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# Age Cohort Effects on Unemployment in the US: Evidence from the Regional Level

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# Age Cohort Effects on Unemployment in the US: Evidence from the Regional Level

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**Abstract**

Since the early 1970s, it was argued that shifts from relatively smaller to larger youth cohorts in the labor force raise the unemployment rate. In contrast, Shimer (2001) comes to a contrary conclusion using US state level data. I provide a theoretical framework for local labor markets that considers age cohort differences in labor market characteristics. Using a spatial panel data model and US county level data (2000-2014), the estimates provide strong evidence that aging of the working age population reduces overall unemployment by almost one percentage point. Long-run effects that consider local feedbacks are even larger.

*Keywords*: Regional Unemployment, Spatial Interactions, Aging, Panel Data, Spatial Model

*JEL classification*: J60, R12, J10, C23

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# 1 Introduction

The baby-boomer generation entered the labor market decades ago, and changes in the labor market related to this cohort (size) have been analyzed. One key finding was that the larger the youth's relative cohort size, the higher the unemployment rate.[1] Today, youth cohorts are relatively smaller, but their unemployment rates are still higher than those of older cohorts in almost all OECD countries.[2]

The hypothesis of cohort crowding, which has been introduced by Richard Easterlin, is primarily concerned with marriage, fertility, wages, and labor market participation. In this context, Perry (1970) discusses first the link between differences in population cohort size and employment. Since then, several authors have argued that an increase in the percentage of youth in the working age population raises the overall unemployment rate because the unemployment rate is higher for younger workers.[3] All of these studies used macroeconomic data.

A different approach is found in Shimer (2001), who used US state level data for the period 1973-1996 to estimate the impact of changes in the percentage of youth aged 16-24 in the working age population on the overall unemployment rate. In his analysis of US state level labor markets, the overall unemployment rate tends to be lower when many young people supply labor. Shimer argues that a high proportion of young workers induces firms to create more new jobs because younger workers undertake more search activities, which reduces firms' recruitment costs. However, Foote (2007) extended Shimer's sample period by nine years (1973-2005) and found no significant relationship between the unemployment rate and the proportion of youth in the working age population.

Apart from that, other aspects should be taken into account. First, many talented young people are still pursuing their education at these ages, so the level of formal education of the youth in the labor market is lower in this

[1] See, for example, Flaim (1979, 1990), Freeman (1979), Korenman and Neumark (2000), and Shimer (1998).

[2] See, for example, Scarpetta et al. (2010), Sachs and Smolny (2015), and Ghoshraya et al. (2016).

[3] See, for example, Bloom et al. (1987), Flaim (1979, 1990), Gordon (1982), Gracia-Diez (1989), and Korenman and Neumark (2000).

cohort than in older age groups. Second, the youth share in the working age population and the labor market participation rate of this age cohort follow different trends, and the labor market participation rates for the 25-64 age group and 16-24 age group do also develop in different directions. From 1948 to 2018, both pairs are correlated positive but moderate—the first 0.424 and the second 0.362. One of the important reasons for this non-conforming trends in labor market participation is that the average duration of education for young people has steadily increased over the last decades.

Third, an interesting stylized fact is that age cohort unemployment rates decline with increasing age in an unchanged order over time, independent of cohort sizes and business cycles. When comparing the series from the seventies onwards to today, no intersection between the series can be observed, as Figure 1 points out. This finding is valid for the baby-boomer cohort in each age cohort (youth, prime-age workers, elderly worker) over the decades in the US. Hence, it seems that primarily age cohorts and not birth cohorts affect the aggregated level of unemployment.

*Figure 1 about here*

Fourth, at the regional level, a further issue is the consideration of spatial interaction between neighbor regions. In small local regions, spatial mobility (in terms of commuting) of workers impacts local labor market tightness. It affects the supply of younger and older workers differently when commuting declines with increasing age.[4] The more the local markets will be aggregated, the less the effects of mobility are observable. For example, using county level data might be more appropriate than state level data. National data, however, cannot cover the issue of within country mobility.

This article's contribution is twofold: First, it provides a theoretical model of local labor markets that considers the role of aging for the level of unemployment. Second, it provides empirical evidence for the US labor market using a spatial econometric model. In contrast to existing literature, the

[4]See Manning and Petrongolo (2017) for the analyses of job search across local labor markets in England and Wales. Monte et al. (2018) provide empirical evidence for commuting flows between US counties, and Bopp et al. (2014) provide evidence on age related differences in mobility for the US.

focus is on local unemployment and its composition concerning age cohorts. The empirical findings are consistent with the predictions of the theoretical model. Both models (theoretical and empirical) can also be applied to other cohorts, e.g., education or gender.

The analysis I offer to identify the demographic effects on unemployment has three advances over the existing literature. First, the theoretical framework considers differences in job finding and separation as well as spatial interactions. I argue that age groups differ in their employment-related attributes (e.g., productivity, matching efficiency, and labor turnover), independent of cohort size. Considering the stylized fact that age cohort unemployment rates decline with increasing age in an unchanged order over time, I argue that age cohort effects on the unemployment rate matter in theory. Second, I use two different regional data for the US, Shimer's (2001) original data at the state level and a new data source at the county level. Using a dynamic space-time panel data model (dynamic spatial Durbin model), the county level results provide new empirical evidence that conforms with the predictions of the theoretical model. Third, I consider different cutoffs for the division between age cohorts because I argue that it is not the youth only that matters. The reported estimates point out that the youth effect is underestimated when no other age cohort is considered. The estimated age cohort elasticities are different from cohort crowding effects because they are independent of the specific age cohort size.

Using data at the state level, I find empirical evidence for neighborhood effects (neighboring state), but no local effects (within the state) - aging in the neighboring state is associated with declining unemployment in the local state. When county level data are considered, the estimates provide strong evidence that (spatial) age cohort changes are an important long-term driver of overall unemployment change. More precisely, aging of the working age population reduces overall unemployment, and according to the estimates, the present changing age structure leads to a long-term reduction of the US unemployment rate. According to the preferred estimates, the long-term decline is almost a quarter of the unemployment rate when only short-run effects are considered. When spatial-time lagged long-run feedback effects are also considered, the estimated reduction of the unemployment rate would be even larger.

The article is organized as follows. Section II presents a model based on the search and matching framework that considers spatial interactions of neighbor regions and their effects on unemployment. Two age cohorts are introduced that carry different labor market characteristics. Section III describes the data, outlines the econometric approach, and reports and discusses the estimated results. The econometric procedure starts with the model considered in Shimer (2001), followed by the dynamic spatial Durbin model that will be considered for the main empirical part. At the end of this section, age cohort effects on the unemployment rate will be discussed. Section IV concludes.

# 2 Theoretical Framework: A Simple Model

In most cases, the literature that has dealt with age and employment or matching is related to specific issues. Pissarides and Wadsworth (1994) and Burgess (1993) found evidence for Great Britain that job separation rates are higher for young workers because they are more likely to conduct job searches while they are employed.[5] Hence, as Coles and Smith (1996) argued in their study on England and Wales, matching may decrease with an older working population. Menzio et al. (2016) provide evidence for the US that the rate of job separation and the rate of job to job change decline with increasing age, and Chéron et al. (2013) provide evidence for the US that the separation rate increase as retirement approaches. Job separations and low hiring rates for older workers could also result from imagined or actual differences in productivity (Haltiwanger et al. 1999, Daniel and Heywood 2007, Feyrer 2007 and 2008, Maestas et al. 2016). Productivity may increase with age when job experience is important (Autor et al., 2003) and decline when human capital depreciates over a lifetime, e.g., in a dynamic technological environment or when manual abilities are central to productivity (Bartel and Sicherman 1993, Hellerstein et al., 1999, Börsch-Supan 2003).

The willingness to create new jobs may also change because of mobility

[5] Davis et al. (1996) found evidence for the US that job flows are higher for young workers.

changes in an aging labor force. According to Brücker and Trübswetter (2007) and Hunt (2000), regional mobility decreases as age increases for high- and low-skilled workers and employed and unemployed people. The causes for this decreasing mobility after a certain point in life are, for example, housing tenure, partner's economic status, and childcare.[6]

Another important issue in the context of mobility is that of spatial dependencies of regional labor markets. The performance of a local labor market depends, among other things, on the characteristics of the regional labor markets in the surrounding area. For example, job creation can be affected by the labor force's age structure in the neighboring districts when regional mobility differs between age groups. Although it seems obvious that regional mobility plays an important role at the regional level, only a few studies have considered spatial interactions in the labor market. Fahr and Sunde (2005) used data at the regional level for West Germany to estimate a matching function. Their results indicate that matching is positively related to the percentage of young participants in the labor market. Using regional data, the spatial dimension in the matching function is considered in Burda and Profit (1996) for the Czech Republic, Petrongolo and Wasmer (1999) for France and the UK, Burgess and Profit (2001) for the UK, and Hujer et al. (2009) for Germany. These studies found empirical evidence for spatial interactions in regional search activities or unemployment rates. Using individual data for Germany, Hofmann (2015) shows that women without family ties that live in high unemployment regions leave unemployment faster when they consider jobs not only in their home region but also in other regions. Manning and Petrongolo (2017) find that unemployed workers apply for jobs in neighboring regions for England and Wales, but the probability of applying declines with the distance to the job. Using data at the US county level, Monte et al. (2018) provide evidence that commuting is more important to explain labor demand shocks than other controls like area and size of the labor market.

