates between 3 and 6. However, as shown in Table 10 and Table 11, upon recalculating the elasticity calculation to specifically target the male labor force consistent with prior studies, the elasticity conforms closely to previously established estimates.

Table 10: Previous literature

Study	Elasticity	Subgroup
Mitchell and Levine (1988)	Complements (partially)	Age
Katz and Murphy (1992)	3.3	Years of exp (Men only)
Card and Lemieux (2001)	4 - 6	Age (Men only)
Borjas (2003)	3.5	Years of exp (Men only)
Ottaviano and Peri (2012)	3.2 - 3.8	Years of exp (Men/Pooled)

Table 11: This study

	Male	Female
FS ($\beta_{1,s}$)	0.939***	0.470***
(IV on N)	(0.104)	(0.062)
RF	-0.258***	-0.067
(IV on W)	(0.087)	(0.057)
2SLS ($\beta_{2,s}$)	-0.274***	-0.142
	(0.100)	(0.121)
Elasticity	3.645***	7.047
	(1.332)	(5.993)
F-statistic	80.81	57.36
Obs	85,365	84,465

4.5 Discussion of weak instruments and F-statistic

A common rule of thumb considers an F-statistic of less than 10 to indicate weak instruments and potential bias in the estimates (Staiger and Stock (1997)). However, this requires a conditionally homoskedastic and serially uncorrelated errors assumption, a condition that is often not met in practice. Recent studies have sparked discussion about the potential errors caused by weak IVs (Lee et al. (2022), Young (2022)). This subsection evaluates whether the F-statistic in this study (103.4) is sufficiently large to avoid serious bias.

Table 12: Weak IV tests

Test	Criteria	Results
Anderson-Rubin Wald test	AR statistic	F(1,38)=42.44
Stock-Yogo weak ID test	F >16.38	F=103.4 >16.38
Angrist and Kolesar test	t >0	t=6.25 >0

Evaluating the weakness of the instrument variable depends on which criterion is used. First, Keane and Neal (2021) suggested the Anderson-Rubin (AR) test (Anderson and Rubin (1949)). They found that when the first-stage F-statistic is on the borderline (10–16.4 range), the AR test can judge whether the weak instruments may be a concern. According to the AR test results, the F statistic in this study is sufficiently large. Second, Stock and Yogo (2005) proposed critical values based on the 2SLS bias/size, the Fuller-k bias, or the limited information maximum likelihood estimator to test whether the instruments are weak, given the first-stage F-statistic. My F-stat surpasses the Stock-Yogo weak ID test's critical values. Third, Angrist and Kolesár (2021) showed that the first-stage t-statistic with a positive sign implies moderate endogeneity and low distortion in the just-identified IV model. The t-statistic in this paper is positive, and thus, the inference strategy is likely reliable. Hence, based on the evidentiary criteria, it remains challenging to assert that the instrumental variable deployed in this research constitutes a weak instrument for identification.

5 Calibration and Numerical Experiments

In earlier sections, I assessed the effects of prime-age worker inflow and the elasticity of substitution. This section delves into the impact of prime-age worker inflow on the welfare of marginal-retirement-age workers. Utilizing the overlapping generations (OLG) model, which addresses questions in which various age cohorts are differently affected by external shocks, I analyze changes in the utility levels of marginal-retirement-age workers resulting from the inflow shock.

Interpreted via the OLG model, the inflow of prime-age labor has the potential to enhance the welfare of workers nearing retirement. This is because such an inflow stimulates economic growth, thereby allowing marginal-retirement-age workers to enjoy increased consumption and leisure time with their higher wages, ultimately leading to improved welfare.

Furthermore, changes in welfare are connected to the elasticity of substitution between prime-age and marginal-retirement-age workers. In economies with lower substitutability between these groups, an inflow shock leads to greater increases in economic output. Consequently, marginal-retirement-age workers in such economies experience higher increases in consumption and leisure compared to those in economies with higher substitutability, significantly enhancing their utility. The following theoretical model, mirroring the empirical analysis, assumes MSA-industry distinctions in all formulas, but for simplicity, these notations are omitted.

5.1 Economic structure

5.1.1 Demographics

People in this model live for 60 periods.[17] I assume that individuals are born at age 25 and live until 84 years old. N_t^g represents the number of people in age g. To align with the setting in prior empirical analysis, the age bracket from 25 to 54 is categorized as the prime-age period, and 55 to 64 as the marginal-retirement-age period.[18] In order to include the realistic aspect that

[17] As Cavounidis et al. (2023) pointed out, concurrent birth and demise of substantial cohorts of workers render the convergence to steady-state employment and wages non-monotonic. Therefore, segmenting the population into more detailed age groups (as done in my paper with 60 generations), along with setting suitable parameter values, aids in establishing a stable convergence and equilibrium.

[18] In line with the empirical structure, outflows are omitted. Whether the inflow stands at 0.2 with an outflow of 0.1 or 0.1 with zero outflow, the net inflow remains 0.1, yielding identical outcomes in this model.

the marginal-retirement-age population has incentives to save as well as consume, ages over 65 is considered the post-retirement period. The total population of an area is comprised of cumulative populations across three age groups. In the following equations, each age group is denoted by subscripts 1, 2, and 3.