To consider differences in cohorts, I extend the standard framework of search and matching equilibrium unemployment by distinguishing between

[6] See, for example, Lindley et al. (2002) for a detailed discussion of these causes.

younger and older workers.[7] The model comprises age cohort differences in separation, matching, productivity, wages, and mobility to consider the literature findings.

To retain simplicity, I treat on-the-job search differently from how it is treated in the standard framework (see Pissarides, 2000). I do not consider the two usual reservation productivity parameters that differentiate between productivity-related job destruction and on-the-job search.[8] In general, this approach helps to explain why employed people decide in favor of on-the-job search. However, this article focuses on the consequences of spatial search activities on matching, job creation, and job destruction.

## 2.1 Unemployment

The labor force is divided into two age groups—younger workers $y$ and older workers $o$—with shares of $p$ and $(1-p)$, respectively. Workers are either employed or unemployed and if they are unemployed, I assume that they seek a new job. The aggregate rate of unemployment $u$ consists of the age-specific rates weighted at the relevant labor force share: $u = pu_y + (1-p)\,u_o$.

New employment relationships are created through a matching technology that forms the number of matches from the number of unemployed workers, the number of on-the-job searchers, and the vacancies. The standard matching technology is enlarged by a rate $e$, which is the percentage of the employed who search on-the-job for new employment. Hence, we have a search rate of $\sigma = u + e$, which is the sum of unemployed and employed job seekers divided by the labor force, with $e \leq 1 - u$.

At the regional level, it is obvious that people apply for jobs in surrounding regions, and workers commute between their home region and their workplace region. Also, the bulk of these commuting dependencies apply to adjacent regions. Thus, I characterize commuting and inter-regional searches as mobility. However, this definition of mobility does not include moves from

[7] I analyze the effects of different age groups in the labor force but ignore the effects of a population size change because most empirical studies find constant returns to scale of matching functions. Petrongolo and Pissarides (2001) provided an overview of the related literature.

[8] Up to half of all new employment relationships result from a job-to-job transition. See, for example, Blanchard and Diamond (1989) and Fallick and Fleischman (2004).

one region to another. To maintain the model's simplicity, I consider job seekers and vacancies only from the local region $l$ and regions adjacent to $l$, which I treat as one homogenous region, $n$.

Equilibrium in search models usually depends on the tightness of the labor market because tightness determines how successful a search is likely to be. The tightness of the local labor market is given by

$$\theta^l = v^l / \left(u^l + e^l + \tilde{u}^n + \tilde{e}^n\right) = v^l / \left(\sigma^l + \tilde{\sigma}^n\right),$$

and the tightness of the adjacent districts' labor market is given by

$$\theta^n = v^n / \left(u^n + e^n + \tilde{u}^l + \tilde{e}^l\right) = v^n / \left(\sigma^n + \tilde{\sigma}^l\right),$$

where $v^l$ ($v^n$) denotes the local (neighborhood) vacancy rate and $\sim$ represents spatial search activities. I assume that job seekers apply for jobs in their home regions, but the number of regional mobile job applicants depends on job seekers' age structure because younger workers are more mobile. Hence, only a part of the older job seekers from neighboring regions applies for jobs in the local region. I refer to $\sigma^l = p^l\sigma_y^l + \left(1 - p^l\right)\sigma_o^l$ and $\sigma^n = p^n\sigma_y^n + (1 - p^n)\,\sigma_o^n$ as local search rates and $\tilde{\sigma}^n = \left[p^n\sigma_y^n + (1 - p^n)\,\sigma_o^n\alpha\right]\frac{L^n}{L^l}$ and $\tilde{\sigma}^l = \left[p^l\sigma_y^l + \left(1 - p^l\right)\sigma_o^l\alpha\right]\frac{L^l}{L^n}$ as spatial search rates.

Workers (employed and unemployed) resident in the local region, $L^l$, are normalized to 1. The rate $\tilde{\sigma}^n$ is related to the labor force in the local labor market, $L^l$, and so has the same denominator as $\sigma^l$. There are two differences between $\tilde{\sigma}^n$ and $\sigma^n$: First, they are related to different labor force sizes—$\tilde{\sigma}^n$ to the local labor force and $\sigma^n$ to the labor force in the adjoining areas, $L^n$. Second, the share of older job seekers is larger in their resident region, $\sigma_o^n > \sigma_o^n\alpha$. The mobility weighting factor $\alpha$, with $0 \leq \alpha < 1$, accommodates older workers' limited spatial mobility. The differences between $\tilde{\sigma}^l$ and $\sigma^l$ are analog to those between $\tilde{\sigma}^n$ and $\sigma^n$.

The age distribution of the job seekers available to local firms differs from both $p^l$ and $p^n$. The proportion of young applicants (from the local and the surrounding area) available to firms in the local labor market is

$p^l \frac{\sigma_y^l}{\sigma^l+\tilde{\sigma}^n} + p^n \frac{\sigma_y^n}{\sigma^l+\tilde{\sigma}^n} \equiv \bar{p}^l$. Hence, job seekers' age structure depends on the age structure of the labor force in both regions.

To introduce a matching technology that reflects the job seekers' age composition, I consider job seekers in efficiency units identified by $\pi$, depending on the share of the young available to local firms $\pi\left(\bar{p}^l\right)$. The number of job seekers in efficiency units $\pi\left(\bar{p}^l\right)(\sigma^l + \tilde{\sigma}^n)$ measures the average age-related search intensity, in addition to a quantitative effect. For example, lower search intensity, as is often assumed for older workers, should reduce unemployment in efficiency units. Therefore, I assume that $\pi' > 0$ and $\pi'' < 0$.

From this follows the local matching function $m^l = m^l(\pi\left(\bar{p}^l\right)(\sigma^l+\tilde{\sigma}^n), v^l)$. A local firm with a vacancy meets a job seeker at a rate of $q^l(\theta^l, \bar{p}^l) \equiv m^l(\pi\left(\bar{p}^l\right)\frac{1}{\theta^l}, 1)$, a rate that decreases with the vacancy-unemployment ratio and increases with the share of young job seekers. Hence, when $\frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \theta^l} < 0$ a low vacancy/job seeker ratio increases the chances of filling a vacancy, but only at a given efficiency level. The derivation $\frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} > 0$ means that the larger the percentage of young job seekers available in the labor force, the easier it is for firms to find a job seeker at a given number of job seekers and vacancies.

Correspondingly, a job seeker finds new employment in the local region at rate $\theta^l q^l(\theta^l, \bar{p}^l) \equiv m^l(\pi\left(\bar{p}^l\right), \theta^l)$, which is identical for both age groups because vacancies do not differentiate between younger and older candidates. A higher percentage of younger job seekers implies efficient matching and, therefore, a higher rate of job search success, $\frac{\partial\left(\theta^l q^l(\theta^l,\bar{p}^l)\right)}{\partial \bar{p}^l} > 0$. Hence, aging decreases the matching efficiency, and both sides—firms and job seekers—will require more time to find the appropriate job (candidate). Finally, a job seeker from the local region finds, on average, new employment at the rate $\theta^l q^l(\theta^l, \bar{p}^l) + \theta^n q^n(\theta^n, \bar{p}^n)$ because of his or her spatially mobile search activities. From this follows that the spatial correlation of unemployment rates is positive. Also, both the local and spatial vacancy rates are negatively correlated with the unemployment rates.

Job-worker matches have a finite time horizon. Separation occurs because of idiosyncratic shocks that hit all matches at the same probability $s$. Age-related shocks are also possible. For example, let $\tau_o$ and $\tau_y$ denote the added risk rates that the match will end based on whether the worker is older or younger, respectively. The rates may also include different quitting rates (labor turnover rates)—for example, because of differences in regional mobility. In addition, I allow for regional differences of (age-specific) separations to accommodate the large regional differences in unemployment.

Finally, from the local region's perspective, I add the probability that a mobile worker loses their job in the surrounding area. The local labor force, $L^l$, can be subdivided into three groups: local unemployed $u^l$, residents employed in the local region $\omega^{l,l}$, and residents employed in the neighbor region $\omega^{l,n}$. Since $L^l = 1$, we have $u^l + \omega^{l,l} + \omega^{l,n} = 1$.

The local unemployment rates of younger and older workers evolve according to job creation and job destruction, with $i = [y, o]$:[9]

$$\begin{aligned} \dot{u}_i^l &= \left(s^l + \tau_i^l\right)\left(1 - \omega_i^{l,n} - u_i^l\right) + \left(s^n + \tau_i^n\right)\omega_i^{l,n} \\ &\quad -\theta^l q^l(\theta^l, \bar{p}^l)u_i^l - \theta^n q^n(\theta^n, \bar{p}^n)u_i^l. \end{aligned} \tag{1}$$

The first term on the right-hand side is the age-related flow from local employment to unemployment. The second term on the right-hand side is the age-related flow from jobs in the neighboring region to local unemployment. The positive flow of newly local unemployed from the surrounding region increases, the higher the region's separation rate. This is the second channel that generates a positive correlation between regional unemployment rates. The third and fourth terms on the right-hand side are the probabilities of transition into a new job in the local and neighbor labor market.

With $\dot{u}_i = 0$ and the summation of the two unemployment rates weighted at the respective local population proportions, $p^l$ and $(1 - p^l)$, we obtain the local equilibrium unemployment rate, that includes the Beveridge curve (BC):

$$u^l = u_o^l + p^l\left(u_y^l - u_o^l\right) \tag{2}$$

$$= \frac{\left(s^l + \tau_o^l\right) + \left(s^n - s^l + \tau_o^n - \tau_o^l\right)\omega_o^{l,n}}{s^l + \tau_o^l + \theta^l q^l(\theta^l, \bar{p}^l) + \theta^n q^n(\theta^n, \bar{p}^n)} + p^l\left(u_y^l - u_o^l\right). \tag{3}$$

The local equilibrium unemployment rate includes spatial and (spatial) aging effects. The second term *in* the *numerator* indicates that local unem-

[9] This implies the simplifying assumption that the spatial flows are of equal size.

ployment increases as the number of spatially mobile workers increase and $s^n > s^l$ and $\tau_i^n > \tau_i^l$. There are two channels concerning the age-related effects: the first effect is "hidden" in the (spatial) job finding rates, and the second effect is related to the differences in age-related unemployment rates. This second term disappears if $u_y^l = u_o^l$. For $u_y^l > u_o^l$ ($u_y^l < u_o^l$), an increasing proportion of younger workers increases (decreases) job destruction and unemployment. The first effect contains the age related matching efficiency and the mobility effect on the neighbor labor market. This effect means that the more younger workers are in the neighboring region, the lower the local market tightness and, hence, the lower the probabilities of transition into a new job for local workers. From this follows that the proportion of older and younger workers in both the local and the surrounding labor market is important to the local unemployment rate. Finally, the unknown $\theta$'s determine equilibrium unemployment and are explained by firms' willingness to create vacancies.

## 2.2 Firms

I consider two types of agents: workers and firms. All agents are risk neutral and discount the future at rate $r$. Vacancies are open equally to younger and older workers. Whether local firms create new jobs or remain inactive is subject to their benefits and the costs they must pay for their market activities. The benefits and costs include the (present-discounted) value of the states: Match with an older worker $J_o$, match with a younger worker $J_y$, and unfilled vacancy $V$. The values satisfy the Bellman equations

$$rJ_o^l = \mu - w_o^l - \left(s^l + \tau_o^l\right)\left(J_o^l - V^l\right), \tag{4}$$

$$rJ_y^l = \mu + \delta - w_y^l - \left(s^l + \tau_y^l\right)\left(J_y^l - V^l\right), \tag{5}$$

$$rV^l = -\gamma + q^l(\theta^l, \bar{p}^l)\left(J^l - V^l\right). \tag{6}$$

Local firms receive revenues $\mu$ from selling their output if an older worker is employed, while they pay the wage $w_o^l$ as compensation. The younger worker produces the value $\mu + \delta$ and earns $w_y^l$. Experience and lower training costs favor older workers, but human capital depreciation is an argument for younger workers' higher productivity. Hence, I do not fix the sign of the output differential, so $\delta \gtreqless 0$.[10] The job-worker match ends at the probability $s^l + \tau_i^l$, in which case the value of an unfilled vacancy replaces the value of the match.

The vacant job costs $\gamma$ per unit time and changes state according to the rate $q^l(\theta^l, \bar{p}^l)$. Given that younger workers are favored, an increase in the percentage of younger workers in the local and surrounding area increases the number of vacancies in the local labor market. The change of state yields net return $J^l - V^l$, where $J^l$ denotes the expected value of a filled vacancy. Since the firm can use two types of workers, I consider that the worker is younger at probability $\bar{p}^l$ and older at probability $\left(1 - \bar{p}^l\right)$. The expected value of filling the local vacancy is

$$J^l = \bar{p}^l J_y^l + \left(1 - \bar{p}^l\right) J_o^l. \tag{7}$$

The expected value of filling the vacancy is locally different if the age-related values $J_y$ and $J_o$ have regional differences and/or if $\bar{p}^l \neq \bar{p}^n$.

The candidates available to local firms are stochastically drawn from the pool of job seekers. Firms will accept the first applicant for work as long as the added costs of rejection are equal to the added gain that could be realized by employing a superior worker. In this case, the expected value of a vacancy is zero because waiting is worthless; eq. (6) turns to $J^l = \gamma / q^l(\theta^l, \bar{p}^l)$. Together with eq. (7) this leads to the second important equation, the local job creation condition (JC):

$$\frac{1}{q^l(\theta^l, \bar{p}^l)} = \frac{1}{\gamma} \left[\bar{p}^l J_y^l + \left(1 - \bar{p}^l\right) J_o^l\right] \tag{8}$$

Market tightness is the only variable parameter, and it guarantees the identity of eq. (8). Firms open more vacancies if $1/q^l(\theta^l, \bar{p}^l)$ increases. Clearly, easy search conditions and high profits foster job creation.

[10] See Börsch-Supan (2003) and Hutchins (2001) on the difficulty of measuring individual age-related productivity.

## 2.3 Effects of Changing Age Cohorts

Next, I analyze the effects of a change in the age structure (in the Appendix, I provide the comparative static effects). A decline in the local share of the young reduces average flows in the labor market if younger workers separate from jobs more often. From this follows that lower total separation corresponds to less equilibrium unemployment. Thus, a higher percentage of older workers reduces the labor turnover, and fewer job-worker pairs must be matched: the BC shifts inwards. The (spatial) effect of the changing matching efficiency is negative because a decline in the young's local share increases the average duration of the search on either side. This aging effect shifts the local BC outwards. However, a higher percentage of older workers in the neighboring region reduces the number of spatially mobile workers, which increases local market tightness and the probabilities of transition into a new job for local workers: This shifts the BC inwards. Concerning a new equilibrium in the local BC, it follows that aging has ambiguous effects.

Hence, a decline in unemployment as a result of aging (given $u_y^l > u_o^l$) cannot be observed if this effect is overcompensated by an increase in unemployment in both age groups because of lower matching efficiency. Also, even if age related separations are equal, aging increases unemployment because the BC shifts outwards (due to a declining matching efficiency). For the spatial age effect, the local unemployment rate responds to a change in the young's spatial share in a similar way.

Aging influences local job creation by two means. The first comes from a possible difference between a match's value with a younger or older worker. If firms attribute a higher value to young workers, an aging labor force reduces job creation and vacancies, and vice versa. The second way that an aging labor force affects local job creation comes from the efficiency of matching. Job creation suffers from aging since it harms matching. However, the total effect can be ambiguous. For example, when firms favor older workers, but the overall effect of aging is still negative, decreasing matching efficiency outweighs the positive effect of older workers' employment characteristics. These findings are related to the age structure in the local and the surrounding labor market. Hence, in principle, the two aging effects can be caused by a change in both regions' age structure.

Figure 2 shows equilibrium in the local vacancy-unemployment space and illustrates the effects that can arise if the age structure influences flows in the labor market. The steady state condition for unemployment is the local BC, which is convex to the origin by the properties of the matching technology. As usual, the BC is downward sloping. The local JC has a positive intercept and shifts when the number of locally employed job seekers or the number of spatially mobile job seekers changes. Firms create more jobs if local unemployment is high (for a given intercept of the JC), and the JC slopes upward.

*Figure 2 about here*

I found four different effects: first, aging reduces job destruction (given that $\tau_y > \tau_o$); second, aging reduces matching efficiency; and third, aging affects productivity (positive or negative). The first effect shifts the BC inward, the second shifts the BC outwards and rotates the JC clockwise, and the third effect rotates the JC either clockwise or counterclockwise.

A fourth effect is that of spatial aging on the number of job seekers. For example, the JC rotates clockwise if the number of mobile job searchers from the surrounding areas decreases because this increases search costs for firms, and this, in turn, decreasing the number of vacancies as well as market tightness.[11] The effect of fewer mobile job searchers on equilibrium employment is ambiguous because the reemployment probability of the local unemployed could increase, which would shift the BC inward.

In the empirical section, I will not be able to identify the individual effects discussed. However, the results in this section help to explain the effects estimated provided in the next section.

[11] The intercept also decreases in this case.

# 3 Empirical Strategy

## 3.1 Facts (Overview)

In this section, I analyze empirically the relation between a change in the age structure of the working age population and the unemployment rate using macroeconomic and regional data for the US. Following the cohort crowding literature, the share of the youth in the working age population is positively correlated with the overall unemployment rate. Figure 3 shows the share of the 16-24 years old in the working age population and the five years smoothed overall unemployment rate for the US and the period 1948 to 2018. As expected, both series are positively correlated but at a moderate level (correlation is 0.26). Overall it does not seem that both series are "synchronized" because the turning point at the maximum value of this cohort share comes early.

*Figure 3 about here*

When the share of the 16-34 years old is considered, the pattern changes a little. Figure 4 shows the share of this age cohort and the smoothed overall unemployment rate. Here, the correlation is 0.37. Using data at the national level, one can conclude a considerable correlation between the end of the 60th and the end of the 90th. The turning point at the maximum value coincides more than for the youth cohort.