$$N_t = \sum_{g=25}^{84} N_t^g = N_{1t} + N_{2t} + N_{3t} \tag{6}$$

In the model, the demographic composition changes as follows. The number of prime-age people is the sum of those who previously lived and survived in the area and the number of net in-migrants. In the real world, a flow of marginal-retirement-age workers also occurs, but the extent is minimal, and thus, it is omitted from the model. The total population, prior to the inflow shock, was normalized to one. Contrasting with the previous empirical analysis that did not differentiate ages among incoming workers, the theoretical model assumes a uniform distribution of worker inflow, specifically those aged 25-54, to solve the model. Consequently, given an inflow shock of 0.01, which is 1% of the total population, each age between 25 and 54 receives an equal share of this percentage, resulting in an inflow rate of 0.0003 (= 0.01/30) for each age within that range. The vectors of survival rates transitioning from each age are different by age and denoted as $\vec{v_a}$, $\vec{v_b}$, and $\vec{v_c}$, respectively.[19]

$$N_{1t} = \sum_{g=25}^{54} N_t^g = \vec{v_{at}} \cdot N_{1t-1} + i_t - o_t \tag{7}$$

$$N_{2t} = \sum_{g=55}^{64} N_t^g = \vec{v_{bt}} \cdot N_{1t-1} \tag{8}$$

$$N_{3t} = \sum_{g=65}^{84} N_t^g = \vec{v_{ct}} \cdot N_{2t-1} \tag{9}$$

The law of motion for population for each age can be described as follows. In a steady-state economy, the net inflow of prime-age workers is expected to be zero ($i^* - o^* = 0$), and the local

[19]Detailed ratios are shown in the Appendix 1.6.

population will remain stable, provided survival rates do not change.

$$\frac{N_{t+1}^{g+1}}{N_t^g} = \begin{cases} 0.995 + \frac{i_{t+1} - o_{t+1}}{N_t^g} & \text{if } 25 \leq g \leq 54, \\ 0.985 & \text{if } 55 \leq g \leq 64, \\ 0.941 & \text{if } 65 \leq g \leq 84. \end{cases} \tag{10}$$

5.1.2 Preferences

The utility function of a person born at time t is as follows. Age is indicated as g. $c \in (0, \infty)$ is consumption, and $l \in (0, 1]$ is leisure. The t in parentheses indicates the time of birth.[20] α is the utility adjustment parameter between consumption and leisure, and the lower the value, the less the marginal utility of leisure, implying a reduced disutility of work. $\beta \in (0, 1)$ is the discount factor.

$$U(c, l) = \sum_{g=25}^{84} \beta^{t-25} \cdot [\ln(c_g(t)) + \alpha \ln(l_g(t))] \tag{11}$$

5.1.3 Endowments

The time endowment for each generation is fixed at one and allocated between leisure (l) and work (h). Post-retirement individuals over 65 are included in the population count but do not supply labor.

$$l_g(t) + h_g(t) = 1 \qquad (25 \leq g \leq 64) \tag{12}$$

$$l_g(t) = 1 \qquad (65 \leq g \leq 84) \tag{13}$$

In period 0, when the model begins, everyone who was born possesses initial savings equal to or greater than zero.

$$s_{26}(t-1), \cdots, s_{60}(t-59) \geq 0 \tag{14}$$

[20]On the other hand, a 'subscript' t signifies the time period.

5.1.4 Production technologies

I assume a two-level constant elasticity of substitution (CES) aggregate production function with prime-age labor, marginal-retirement labor, and capital as inputs.[21]

$$Y_t = A_t \cdot [\kappa \cdot \underbrace{[(\rho \cdot {H_{1t}}^{\theta} + (1-\rho) \cdot {H_{2t}}^{\theta})^{\frac{1}{\theta}}]}_{H_t}{}^{\psi} + (1-\kappa) \cdot {K_t}^{\psi}]^{\frac{1}{\psi}} \tag{15}$$

Total labor demand, H_t, is calculated as a CES aggregate of the two labor cohorts. H_{1t} and H_{2t} indicate the labor input of employed prime-age laborers at the point of time t and marginal-retirement-age laborers at $t-1$, respectively, while N_{1t} and N_{2t} denotes the number of their population. The technical progress, A_t, affecting all input factors is exogenously determined, independent of the inflow shock. κ determines the labor share in an economy, and ρ decides the share of prime-age workers to production relative to all workers. The parameter θ determines the degree of substitution between the two labor factors, and ψ determines the degree of substitution between labor and capital.

5.2 Solving the model

The model assumes rational expectations. Individuals accurately anticipate their future wages throughout their lifespan. Given their lifetime wealth, individuals determine their consumption, labor supply, and savings from their current age up to age 84. For those over 65 who have already retired, the labor supply is fixed at zero; hence, they only make optimal choices for consumption based on their accumulated savings. Annually, as one generation reaches the age of 84 and exits, a new set of 25-year-olds is born. These newcomers calculate their lifetime wealth, making optimal decisions for the upcoming 60 years.[22]

[21]The lowercase h represents individuals' labor supply, and the uppercase letter H represents the aggregated labor supply.

[22]In the presence of exogenous shocks, such as an inflow of workers, the wage dynamics alter, affecting lifetime wealth differently depending on an individual's birth year. For instance, a surge in worker inflow impacts the number of workers, consequently altering current and future employment and wage dynamics. The lifetime wealth of people born at $t=1$ is calculated based on wages from $t=1$ to $t=40$, while for an individual born at $t=2$, it's based on wages from $t=2$ to $t=41$. As a result, their consumption and leisure dynamics may differ from those of the previous generation. The labor supply provided by individuals newly born at 25 years of age, existing workers, and external labor forces together form the total labor supply at any given time.

Firms demand labor and capital where marginal productivity and factor prices equilibrate. The factor prices of labor, wages, are determined annually at the point where total labor supply meets total labor demand. The model assumes that the factor prices of capital and the prices of consumer goods remain constant. This section details the optimization problems for individuals and firms and market-clearing conditions.

The model is resolved utilizing Python's $fsolve$ module, which is effective for identifying roots of non-linear equations using the optimization algorithm known as Powell's dog leg method. Specifically, to adhere to the rational expectation assumption, I initially guessed the wages of prime- and marginal-retirement-age workers over 60 periods (making 120 guesses) as 1 and then determined the convergence values that equate supply and demand in two labor markets across a 60-period timeframe.