*Figure 4 about here*

When the share of the 16-44 years old is considered, the pattern changes again (Figure 5). Here, the correlation is 0.1. Using this age cohort, it seems that the turning point is too late. However, this cohort is almost 30 years large, and the employment relevant characteristics of the workers included are different. The remaining 20 years (cohort 45 to 64) is the remaining part of the working age population and negatively correlated with the unemployment rate.

*Figure 5 about here*

Based on this simple comparison, it appears to be meaningful to analyze the relationship of different age cohorts and unemployment. Since macroeconomic data analysis would provide no substantial new findings, regional data will be applied because they allow considering a more differentiated pattern. The primary empirical analysis will consider county level data. To show that the level of aggregation is essential, I also consider data at the state level.

## 3.2 Data

I consider the original data used in Shimer (2001) and Foote (2007). They use the unemployment rate and the share of the working age population (ages 16-64) who are aged 16-24 at the US state level. Unemployment rates are taken from the CPS, and shares are taken from Census. The data are annual for 51 US states and the period 1973-1996 and 1973-2005.

The data at the county level are new. I use the unemployment rate and shares of different age cohorts at the US county level. The latter group is considered in the following definitions: share of the working age population (ages 15-64) aged 15-24, aged 25-34, aged 25-39, aged 25-44, aged 25-49, aged 25-54, aged 35-49, aged 35-54, aged 40-49, and aged 40-54. For the youth share, I follow Shimer's and Foote's definition but argue that it is not only the youth share that matters. Considering the discussion above, I argue that other age cohorts matter, but the ideal delimitation is an empirical issue. I use these different definitions of age cohorts because I believe that many individual characteristics relevant to job creation and job destruction alter when workers reach middle age.[12] The unemployment rates are taken from the BLS, and shares are taken from Census. The analysis considers annual data for 3074 counties and the period 2000 to 2014. Before 2000 the shares are not available at the county level.

For the percentages of the age cohorts used, there are considerable differences between regions at the state level and, in particular, at the county level. The state level data for the period 1973-1996 have an average unemployment rate of 6.4 percentage points (standard deviation of 2.1) and ranges from 1.9

[12] For example, Börsch-Supan (2003) showed that the typical age-productivity profile usually peaks when workers are in their 40s. The Federal Institute for Employment Research in Germany came to the same conclusion.

to 17.4 percentage points. The data extended to 2005 do not differ much: the average unemployment rate is about 6.0 percentage points (standard deviation 2.0) and the range is not different from the former. The youth share (aged 16-24) in 1973-1996 is, on average, equal to 0.24 (standard deviation is 0.03) and ranges from 0.16 to 0.33. For the extended period, we have an average of 0.23 (standard deviation of 0.04) and minimum/maximum values as before.

At the county level (period 2000 to 2014), we have an average unemployment rate of 6.4 (standard error of 2.7), ranging between 0.8 and 29.7. Concerning the youth share, we get an average of 0.21 (standard error is 0.04) and minimum and maximum values of 0.06 and 0.62. As expected, at the county level is more variation in the data. For details concerning the other shares, see the summary table in the Appendix.

### 3.3 Econometric Approach and Results

In this section, we consider different specifications of the reference age cohort and the econometric model. First, we start with state level data and the econometric model considered in Shimer (2001):

$$\ln u_{it} = \alpha \ln youth_{it} + c_i + \theta_t + \epsilon_{it} \tag{9}$$

where $\ln u_{it}$ is the logarithm of the overall unemployment rate in region $i$ and year $t$, $\ln youth_{it}$ is the logarithm of the youth share (share of the working age population who are aged 16-24) in region $i$ and year $t$, $c_i$ are regional and $\theta_t$ time effects, and $\epsilon_{nt}$ is an error term. The parameter $\alpha$ is negative in Shimer (2001), which means that a larger share of the youth in state $i$ and year $t$ correspond to a lower unemployment rate this year and state. This result contradicts the cohort crowding hypothesis and related to the current demographic change this would mean that unemployment is positively correlated with aging. The basic regressions provided in Table 1 show that the results are sensitive to the consideration of unobserved heterogeneity, particularly for time fixed effects.

*Table 1 about here*

To consider that young people are likely to migrate to states with relatively low unemployment rates, Shimer uses lagged birth rates as instruments. Such migration flows can cause a spurious negative correlation between unemployment rates and youth shares, foster aging in regions with high unemployment rates, and decrease market tightness (increases unemployment) in the preferred region, given that $u_y > u_o$. However, Shimer concludes that the instrumental variable estimates do not yield statistically different results, and in some cases, it turns out that the youth share is not endogenous.[13]

To take a closer look at this, I compare the one year lagged change in the log unemployment rate with the change in log youth share (Figure 6). While the dots and the solid line represents the whole sample, the short dashed line shows the relationship for regions with unemployment rates above 7% (427 obs), and the long dashed line represents regions with unemployment rates below 5% (563 obs). The average overall is 6% (1,683 obs). When the youth's migration causes a negative correlation in this relationship, the slope will become negative because a decline in the unemployment rate would be associated with a rise in the youth share (and the other way around). The correlation for all data is 0.04, and even a fixed effects regression provides no empirical evidence.[14] This is no evidence that migration does not matter, but it shows that other effects could be stronger. Two arguments might be relevant: First, migration could be more important to the working age

[13]Foote (2007) considers the same instrumental variable (IV) procedure as Shimer does, but the results do not change. In addition, Foote uses corrected standard errors, as suggested by Driscoll and Kraay (1998). They provide a method that considers spatial correlation in addition to heteroskedasticity and autocorrelation. Foote concludes that the consideration of spatial correlation (by using Driscoll and Kraay standard errors) is a further argument why the effects in Shimer's data are in fact not significant.

[14]For the relationship between aging and unemployment, both directions are possible. In the supply side's "migration effect," young people move into regions with comparatively low unemployment rates, and this movement results in an increased percentage of older workers in regions with high unemployment rates. In the demand side effect, firms could prefer younger workers, and in regions with a larger percentage of older workers, the unemployment rate is higher. Concerning migration, one could argue that two opposing effects balance regional unemployment rates to a certain extent. First, young people choose regions with comparatively low unemployment rates, which decrease the market tightness in the chosen region. Second, given that $u_y > u_o$, emigration should decrease the overall unemployment rate.

population 25 years and over. Second, different birth cohort sizes will cause different age cohort shares over time. It follows that it seems to be more important to consider other age cohort shares too. Before considering other age cohorts, we introduce spatial dependence and enlarge the specification of eq. (9).

*Figure 6 about here*

First, I consider the effect of the youth share in the neighboring region on local unemployment. In principle, the local youth share captures changes in matching efficiency, differences in job destruction, and differences in the value of a match with a younger or older worker that stems from a change in age composition in the local region. Since the youth in both regions hold, on average, the same job relevant characteristics, I do not argue that, e.g., the youth in neighboring regions is more productive than the youth in the local region. This is not possible because, in the estimates, every share is considered as a local region and as a neighbor region (I am the neighbor of my neighbor). However, the neighboring region's youth needs to be spatially mobile (in terms of commuting) to work in the local region.[15] This is why I consider the youth share's effect in the neighbor region on local unemployment in the estimates.

Second, to account for additional unobserved time and spatial varying effects at the local level, time lagged and spatial lagged effects of the dependent are considered (eq. 10). To generate spatially lagged counterparts, I constructed a spatial weight matrix, $W$, that indicates the contiguity of regions and defined contiguity between two regions as those that share a common border.[16] First, the matrix has the entry 1 if two regions share

[15] I distinguish this from the fact that they could move to the region where they work because, in this case, they live and work in the same region.

[16] The data do not provide commuting distances of individuals or information on commuter distribution within a county. Alternatively, I have considered distance-based spatial weights matrices. Due to differences in county size, not all counties have neighbors, while others have many. As a compromise, I have mixed distance-based and first-order contiguity information. However, since this is somewhat arbitrary and the results are very similar to the first-order contiguity, I consider only the more general first-order contiguity matrix. The only difference is that the spatial age cohort effects decline with increasing distance, which is expected.

the same border and 0 otherwise. Then, I row normalize $W$, which ensured that all weights were between 0 and 1 and that weighting operations can be interpreted as an average of the neighboring values. $\ln u_{i,t-1}$ is the time lagged dependent variable and $\gamma$ the autoregressive time dependence parameter. $W \ln u_{it}$ generates the average values of the regions adjacent to region $i$, and $\lambda$ is the spatial dependence parameter - the spatial lagged effect of the dependent variable. $W \ln u_{i,t-1}$ is the combined spatial and time lagged dependent variable and $\pi$ the spatio-temporal diffusion parameter. The inclusion of the spatial and time lagged dependent variable could serve as a control for omitted variables, or at least reduce omitted variable bias (LeSage and Pace (2009)).

To sum up, I consider a spatial and time dynamic model that is also known as the dynamic spatial Durbin model (with time and fixed effects):

$$\begin{aligned}
\ln u_{it} \;=\; & \gamma \ln u_{i,t-1} + \lambda W \ln u_{it} + \pi W \ln u_{i,t-1} \\
& + \alpha \ln youth_{it} + \beta W \ln youth_{it} \\
& + c_i + \theta_t + \epsilon_{it}
\end{aligned} \tag{10}$$

where $\ln u_{it}$, $\ln youth_{it}$ and $\epsilon_{it}$ are stacked $Tn \times 1$ column vectors, $W$ is a row normalized $n \times n$ spatial weights matrix that is nonstochastic, and that generates the spatial dependence between cross sectional units, $c_i$ are regional and $\theta_t$ are time effects. The bias-corrected quasi maximum likelihood approach provided by Yu et al. (2008) is considered for the dynamic models.[17] The effects of the time and spatial lagged dependent variable will not be discussed below.[18] However, these lags help afterward to calculate the dynamic long-run effects. In all regressions, robust standard errors are considered.

The interpretation of the parameters $\alpha$ and $\beta$ is somewhat different from eq. (9) because in eq. (10) they cannot be interpreted as elasticities or partial

[17] All spatial regressions are estimated using STATA and the xsmle code.

[18] Using OLS based methods instead would produce biased coefficients for the time and spatial lagged effects of the dependent. See, for example, Nickell (1981) for the asymptotic bias of OLS estimation using the time lagged effect, and Kelejian and Prucha (1998) for information on biased OLS estimates when spatial lagged effects are considered.

derivatives due to spillover effects.[19] Therefore, I first provide the estimated coefficients and subsequent the resulting elasticities. For the spatial effect of the youth share, $\beta$, I argue, as outlined above. Because of their limited mobility, not all older workers in the neighboring region apply for jobs in the local region, and therefore, the spatial youth share, $W \ln youth_{it}$, serves mostly as a proxy variable for mobility in terms of commuting.

An increase in the neighboring youth share induces more applications for jobs at firms in the local region. This, in turn, decreases search costs and increases the vacancy rate. However, this also decreases the local market tightness and the probability of transition into a new job for local job seekers. This effect is likely larger than the effect on vacancies (more jobs). In this case, the parameter $\beta$ is positive. According to the model in section 2, $\alpha$ is positive if, for example, the youth is overall less attractive for firms.

If the spatial effect of the working age population's age structure is essential, we have to consider the bias on $\alpha$ if we neglect $\beta$. Let $\omega$ be the parameter for the local effect when the spatial effect is neglected. The standard result is then $\omega = \alpha + \beta\delta$, where $\delta$ is a measure for the covariance of the local and the spatial age structure. The latter is positive in the data, and I expect $\beta$ to be positive, which yields a positive bias on $\omega$.

Table 2 provides the dynamic spatial Durbin model results using Shimer's and Foote's state level data. In Regressions (1) and (4), only the spatial lagged dependent is considered ($\gamma = \pi = 0$), while in (2) and (5), also the time lagged effect is included ($\pi = 0$). In (3) and (6), all lagged effects are considered. Since all spatial and time lagged effects provide strong empirical evidence and the Bayesian information criterion (BIC) is lower (compared to the other two specifications), I prefer (3) and (6) as best specification. In this case, we find no empirical evidence for the local effect of the youth share on unemployment. The empirical evidence for the spatial effect means that a larger youth share in the neighboring regions corresponds to a higher local unemployment rate.

*Table 2 about here*

The results in table 2 can be interpreted in different ways. On the one

[19] See, for example, LeSage and Pace (2009) for a detailed discussion.

hand, it is possible that the local difference between younger and older workers is too small to be statistically important at the local level. On the other hand, it is also possible that opposing effects cancel out each other. For example, if younger workers undertake job search more intensively, but older workers are more productive, the overall effect can be small. Another explanation is related to the regions' size: Many spatial mobile workers are measured as local workers. Also, the share of the young in a neighbor state might be less related to a local state than, for example, the share of the young in a neighbor and local county. If this argument of the wrong regional size is relevant, the results are different when county level data are considered.

I, therefore, turn to counties as regions. The results in Table 3 provide different basic specifications. Regressions (1) and (5) are estimates of the specification (9) and comparable to the results in Table 1. Both regressions provide empirical evidence for the local youth share. In regressions (2)-(4) and (6)-(8), we extend the dynamic specification of the regressions. In regressions (5)-(8), we control additionally for the change in the local labor force size.[20]

Overall, regression (8) is the preferred specification, and the results provide empirical evidence for positive local and spatial youth share effects on local unemployment. Finally, I test specification (8) against a spatial autoregressive model and a spatial error model and find strong empirical evidence in favor of the preferred dynamic spatial Durbin model.

*Table 3 about here*

Next, I extend the specification of eq. (10) by additional age cohorts and differentiate in Table 4 between four reference age cohorts from 40-64 years old to 55-64 years old. In addition to the youth share, a second age cohort is added with different age cohort ranges starting with age 25 and end with age 39, age 44, age 49, or age 54. The dynamic spatial Durbin model is in all cases the preferred specification (regressions (3), (6), (9), and (12)). In all four regressions, the coefficients of the shares provide strong empirical evidence for a positive relationship with the local unemployment rate. The

[20] This variable is considered to separate the overall size effect from the share effects.

economic interpretation will be conducted using elasticities below. For the parameters $\gamma$, $\lambda$, and $\pi$, I find that they collectively pass the stationarity conditions in the preferred specifications (regressions (3), (6), (9), and (12)). According to Baltagi et al. (2018) and Debarsy et al. (2012) the stationarity conditions are: $\lambda + \pi \geq 0$; $|\gamma| + (\lambda + \pi) < 1$; $\lambda - \pi < 1$; $\gamma - (\lambda - \pi) > -1$.

*Table 4 about here*

For an enhanced analysis of the relationship between age cohorts and unemployment, a third age cohort will be considered in addition to the reference age cohorts 50 to 64 years and 55 to 64 years, respectively (Table 5).[21] The youth share is always considered. The first cohort cut is at the age of 34 or 39 years, and the second cut at 49 or 54 years. For all local and spatial age cohort shares, we find a positive relationship with the local unemployment rate in the relevant specifications ((3), (6), (9), and (12)). In all cases, the parameters are larger when the reference cohort is 55 to 65 years old. The results in Table 5 for the preferred models indicate stationarity and dynamic stability.

*Table 5 about here*

Although the dynamic spatial Durbin specification reduces potential omitted variable bias, other effects, e.g., education, are still possible. Annual information on the distribution of education at the county level is not available. Aggregated data show a trend to a more educated population. As mentioned in the introduction, the cohort 15 to 24 is acquiring education, so the youth's formal education level in the labor market is lower than in older age groups. The most educated age cohort is 25-34 years old. However, according to the OECD online education database, the difference to the population 25 to 64 years old is small. For example, in 2000, the percentage of the population 25 to 64 years old who completed high school is 87.4, and for the cohort 25 to 34, we have 88.2. Until 2015 both numbers rise very similarly, cohort 25 to 64 by 2.1 percentage points and cohort 25 to 34 by 2.3. The percentage of the population 25 to 64 years old who attained any postsecondary degree is

[21] Due to multicollinearity, estimates with more age cohort shares are not advantageous.

36.5 in 2000, and 38.1 for the age cohort 25 to 34. In 2015 they are 44.6% (25 to 64 years) and 46.5% (25 to 34 years). From this, I conclude that overall education has increased and the age cohorts considered have minor differences concerning the distribution of education at the national level. Hence, the education mix has changed less across the age cohorts compared to the change in age cohort shares. However, due to potential omitted variable bias, the interpretation of the results should be made carefully.

## 3.4 Interpretation of County Level Findings

The county level estimates provide no empirical evidence for the Shimer effect. For the cohort crowding effect, I argue that the above provided theory of age cohort differences in job finding and separation matters, not (only) the youth cohort's size. For periods of demographic change, the results provide strong evidence that age cohort related differences in labor market characteristics are an important driver of the overall unemployment change.

To interpret the estimates, we calculate direct (local) and indirect (spatial) as well as short-term and long-term effects.[22] The direct effect measures the change in the dependent variable due to changes in the same region's explanatory variable (averaged over all regions). In contrast, the indirect effect measures the dependent variable's change due to changes in the neighbor region's explanatory variable (averaged over all regions). The direct and indirect effects add up to the total effect. The short-term effects quantify the dependent variable response in each region at time $t$ to changes in the explanatory variables at time $t$. The long-rung effects cumulate the dependent variable responses over time to change in the explanatory variables at time $t$. The marginal effect will be calculated for each time period and decay over time. Since this takes some years (for annual data at least 15 years), the cumulative long-term effects are larger in magnitude than the contemporaneous short-term effects.

Table 6 provides elasticities for selected regressions of Table 4 and Table 5.[23] In principle, short-run elasticities are smaller, and the total effects vary

[22] See Belotti et al. (2017) for a more detailed discussion.

[23] The effects are calculated according to Elhorst (2014) and are averages over 500 Monte Carlo replications (LeSage and Pace (2009)).

around unity. In the long-run, indirect and total effects are elastic, while the direct effects remain inelastic in nearly all cases. Concerning the youth share, it turns out that substituting the reference cohort 50-64 years is less costly in terms of unemployment. This finding emphasizes the difference in labor market characteristics of age groups. For regressions that include merely a second age cohort, only the 25-39 years cohort has lower elasticities than the youth. This would suggest less negative labor market effects when the youth substitute older workers (reference cohort).

However, when we take the elasticities of the last two regressions in Table 6 into account, we can conclude that the youth and the age cohort 25-39 years have very similar elasticities, compared to the reference. The elasticities of the third age cohort (40-49 and 40-54) let us presume less negative unemployment effects. This is further evidence for the discussion in section 3.1 and in line with the theory provided above.