5.2.1 Households

Representative individuals choose consumption level and leisure (or labor supply) to maximize their utility, given the following budget constraints. For notional brevity, the subscript t is omitted from the formula.

$$Max \quad U(t) = \sum_{g=25}^{84} \beta^{g-25} \cdot [\ln(c_g(t)) + \alpha \ln(1 - h_g(t))] \tag{16}$$

subject to

$$c_g(t) + s_g(t) = w_{1t} \cdot h_g(t) + (1+r) \cdot s_{g-1}(t) \qquad (25 \leq g \leq 54) \tag{17}$$

$$c_g(t) + s_g(t) = w_{2t} \cdot h_g(t) + (1+r) \cdot s_{g-1}(t) \qquad (55 \leq g \leq 64) \tag{18}$$

$$c_g(t) + s_g(t) = (1+r) \cdot s_{g-1}(t) \qquad (65 \leq g \leq 84) \tag{19}$$

Earnings, w_1 from prime-age and w_2 from marginal-retirement-age, for each period are utilized for consumption and savings throughout a lifetime. The normalized price of consumption goods is set to 1. Additionally, households fully expend all assets accumulated over their lifetimes by the time they reach the end of their lives. The optimal solutions are to choose $\{c_g(t)^*\}$, $\{h_g(t)^*\}$, and $\{s_g(t)^*\}$ given $\{w_t\}$ and $\{r\}$. Wages fluctuate with the economy, yet individuals within the same age bracket earn identical salaries annually. That is, workers aged 25-54 earn $\{w_{1t}\}$, while those 55-64 receive $\{w_{2t}\}$. I assume an open economy in which the world interest rate, r, is exogenously given. The aggregate labor supply in an economy is the sum of individual labor contributions based on optimal choices.

5.2.2 Firms

Firms employ capital up to the point where the net marginal product of capital equals the externally set world interest rate. They hire the two labor cohorts until the wages correspond to the marginal productivity of each labor type.

$$r_t = Y_t^{1-\psi} \cdot A_t^{\psi} \cdot (1-\kappa) \cdot {K_t}^{\psi-1} - \delta \tag{20}$$

$$w_{1t} = Y_t^{1-\psi} \cdot A_t^{\psi} \cdot \rho \cdot \kappa \cdot H_t^{\psi-\theta} \cdot H_{1t}^{\theta-1} \tag{21}$$

$$w_{2t} = Y_t^{1-\psi} \cdot A_t^{\psi} \cdot (1-\rho) \cdot \kappa \cdot H_t^{\psi-\theta} \cdot H_{2t}^{\theta-1} \tag{22}$$

The optimal solutions for firms are to choose $\{H_{1t}^*\}$, $\{H_{2t}^*\}$, $\{K_t^*\}$ given $\{w_{1t}\}$, $\{w_{2t}\}$, $\{r\}$, and $\{A_t\}$. The wage differential equals the ratio of each worker type's marginal productivity, which derives the relationship between relative employment and relative earnings and the elasticity of substitution.

$$\sigma = \frac{1}{1-\theta} = \frac{\partial \ln\left(\frac{H_{1t}}{H_{2t}}\right)}{\partial \ln\left(\frac{w_{1t}}{w_{2t}}\right)} \tag{23}$$

5.2.3 Rational expectations

This model operates under the assumption of rational expectations, where all economic agents accurately predict their future wages. Observing any inflow of prime-age workers, they adjust their consumption, labor supply, and labor demand accordingly. In an unanticipated inflow shock, individuals may revise their consumption, savings, and labor supply decisions for all subsequent periods. The inflow shock is perceived as a temporary phenomenon. Yet, as mentioned earlier, a 1% increase in the prime-age worker population uniformly affects those aged 25-54. Thus, this shock will gradually fade in 60 periods.

5.2.4 Market clearing

In equilibrium, labor demand matches labor supply for prime-age and marginal-retirement-age workers. Labor supply aggregates the optimal labor contributions from households. At time t, the total labor supply is determined by multiplying the labor cohort's population, N_t^g, with the labor supply from individuals in the cohort, $h_g(\cdot)$.

$$H_{1t} = \sum_{g=25}^{54} N_t^g \cdot h_g(\cdot) \tag{24}$$

$$H_{2t} = \sum_{g=55}^{64} N_t^g \cdot h_g(\cdot) \tag{25}$$

Under the open economy assumption regarding capital, the capital utilized in the current period consists of capital remaining after depreciation and accumulated local savings from previous periods. Total savings in an economy are the sum of prime-age, marginal-retirement-age, and post-retirement-age people's savings.[23]

$$K_{t+1} = (1-\delta) \cdot K_t + \sum_{g=25}^{64} N_t^g \cdot s_g(\cdot) + \sum_{g=65}^{83} N_t^g \cdot s_g(\cdot) \tag{26}$$

Total output consists of aggregate consumption and overall savings, thus balancing the goods market. Aggregate consumption is the sum of present consumption from all age groups. Total savings are calculated from the accumulated savings of the 59 generations, excluding those aged 84.

$$Y_t = \sum_{g=25}^{84} N_t^g \cdot c_g(\cdot) + \sum_{g=25}^{83} N_t^g \cdot s_g(\cdot) \tag{27}$$

5.3 Calibration

The model is calibrated on an annual basis, with economic parameters selected either externally or by matching moments. I specifically aim at the U.S. labor market from 2002 to 2019. Table 13 shows the parameters incorporated in the model. Consistent with the empirical results, the elasticity of substitution between prime- and marginal-retirement-age workers is assumed to be around 7.7. The

[23]Note that savings during the final period of life are set to zero ($s_{84}(t-59) = 0$).

parameter representing the disutility of work is calculated to bring it closer to the U.S. prime-age labor force participation rate of 82.2% in 2010.[24] The total population is normalized to 1, and the prime-age, marginal-retirement-age, and post-retirement-age populations are 0.6313, 0.1801, and 0.1886, respectively. Survival rates are determined to closely match the actual population distribution of the United States in 2010. In specific, the survival rate would diminish by 0.5% for each added year of age in the prime-age group, by 1.5% in the marginal-retirement-age group, and by 5.9% among those in the post-retirement group. In the baseline model, the number of individuals aged 25 at birth and the survival rates remain constant in each period. Hence, the total population remains unchanged as long as the net inflow is zero. The elasticity of substitution between prime- and marginal-retirement-age and population share will be varied in the extended welfare analysis.