All total long-run elasticities are elastic and, hence, any change in the demographic composition in the labor force seems to have substantial implications for the level of overall unemployment. Also notable is the finding that the indirect effect is stronger than the direct effect. This is an important argument for analysis at the local (county) level because spatial interactions cannot be considered (adequately) at the national or state level.

The results reflect that younger workers are more mobile than older workers, and labor market mobility declines with age. Related to the theoretical model, this means that the larger the number of younger well-trained job seekers in the neighboring district, the more (mobile) workers are available for local jobs. This, in turn, decreases market tightness to the disadvantage of local job seekers.[24] From this, I conclude that spatial mobility in terms of commuting is of importance for the local unemployment rate. A second reason for the larger indirect effect is related to regions with metropolitan areas in the neighborhood. In this case, many spatially mobile workers affect rural neighbor regions much more than the reverse effect. Overall, based on the estimates, aging of the labor force reduces the share of regional mobile

[24] These findings may improve our understanding of the differences between regional and national level findings. As Shimer (2001) emphasized in his study of the impact of young workers on the aggregate labor market, the relative importance of competing effects at different aggregation levels is puzzling. Our results may provide the key to the puzzle.

workers, and this reduction decreases the local unemployment rate.

*Table 6 about here*

We now use the elasticities and the continuously compounded rate of change of the age cohorts to assess the strength of cohort effects on the overall unemployment rate. Table 7 provides for the elasticities already considered in Table 6 in column (a) average continuously compounded rate of change of the age cohorts in %, and overall average changes between 2000 and 2014 in % in column (b). Columns (c) to (h) provide the product of column (a) and the corresponding elasticity reported in Table 6. The cumulative percentage change of the total short-run and total long-run is provided in (i) and (j).

For example, according to regression (3) in Table 4, the annual short-run direct effect of the youth share on the unemployment rate is $-0.043$ percentage. In the long-run, the direct effect is $-0.146$. Due to the larger indirect effects, the unemployment rate declined in the long-run for $-1.7$ percent, when the youth share declines from one year to the next (for the benefit of workers 40 years and older) by $-0.245$ percent. Together with the share 25-39, the cumulated short-run effect is $-10.9$ percent. When the spatial-time lagged long-run feedback effects are also taken into account, the unemployment rate would be nearly halved. However, these calculated effects take about 30 years; hence, we have to be careful by taking these effects too seriously.[25] Another reason for the somewhat surprising aggregated long-run effects is the size of the spatial and time lagged effects of the dependent. The larger these coefficients, the larger the long-run effects. Potentially, these effects are overestimated because of the included great recession 2008-2009. However, the estimated coefficients have consistently low standard errors.

The preferred specification of regression (6) in Table 5 yields similar results for the age cohorts considered in regression (3) in Table 4. Together with the share 40-49, the long-term decline is almost a quarter of the unemployment rate when only short-run effects are considered and about three-fourths when spatial-time lagged long-run feedback effects are also taken into

[25] 15 years are in the data set, and about additional 15 years it takes until the total long-run effect of one year fades away.

account. The reported effects in Table 7 clarify that shifts in the age distribution of the working age population seem to have substantial long-run effects on overall unemployment. From 2000 to 2014 these cohorts (including the reference cohort) change as follows: youth share $= -0.720$, share 25-39 $=$ $-3.239$, share 40-49 $= -4.286$ and share 50-64 $= +8.245$ percentage points.[26] Hence, the baby-boomer cohort has entered the last age cohort in the labor force with the lowest unemployment rate, leading to a decline in all other age cohort shares (associated with larger unemployment rates).

This pattern of shifts in age cohort size can also be observed when we consider the rural-urban continuum. The average unemployment rates by the classification into metropolitan $(6,2\%)$, urban $(6,7\%)$, and rural $(6,0\%)$ are not so much different. In rural areas, the shares of the 15 to 39 years old are below the average, and the share of the 50 to 64 years old is above the average. This is in line with the findings above, that regions with a larger share of the age cohort 50 to 64 have, on average, lower unemployment rates.

At the same time, the national unemployment rate rises from $4,0\%$ to 6.2% (a growth factor of 1.55). Considering the overall short-run changes (regression (6) in Table 5), the unemployment rate in 2014 would have been about 7.1% when age cohorts would have been unchanged over the period considered. The overall long-run changes would have an even more substantial effect on the unemployment rate, but in 2014 only a part of this effect would have taken place. Hence, we cannot directly compare the overall long-run unemployment rate reduction of about 3 percentage points with the unemployment rate in 2014.[27]

*Table 7 about here*

A final application of the estimates is related to national data. The youth cohort of the baby boomer generation has its peak in 1981. In 1995 this population cohort showed the least value. I take this period to compare

[26] The average neighborhood values are very similar. These cohorts change from 2000 to 2014 as follows: youth share $= -0.715$, share 25-39 $= -3.240$, share 40-49 $= -4.273$ and share 50-64 $= +8.228$ percentage points.

[27] Except regression (3) in Table 4, the considered models estimate an overall short-term effect on the unemployment rate of $-0,8$ to $-1.0$ percentage points. The long-run changes are between $-2.7$ and $-3.2$ percentage points.

what happens when the youth cohort declines and the aging process starts. Again, the elasticities of regression (6) in Table 5 will be considered. The neighborhood value will be approximated by the same value as the local (national) region. This is acceptable because the correlation between local and spatial age cohorts at the county level is quite high. The cohorts change from 1981 to 1995 as follows: youth share = $-6.121$, share 25-39 = 1.741, share 40-49 = 6.782 and share 50-64 = $-2.402$ percentage points. Hence, in this period, the share of prime-age workers rises, while the shares for the youth and older workers decline. The unemployment rate declined from 7.6% in 1981 to 5.6% in 1995. According to the cumulated short-run effects, the unemployment rate declines by about 0.5% due to the observed demographic change. Hence, according to this calculation, a quarter of the reduction is due to shifts in the working age population's age distribution. In contrast to the period 2000-2014, the effect of the strong decline in the youth share will be partially compensated by the rising share of prime-age workers.

# 4 Conclusions

In this article, I examined the relationship between the (spatial) age structure of the working age population and unemployment at the regional level using both a theoretical and an empirical model. The theoretical model points out that when age cohorts differ in their labor market characteristics, a change in the working age population's age distribution affects the overall unemployment rate. In the empirical part, I consider two different aggregation levels to approximate local regions in the USA: the state and county levels. For the county level, the period considered (2000-2014) is characterized by an aging process of the working age population with a substantial increase of older workers (50 years and older). In contrast to the theory of cohort crowding, I argue that age cohorts differ in job finding, separation, matching, and mobility in terms of commuting - and this is more important than the size of a cohort. The local effects I found, provide empirical evidence for a declining unemployment rate along with aging. The effect of aging in the surrounding areas strengthens the local effect because younger workers are more mobile (in terms of commuting) than older workers are.

Based on the results, I would suggest that regions with a larger percentage of older workers (like rural areas) have to attract younger ones. This means that policymakers have to provide incentives to create more jobs for younger workers and/or for start-ups of young workers or at least better job perspectives. Since higher unemployment rates are associated with this age cohort, this policy implies importing unemployment when the youth from the surrounding areas move to this region. According to the theoretical model, this can also have two opposing effects when the share of the youth is not increasing too fast: (a) The matching efficiency increases because, on average, younger workers find new jobs faster, and (b) firms become more willing to create jobs because firms search costs decrease when the job-worker match takes less time. Both can mitigate the rise of the local unemployment rate.

Using the youth share only to analyze cohort effects neglects other age cohort effects and leads to inconclusive results. This might explain why Shimer (2001) found a negative youth share effect on overall unemployment. From the beginning of the 80s, the youth share declines and the effect on the unemployment rate was negative. At the same time, however, other age cohort shares increase, and the correlation between the shares could induce a spurious negative correlation. Since the analysis of Shimer covers this period, such an effect may happen. This also agrees with Foote's (2007) findings of no empirical evidence, who extends the period about ten years after the youth share turning point in 1995.

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# 6 Appendix

**Effects of Aging on the Beveridge Curve (BC):** The effects on the local BC of eq. (2) arises through a change in the age composition of job seekers. The first effect comes from a change in the local age composition of the job seekers available to local firms:

$$\left.\frac{\partial u^l}{\partial p^l}\right|_{\partial\theta^l=0} = \left(u_y^l - u_o^l\right) + p^l \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma_y^l}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma_y^l}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \begin{pmatrix} \frac{-u_y^l}{s^l+\tau_y^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \\ -\frac{-u_o^l}{s^l+\tau_o^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \end{pmatrix} + \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma_y^l}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma_y^l}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \frac{-u_o^l}{s^l+\tau_o^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)}. \tag{11}$$

The first term is positive if $\tau_y > \tau_o$. A higher percentage of older workers reduces the labor turnover such that fewer job-worker pairs must be matched: the BC shifts inwards. The second and third terms represent the (spatial) effect of the change in matching efficiency; this effect is negative because a decline in $p^l$ increases the average duration of the search on either side; hence, the aging effect shifts the local BC outwards. With respect to a new equilibrium in the local BC, it follows that aging has ambiguous effects. The first and second term would be zero if $\tau_y = \tau_o$, however, even in this case, aging increases unemployment because the third term still shifts the BC outwards.