Table 13: Parameteric values

Parameter	Value	Source
Subjective discount factor	1.011	Kim and Hewings (2013)
Depreciation rates	0.045	Hasanhodzic and Kotlikoff (2013)
ELS between L and K	0.7	Mućk et al. (2017)
ELS between P and MR	7.7	Empirical results from this paper
Interest rate	1.08%	The average of real interest rate (FRED)
Labor income Share	0.601	The average of labor share (BLS)
Prime-age labor income share	0.806	The average of prime-age labor share (QWI)
Disutility of work for P	0.46	Calibrated results in this the model
Disutility of work for MR	1.7	Calibrated results in this the model
Survival rates	Appendix 1.6	The U.S. population in 2010 (by Census)
Technological progress	1	Model assumption

5.4 Welfare analysis

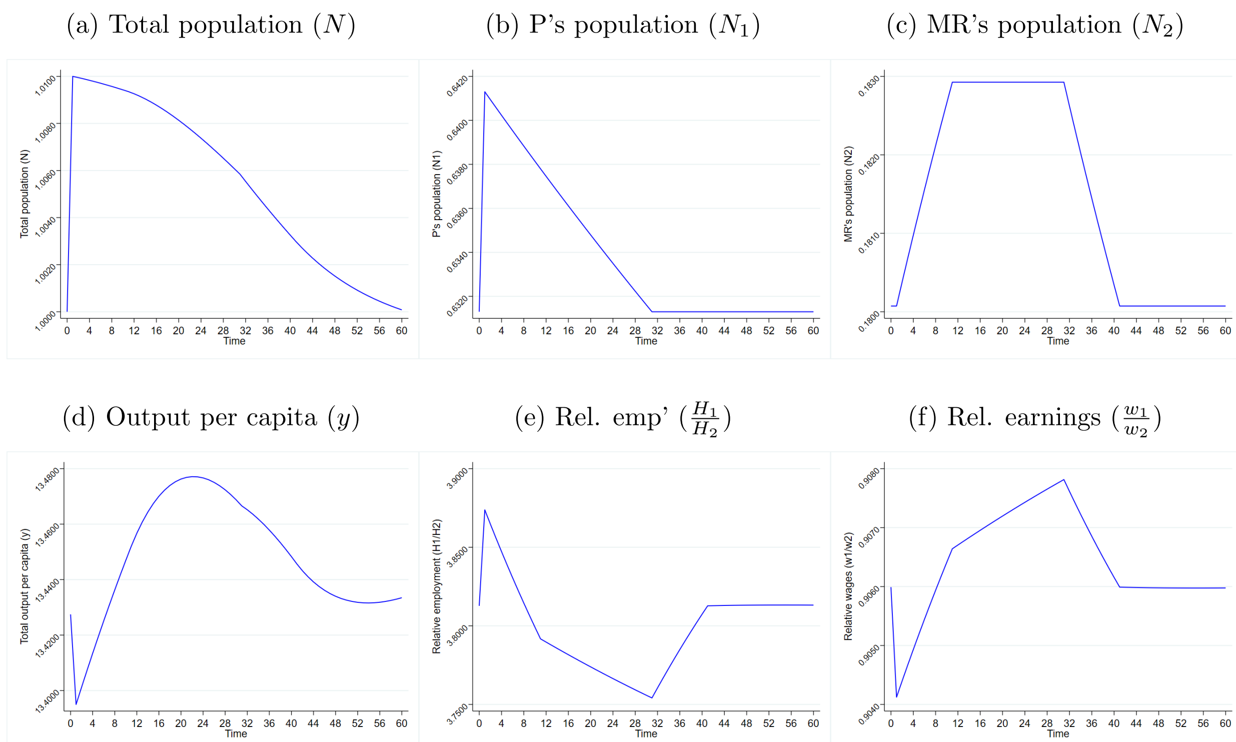
This section presents the simulation outcomes of the baseline model. To evaluate the effect of prime-age worker inflow on the utilities of the marginal-retirement-age population, the computational results with the inflow of prime-age workers will be compared with outcomes absent the inflow shock. I depict the transitional dynamics.

[24]My value is 82.6%.

5.4.1 Effects of the inflow shock

I assume an inflow of the prime-age population amounting to 1% of the local population. The model presumes that the entire prime-age population across 30 generations is increasing by 1%, with the population of each generation aged 25-54 increasing by 0.03%. Figure 9 illustrates the dynamics of variables over a period of 60 years. The focus is on the first decade following the shock, aligning with the empirical analysis. An inflow shock in this model took place at time 0.

Figure 9: Impulse response to an inflow shock

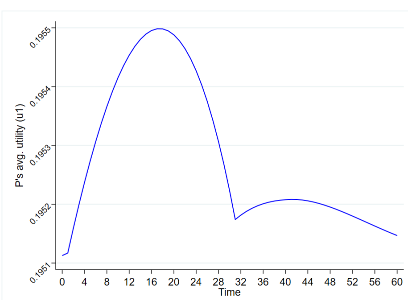


Initially, the total population grows by 1% from 1 to 1.01, then gradually declines following assumed survival rates. Based on the pre-existing population distribution, the prime-age population increases by about 1.59% right after the inflow shock. Since the population boost spans all age groups within the 25-54 year bracket, the inflow's impact on the prime-age population completely vanishes after 30 periods. In one period post-inflow shock, the population aged 54 becomes 55 and starts being categorized as marginal-retirement-age, leading to an increase in their numbers as well. From the 11th to the 31st period following the shock, the number of prime-age workers supplied remains steady. Hence, the marginal-retirement population stays constant, then reverts to its pre-shock state.

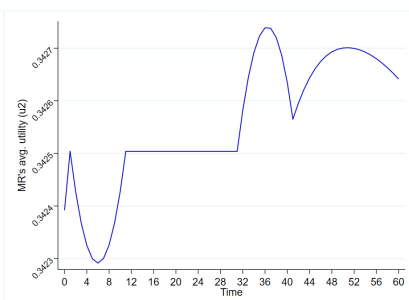
Per capita output drops immediately following the inflow shock. As capital does not rise proportionally with the labor increase, total output grows by just 0.76%, reducing per-person production by 0.24%. Nevertheless, the spike in the prime-age populace, who save substantially, boosts savings and capital as time goes by, thereby elevating per capita output above pre-shock levels. However, with the decline in growth of the prime-age segment and the rising proportion of marginal-retirement-age individuals, savings reduce, and per capita output correspondingly decreases. In response to the inflow shock, relative employment ascends by 1.60%, and relative wages dip by 0.21%, suggesting an elasticity of substitution around 7.77. As demonstrated in Appendix 1.7, the employment rates of prime- and marginal-retirement-age groups align precisely with their population sizes. Given the linear population changes, the ratio is depicted with kinked points. Concurrently, as individual's optimized leisure inversely relates to relative wages, the latter inversely mirrors the movements in relative employment.

Figure 10: Transitional dynamics of the welfare

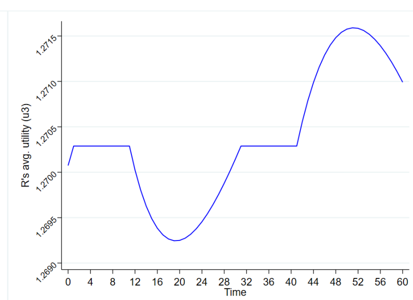
(a) P's utility (U_1)



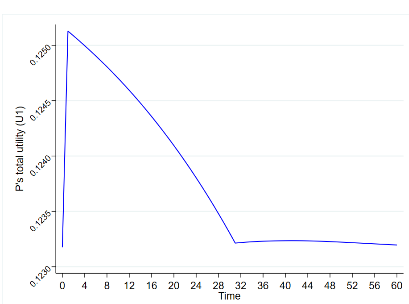
(b) MR's utility (U_2)



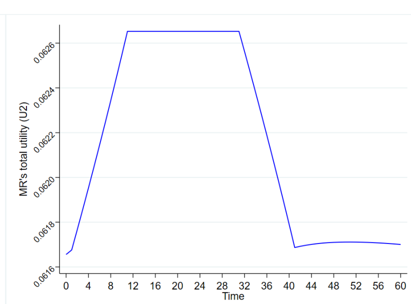
(c) R's utility (U_3)



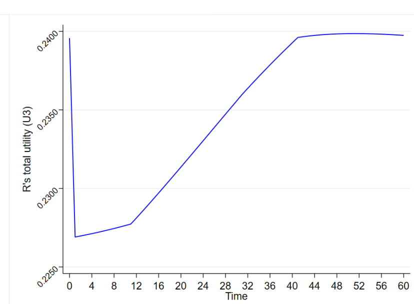
(d) P's total utility (U_1)



(e) MR's total utility (U_2)



(f) R's total utility (U_3)



The impact of an inflow shock on welfare is illustrated in Figure 10. It shows the average utility dynamics for three age groups: prime-age (25-54), marginal-retirement-age (55-64), and post-retirement-age (65-84). The graphs in the first row represent the average utility for each age group, and those in the second row represent their total utility.[25] Notably, all three graphs in the first row display convex curves. This is a result of dividing linear total utility changes by non-linear population shifts.[26] In this study, population dynamics are a key variable, and welfare dynamics reflect population impacts well.

Table 14: Changes in average consumption, leisure, and wages (%)

	Consumption	Leisure	Wages
Prime-age	0.0169	-0.0266	-0.1070
Marginal-retirement-age	0.0169	0.0356	0.0993

The inflow of prime-age workers increases marginal-retirement-age individual's welfare. This is due to an increase in wages, consumption, and leisure for the marginal-retirement population as indicated in Table 14.[27] However, with the rapid growth of this population segment, average welfare begins to decrease. Therefore, it is essential to foster economic conditions that mitigate the decline in welfare for the marginal-retirement-age population following the inflow of prime-age workers. This paper suggests that lowering the elasticity of substitution, leading to increased economic output, consumption and leisure, could be a viable strategy to accomplish this.

I analyze three distinct economies, characterized by elasticity of substitution values of 5.5, 7.7, and 10. My findings indicate that the marginal-retirement-age population benefits from higher welfare with lower elasticity in response to the inflow shock. As demonstrated in Table 15, a lower elasticity of substitution corresponds to increased consumption and labor supply by marginal-retirement-age individuals. While increased work may initially seem to negatively impact utility, it

[25]In these figures, individual utilities are transformed as an exponential form and summed to determine the overall utility. Utilizing the log utility function allows for welfare to be computed as a negative value. However, to maintain the ordinal utility system, negative values are converted to positive ones.

[26]The linearity of total utility changes stems from individuals operating under rational expectations, enabling precise calculation of lifetime total wealth and effective consumption smoothing. As leisure is planned to be inversely proportional to consumption given wages, individual utility at each age is linearly plotted. Consequently, total utility, being a weighted sum of these, also appears linear. However, when this total utility is divided by the varying sums of each population cohort, it shows a curved form.

[27]Refer to Appendix 1.7 for the dynamics plot.

ultimately contributes to welfare improvement by enabling greater earnings and consumption. The post-inflow shock observations indicate that a lower elasticity of substitution correlates with higher growth rates in consumption, leisure, and wages, thereby further enhancing welfare.