With respect to the spatial age effect, the local unemployment rate responds to a change in $p^n$ according to:

-

$$\left.\frac{\partial u^l}{\partial p^n}\right|_{\partial\theta^l=0} = p^n \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma_y^n}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma_y^n}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \begin{pmatrix} \frac{-u_y^l}{s^l+\tau_y^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \\ -\frac{-u_o^l}{s^l+\tau_o^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \end{pmatrix} + \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma_y^n}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma_y^n}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \frac{-u_o^l}{s^l+\tau_o^l+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)}. \tag{12}$$

Both terms on the right-hand side are similar to the second and third term in eq. (11), and the interpretation is the same.

**Effects of Aging on job creation (JC):**To analyze the effects of aging on the local job creation condition (8), we reorganize (8) and make use of an implicit differentiation. The two arguments in $q^l$ are $\theta^l$ and $\bar{p}^l$. For $F\left(\theta^l, \bar{p}^l\right) = 0$, we differentiate $\theta^l$ with respect to $\bar{p}^l$ and make use of $-\frac{\partial F/\partial \bar{p}^l}{\partial F/\partial \theta^l}$:

$$\frac{\partial \theta^l}{\partial \bar{p}^l} = -\frac{\begin{array}{c} q^l(\theta^l, \bar{p}^l)\left(J_y^l - J_o^l\right) \\ +\frac{\partial q^l(\theta^l, \bar{p}^l)}{\partial p^l}\left[\begin{array}{c} \bar{p}^l J_y^l \left(1 - \frac{\partial J_y^l}{\partial q^l(\theta^l, \bar{p}^l)} \frac{q^l(\theta^l, \bar{p}^l)}{J_y^l}\right) \\ +\left(1 - \bar{p}^l\right) J_o^l \left(1 - \frac{\partial J_o^l}{\partial q^l(\theta^l, \bar{p}^l)} \frac{q^l(\theta^l, \bar{p}^l)}{J_o^l}\right) \end{array}\right] \end{array}}{\begin{array}{c} \bar{p}^l \left(J_y^l \frac{\partial q^l(\theta^l, \bar{p}^l)}{\partial \theta^l} + q^l(\theta^l, \bar{p}^l) \frac{\partial J_y^l}{\partial \theta^l}\right) \\ +\left(1 - \bar{p}^l\right)\left(J_o^l \frac{\partial q^l(\theta^l, \bar{p}^l)}{\partial \theta^l} + q^l(\theta^l, \bar{p}^l) \frac{\partial J_o^l}{\partial \theta^l}\right) \end{array}}. \tag{13}$$

The denominator of (13) is negative because $J_i^l \frac{\partial q^l(\theta^l, \bar{p}^l)}{\partial \theta^l} + q^l(\theta^l, \bar{p}^l) \frac{\partial J_i^l}{\partial \theta^l}$ is negative if elasticity $\frac{\partial J_i^l}{\partial q^l(\theta^l, \bar{p}^l)} \frac{q^l(\theta^l, \bar{p}^l)}{J_i^l}$ is smaller than unity, with $i \in \{l, o\}$. Because $\frac{\partial J_i^l}{\partial q^l(\theta^l, \bar{p}^l)} < 0$, we have a strict negative denominator; hence, the sign of (13) depends on the numerator. We have $\frac{\partial \theta^l}{\partial \bar{p}^l} > 0$ if the numerator is positive or the other way around. With $\frac{\partial J_i^l}{\partial q^l(\theta^l, \bar{p}^l)} < 0$, it is clear that the second term in the numerator becomes positive. Hence, (13) is positive if the first term is positive as well, that is, if $J_y^l > J_o^l$; if not, the sign of $\frac{\partial \theta^l}{\partial \bar{p}^l}$ depends on whether the first or the second term in (13) dominates the total effect.

# 7 Figure and Tables

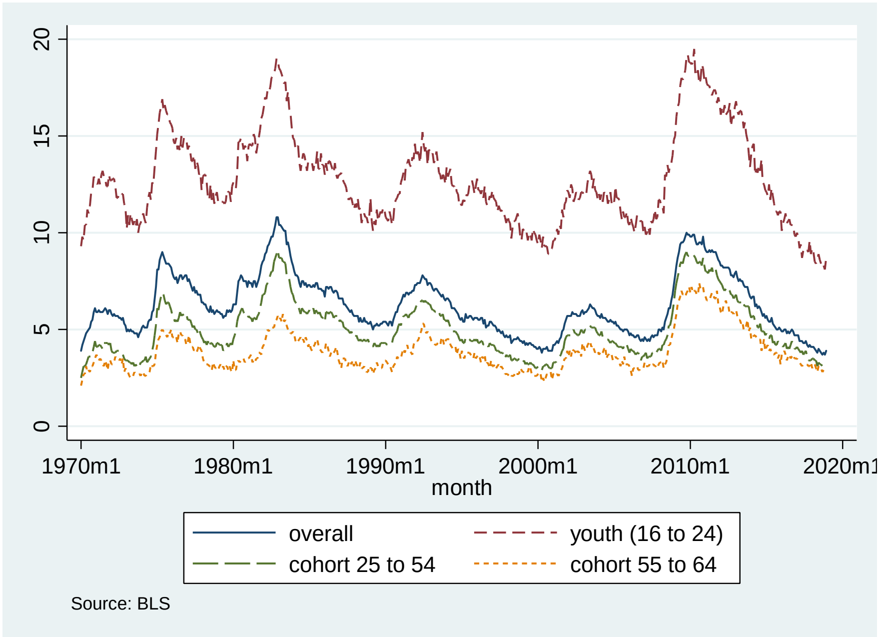


Figure 1: US Unemployment Rates, Overall and by Age Groups, 1960-2018 (monthly data)

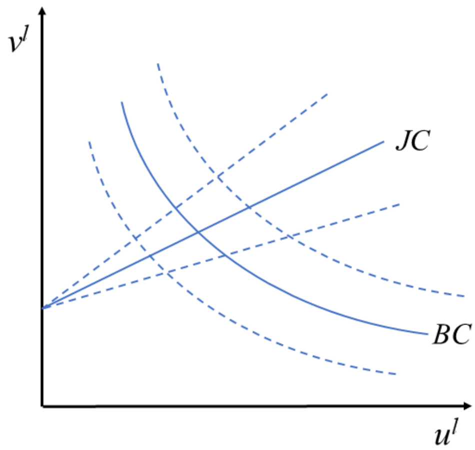


Figure 2: Effects of Changing Age Cohort Shares on Search Equilibrium

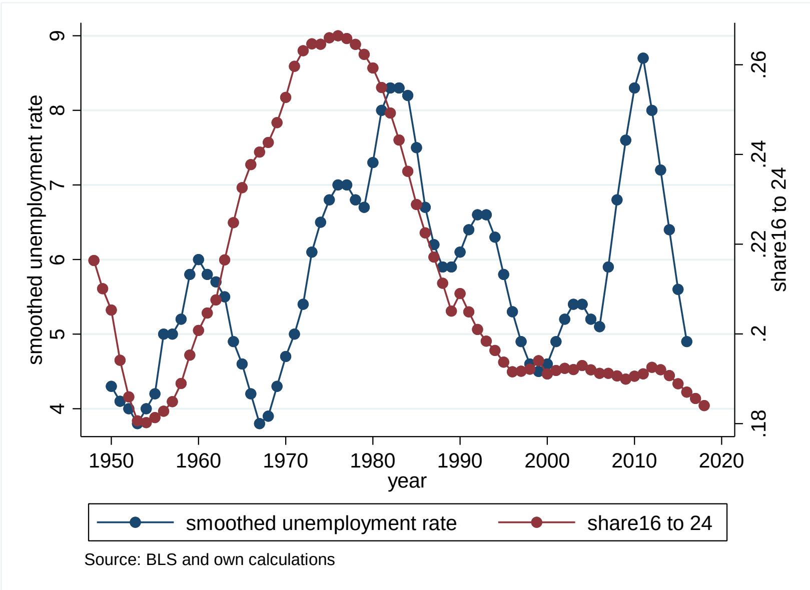


Figure 3: Share of the 16-24 Years Old and Smoothed Unemployment Rate, USA, 1948-2018

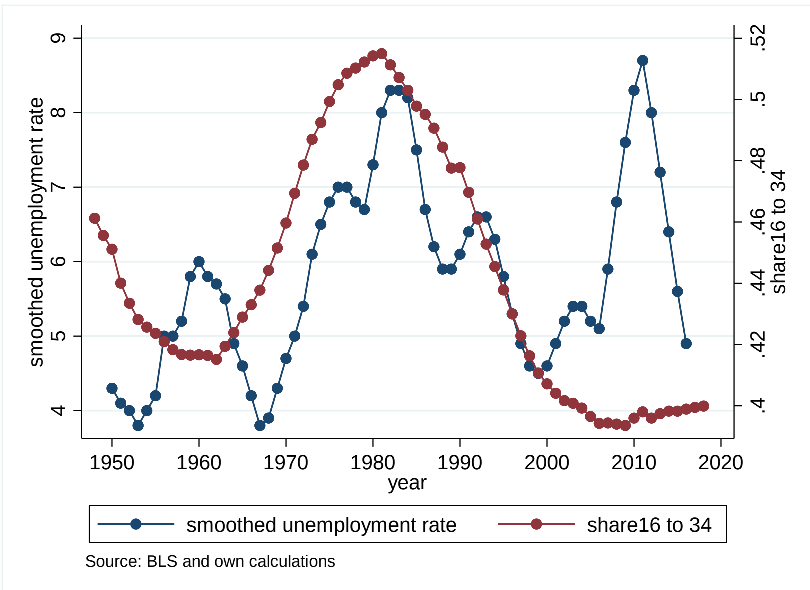


Figure 4: Share of the 16-34 Years Old and Smoothed Unemployment Rate, USA, 1948-2018