Table 15: Differential impacts of the inflow shock on marginal-retirement-age population

Baseline without the inflow shock	Consumption (c_2)	Leisure (l_2)	Wages (w_2)	Utility (U_2)
$\sigma = 5.5$	0.7853	0.2281	1.5835	0.3985
$\sigma = 7.7$	0.6593	0.2400	1.2637	0.3424
$\sigma = 10.0$	0.6013	0.2473	1.1184	0.3166
Effects of the inflow shock (%)	Δc_2	Δl_2	Δw_2	ΔU_2
$\sigma = 5.5$	0.0240	0.0439	0.1372	0.0434
$\sigma = 7.7$	0.0169	0.0356	0.0993	0.0327
$\sigma = 10.0$	0.0129	0.0293	0.0769	0.0259

6 Concluding remarks

This study examines the impacts of prime-age labor inflow and its substitutability with near-retirement labor across 320 U.S. Metropolitan Statistical Areas from 2002 to 2019. The inflow alters the relative employment and earnings between prime-age and marginal-retirement-age workers, from which the elasticity of substitution is derived. Then, utilizing the overlapping generations model, I analyze changes in the utility levels of the marginal-retirement-age population resulting from the inflow shock.

This study addresses potential biases from reverse causation by constructing the supply-push instrumental variables and gauges the evolutionary trajectory of employment and wages over time by using the local projection method. The findings reveal that a 1% increase in prime-age worker inflows results in a 1.39% increase in relative employment and a 0.18% decrease in relative earnings for prime- to marginal-retirement-age workers, suggesting an elasticity of substitution of around 7.7 between these cohorts.

Moreover, using an overlapping generations (OLG) model, this paper finds that prime-age worker inflows generally benefit the utility of marginal-retirement-age workers. It is important to note that the welfare of those nearing retirement does not uniformly increase. In regions where the elasticity of substitution is high, the positive effects on the welfare of the near-retirement population are less pronounced compared to areas with low elasticity.

This study provides crucial insights for aging societies, especially in the formulation of welfare policies focused on near-retirement workers. An aging society often leads to economic slowdown. To mitigate this impact, the inflow of prime-age workers can be a potential solution, provided there is low substitutability between prime-age and marginal-retirement-age workers. The lower elasticity of substitution is associated with increased consumption, leisure, and wage growth, further enhancing welfare. However, considering the high elasticity of substitution observed in the United States since 2002, the overall welfare of workers nearing retirement could potentially be negatively impacted despite the inflow of prime-age workers in the region. Therefore, this paper recommends reducing the elasticity of substitution in contexts with inflows of prime-age workers as a strategic approach to improving the welfare of the near-retirement population.

A1 Appendix

A1.1 Migration patterns

The migration pattern in 1940 adequately explains the current migration pattern. Recent migration patterns have been computed using the American Community Survey (ACS). It focuses on all the 384 MSAs included in the J2J data. Table A1 illustrates the correlation of migration shares, and the number of comparable MSA pairs is indicated in parentheses.

Table A1: Correlation between migration shares

	Y1940	Y2006	Y2008	Y2010	Y2012	Y2014	Y2016	Y2018	Y2019
Y1940	1								
	(73,545)								
Y2006	0.71	1							
	(9,765)	(10,945)							
Y2008	0.7007	0.7805	1						
	(9,517)	(5,928)	(10,672)						
Y2010	0.7006	0.7677	0.7647	1					
	(9,178)	(5,866)	(5,707)	(10,278)					
Y2012	0.69	0.7468	0.7487	0.7693	1				
	(8,858)	(5,013)	(4,945)	(4,890)	(9,870)				
Y2014	0.677	0.757	0.7709	0.752	0.7505	1			
	(9,046)	(5,093)	(5,069)	(5,024)	(5,513)	(10,061)			
Y2016	0.6823	0.7535	0.784	0.7764	0.7626	0.7811	1		
	(9,098)	(5,166)	(5,062)	(4,969)	(5,594)	(5,694)	(10,171)		
Y2018	0.7016	0.7597	0.7465	0.7673	0.7572	0.7383	0.7639	1	
	(9,235)	(5,161)	(5,076)	(4,963)	(5,655)	(5,674)	(5,770)	(10,332)	
Y2019	0.6643	0.7607	0.7583	0.7605	0.7449	0.7483	0.7508	0.7657	1
	(9,284)	(5,219)	(5,103)	(4,963)	(5,674)	(5,705)	(5,767)	(5,840)	(10,335)

This reveals a significant overlap of approximately 70% in migration patterns, indicating that the shares in 1940 represent recent migration patterns well enough. Recent samples possess less comparable MSAs because the ACS conceals MSA information in most samples to prevent personal identification. Consequently, significant inter-MSA migration network information is lost, and the relationship between even recent consecutive years does not exceed 80%. Hence, this study calculates migration patterns using the most recent full Census. It demonstrated that an instrumental variable has robust first-stage results and a high F-statistic even using the 1940 migration patterns.

A1.2 Varying elasticity of substitution based on the exclusion rules

The pull factor from a receiving MSA can indirectly impact the outflows in sending MSAs. This leads to reverse causality if a sending MSA exhibits a similar industrial composition to a receiving MSA or is geographically proximate to the receiving MSA. In the main analysis, MSAs falling within the lowest 1% percentile for either the $D_{1,(i,j)}$ or $D_{2,(i,j)}$ index are excluded. To check the robustness of the exclusion rule, I compare the elasticities from the instrument variables excluding the lowest 0%, 5% and 10% percentile of the similarity index. All three results are statistically significant.

Table A2 shows that instrumental variables incorporating stronger exclusion rules primarily assess the inflow of workers migrating from distant locations. As the exclusion rule becomes more stringent, there is an increase in the elasticity of substitution. This suggests that workers from distant MSAs possess higher education levels or abilities (greater competence), which more effectively displace workers nearing retirement age.

Table A2: Elasticity of substitution

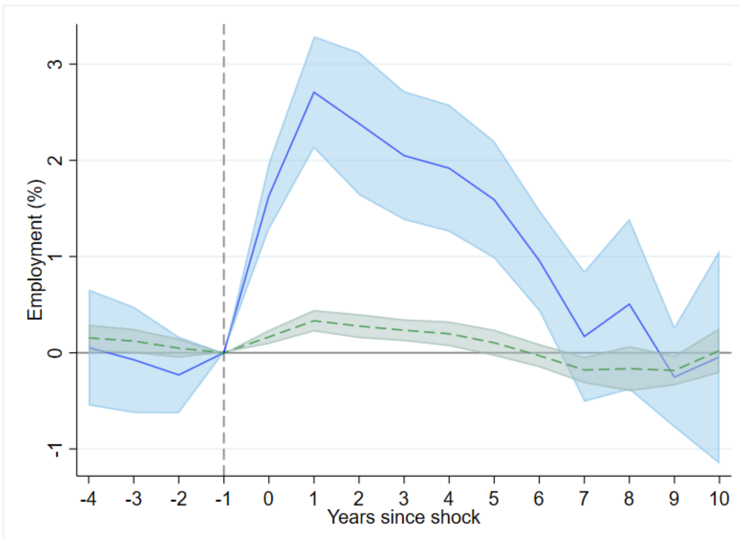
	No exclusion	5% exclusion	10% exclusion
FS ($\beta_{1,s}$)	1.211***	2.483***	3.521***
(IV on N)	(0.114)	(0.338)	(0.527)
RF	-0.140**	-0.276**	-0.263*
(IV on W)	(0.052)	(0.118)	(0.132)
2SLS ($\beta_{2,s}$)	-0.116**	-0.111**	-0.075*
	(0.044)	(0.045)	(0.037)
Elasticity ($-\frac{1}{\beta_{2,s}}$)	8.624**	9.001**	13.37*
	(3.236)	(3.624)	(6.630)
Kleibergen-Paap F	112.4	54.11	44.57
Observations	85,875	85,875	85,875

Note: The first row illustrates the result of regressing the log changes in the relative employment between young and old workers on the instrument variable. The second row illustrates the result of regressing the log changes in the relative earnings on the instrument variable. The third row illustrates the result of regressing the log changes in the relative earnings on the instrument variable in the 2SLS. The fourth row shows the elasticity of substitution, which is equal to the negative reciprocal of the 2SLS estimate. The reciprocal numbers are slightly different because of rounding. A set of control variables incorporates three lags of the instrument and shift-shares for marginal retirement-age workers. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A1.3 Asymmetric impacts on the employment of young and old workers

The impacts on relative employment are derived from the asymmetric effects of younger worker inflows on the employment of different worker types. Since the effects on young workers significantly outweigh the latter, an increase in relative employment transpires. The specifications in equation (3) are employed, but the outcome variable is either the log-transformed employment share of young or old workers relative to the local population.

Figure A1: Impacts on employment of prime-age and marginal-retirement-age workers



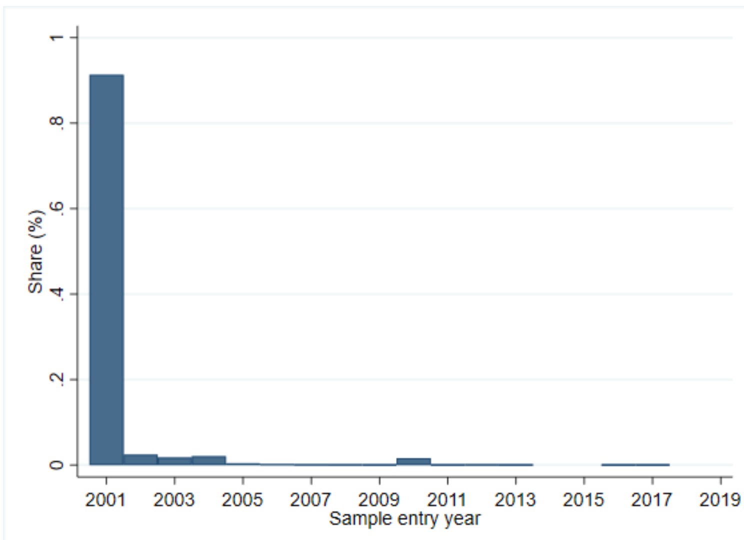
Note: All specifications are analogous to those in equation (3), but the outcome variable is either the log-transformed employment share of younger or older workers relative to the local population. It reports coefficient estimates for $\beta_{1,s}$ and 95% confidence intervals for these estimates.

Figure A1 illustrates that with a 1% increment in the IV, the employment of young workers increases by 1.63%, and that of older workers enhances by 0.16%, relative to the local population. Because the former significantly outweighs the latter, a surge in relative employment is observed.

A1.4 Calculation on instrumental variable

In this paper, the instrumental variable is utilized to measure changes in the annual inflow of younger workers. There are two ways to calculate this. One method involves measuring the difference in the shift-share using the outflow itself, while the other method is multiplying the change in outflow by the exposure. The former calculation ($\Delta SS^y_{k,i,t}$) has exactly the same implication as the weighted sum of changes in the outflow ($\sum s_{i,j} \Delta m^a_{k,j,t}$). However, the actual calculation results are slightly different due to the utilization of unbalanced panel data (Job-to-Job (J2J)). Figure A2 shows that approximately 91% of the MSAs emerged from 2001, with additional MSAs added during 2002-2004 and in 2010.

Figure A2: Sample entry year



Note: The figure indicates the years when an MSA first appeared, highlighting that the data is an unbalanced panel. Sources: LEHD; Job-to-Job Flows (2001-2019)

$$IV_{k,i,t} = \Delta SS^y_{k,i,t} = \sum_{j \neq i} s_{i,j} m^y_{k,j\to j^-,t} - \sum_{j \neq i} s_{i,j} m^y_{k,j \to j^-,t-1}$$

$$IV_{k,i,t} = \sum_{j \neq i} s_{i,j} \Delta m^y_{k,j\to j^-,t} = \sum_{j \neq i} s_{i,j} (m^y_{k,j\to j^-,t} - m^y_{k,j\to j^-,t-1})$$

This study used the latter calculation method to avoid jumps caused by adding MSAs over the years. For this purpose, the analysis is conducted in a strongly balanced panel, excluding MSAs entered after 2001 and MSA-industry pairs with incomplete information. Nonetheless, the correlation between the two measurements is high (98.6%), suggesting the results are nearly identical regardless of the method used.

A1.5 An outflow shock level analysis

I use the strategy suggested by Borusyak et al. (2022). Using the *ssaggregate* module in Stata, I conduct a shock level analysis. Table A3 shows that the estimates are statistically significant, and the standard errors obtained using this approach are comparable to those derived from the instrument level analysis.

Table A3: Elasticity of substitution

	IV approach	Shock level approach
FS ($\beta_{1,s}$)	1.466***	3.072***
(IV on N)	(0.146)	(0.206)
RF	-0.189**	-0.366***
(IV on W)	(0.077)	(0.0489)
2SLS ($\beta_{2,s}$)	-0.129**	-0.119***
	(0.052)	(0.0175)
Elasticity ($-\frac{1}{\beta_{2,s}}$)	7.743**	8.400***
	(3.139)	(1.236)
Kleibergen-Paap F	100.4	221.7
Observations	85,875	85,875

Note: The second column used the strategy of Borusyak et al. (2022). It only includes three lags of the instrument as a control. The shift-shares for marginal retirement-age workers are dropped. Industry by MSA and MSA by year fixed effects are added. The shift-shares and employment are normalized by the metropolitan population one year ago, and standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A1.6 Survival rates

Table A4: Survival rates between ages

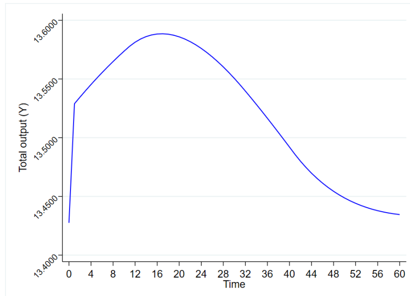
Age	Probability	Age	Probability	Age	Probability	Age	Probability
25	1.000	40	0.928	55	0.852	70	0.516
26	0.995	41	0.923	56	0.839	71	0.486
27	0.990	42	0.918	57	0.826	72	0.457
28	0.985	43	0.914	58	0.814	73	0.430
29	0.980	44	0.909	59	0.802	74	0.405
30	0.975	45	0.905	60	0.790	75	0.381
31	0.970	46	0.900	61	0.778	76	0.358
32	0.966	47	0.896	62	0.766	77	0.337
33	0.961	48	0.891	63	0.755	78	0.317
34	0.956	49	0.887	64	0.743	79	0.299
35	0.951	50	0.882	65	0.700	80	0.281
36	0.946	51	0.878	66	0.658	81	0.264
37	0.942	52	0.873	67	0.619	82	0.249
38	0.937	53	0.869	68	0.583	83	0.234
39	0.932	54	0.865	69	0.549	84	0.220

Note: The survival rate would diminish by 0.5% for each added year of age in the prime-age group, by 1.5% in the marginal-retirement-age group, and by 5.9% among those in the post-retirement group. The survival probability is calculated to closely match the actual population distribution of the United States in 2010.

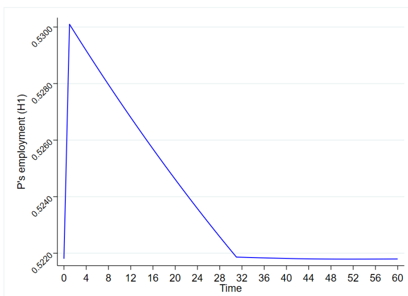
A1.7 Transition dynamics of the variables

Figure A3: Impulse response to an inflow shock

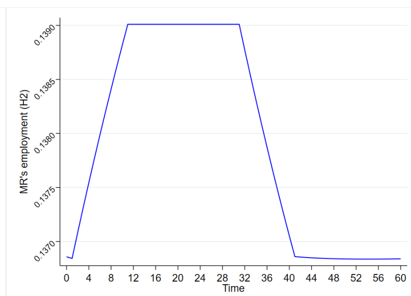
(a) Total output(Y)



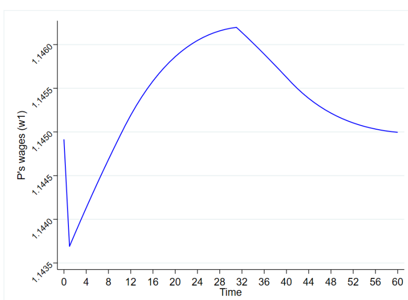
(b) P's employment (H_1)



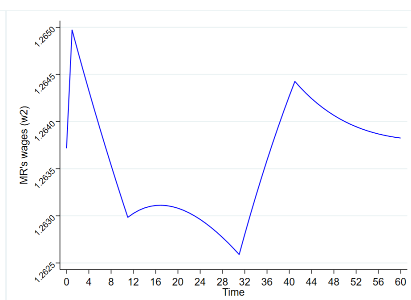
(c) MR's employment (H_2)



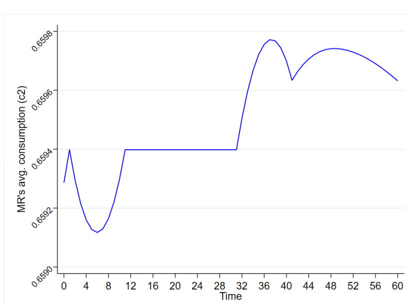
(d) P's wages (w_1)



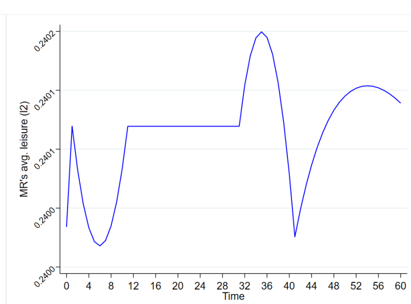
(e) MR's wages (w_2)



(f) MR's avg. consumption (c_2)



(g) MR's avg. leisure (l_2)



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