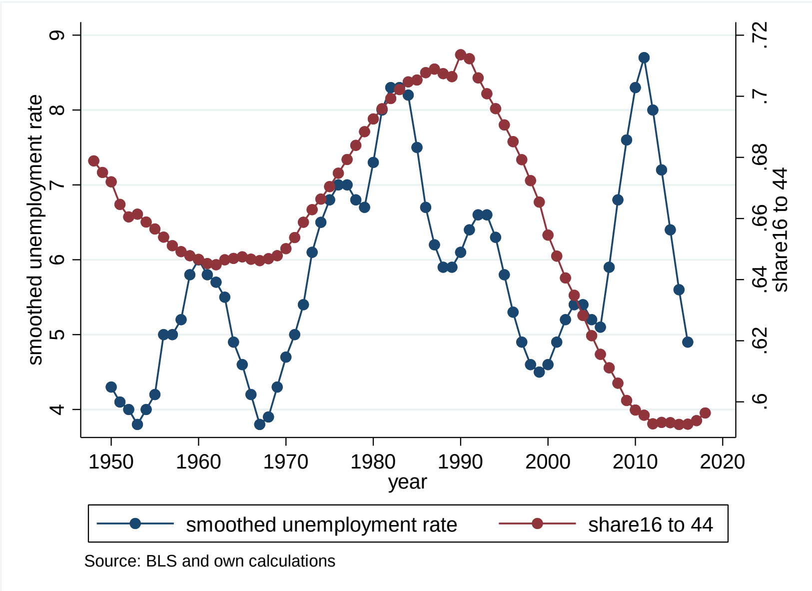


Figure 5: Share of the 16-44 Years Old and Smoothed Unemployment Rate, USA, 1948-2018


Figure 6: First difference of log youth share and lagged first difference of unemployment rate, state level data, 1973-2005

Table 1: Basic Results for US State Level Data of Former Studies

| | Dependent variable: ln unemployment rate | | | | | |
|---|---|---|---|---|---|---|
| | 1973 - 1996 | | | 1973 - 2005 | | |
| age cohort | (1) | (2) | (3) | (4) | (5) | (6) |
| ln youth share | 0.315 | 0.325 | -1.227 | 0.550 | 0.741 | -0.340 |
| | (0.084) | (0.053) | (0.397) | (0.051) | (0.069) | (0.227) |
| fixed effects | no | yes | yes | no | yes | yes |
| time effects | no | no | yes | no | no | yes |
| (within) $R^2$ | 0.031 | 0.031 | 0.493 | 0.068 | 0.160 | 0.584 |
| BIC | 723.4 | 66.7 | -571.0 | 955.2 | 56.5 | -887.3 |
| observations | 1,224 | 1,224 | 1,224 | 1,683 | 1,683 | 1,683 |

Notes: Dependent variable: ln of unemployment rate; ln youth share: ln of youth share (15-24 years); BIC: Bayesian information criterion; State-cluster-robust standard errors are in parentheses.

Table 2: Spatial and Time Lagged Model Results for US State Level Data

| | Dependent variable: ln unemployment rate | | | | | |
|---|---|---|---|---|---|---|
| | 1973 - 1996 | | | 1973 - 2005 | | |
| age cohort | (1) | (2) | (3) | (4) | (5) | (6) |
| ln youth share | -0.473 | 0.182 | 0.164 | -0.010 | 0.166 | 0.099 |
| | (0.284) | (0.130) | (0.111) | (0.201) | (0.076) | (0.064) |
| W(ln youth share) | -0.674 | 0.440 | 0.476 | -0.275 | 0.253 | 0.335 |
| | (0.298) | (0.070) | (0.060) | (0.187) | (0.062) | (0.072) |
| W(ln $u_t$) | 0.602 | 0.379 | 0.496 | 0.600 | 0.311 | 0.507 |
| | (0.039) | (0.032) | (0.051) | (0.035) | (0.024) | (0.047) |
| ln $u_{t-1}$ | no | 0.741 | 0.810 | no | 0.730 | 0.821 |
| | | (0.030) | (0.030) | | (0.027) | (0.029) |
| W(ln $u_{t-1}$) | no | no | -0.250 | no | no | -0.254 |
| | | | (0.059) | | | (0.053) |
| within $R^2$ | 0.030 | 0.545 | 0.523 | 0.159 | 0.677 | 0.670 |
| BIC | -1,165 | -2,119 | -2,161 | -1,594 | -3,093 | -3,138 |
| observations | 1,224 | 1,173 | 1,173 | 1,683 | 1,632 | 1,632 |

Notes: Dependent variable: ln of unemployment rate; ln youth share: ln of youth share (15-24 years); W(ln youth share): spatial lagged ln of youth share (15-24 years); BIC: Bayesian information criterion; all regression include fixed and time effects; State-cluster-robust standard errors are in parentheses.

Table 3: First Results using US County Level Data - Two Age Cohorts

| | Dependent variable: ln unemployment rate | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| age cohort | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln youth share | 0.629 | 0.093 | 0.036 | 0.056 | 0.686 | 0.129 | -0.010 | 0.075 |
| | (0.043) | (0.028) | (0.020) | (0.016) | (0.046) | (0.029) | (0.021) | (0.017) |
| W(ln youth share) | | 0.248 | -0.035 | 0.084 | | 0.211 | -0.541 | 0.051 |
| | | (0.041) | (0.030) | (0.024) | | (0.041) | (0.031) | (0.026) |
| ln labor force growth | no | no | no | no | yes | yes | yes | yes |
| W(ln labor force growth) | no | no | no | no | no | yes | yes | yes |
| W(ln $u_t$) | no | 0.808 | 0.652 | 0.752 | no | 0.819 | 0.904 | 0.763 |
| | | (0.005) | (0.006) | (0.005) | | (0.005) | (0.006) | (0.005) |
| ln $u_{t-1}$ | no | no | 0.429 | 0.665 | no | no | 0.512 | 0.611 |
| | | | (0.006) | (0.007) | | | (0.005) | (0.007) |
| W(ln $u_{t-1}$) | no | no | no | -0.471 | no | no | no | -0.421 |
| | | | | (0.008) | | | | (0.009) |
| within $R^2$ | 0.711 | 0.149 | 0.558 | 0.548 | 0.721 | 0.114 | 0.560 | 0.558 |
| BIC | -46,799 | -84,750 | -94,595 | -98,851 | -48,381 | -88,759 | -97,516 | -101,082 |
| observations | 46,110 | 46,110 | 43,036 | 43,036 | 46,110 | 46,110 | 43,036 | 43,036 |

Notes: Dependent variable: ln of unemployment rate; ln youth share: ln of youth share (15-24 years); W(ln youth share): spatial lagged ln of youth share (15-24 years); BIC: Bayesian information criterion; all regressions include fixed and time effects; county-cluster-robust standard errors are in parentheses, period: annual data for 2000-2014; balanced county level data.

Table 4: Results for US County Level Data - Three Age Cohorts

| | Dependent variable: ln unemployment rate | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | reference: cohort 40-64 | | | reference: cohort 45-64 | | | reference:cohort 50-64 | | | reference:cohort 55-64 | | |
| age cohort | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| ln youth share | 0.114 | 0.150 | 0.121 | 0.156 | 0.109 | 0.120 | 0.167 | 0.013 | 0.112 | 0.178 | 0.105 | 0.122 |
| | (0.030) | (0.022) | (0.019) | (0.032) | (0.024) | (0.020) | (0.032) | (0.023) | (0.019) | (0.034) | (0.025) | (0.020) |
| W(ln youth share) | 0.049 | 0.296 | 0.122 | 0.169 | -0.0001 | 0.105 | 0.220 | -0.627 | 0.084 | 0.220 | -0.072 | 0.099 |
| | (0.046) | (0.035) | (0.029) | (0.045) | (0.034) | (0.028) | (0.045) | (0.034) | (0.028) | (0.048) | (0.036) | (0.030) |
| ln share 25-39 | -0.001 | 0.179 | 0.103 | | | | | | | | | |
| | (0.030) | (0.022) | (0.018) | | | | | | | | | |
| W(ln share 25-39) | -0.242 | 0.657 | 0.063 | | | | | | | | | |
| | (0.044) | (0.032) | (0.028) | | | | | | | | | |
| ln share 25-44 | | | | 0.114 | 0.222 | 0.164 | | | | | | |
| | | | | (0.037) | (0.029) | (0.024) | | | | | | |
| W(ln share 25-44) | | | | -0.157 | 0.492 | 0.107 | | | | | | |
| | | | | (0.057) | (0.043) | (0.036) | | | | | | |
| ln share 25-49 | | | | | | | 0.178 | 0.162 | 0.173 | | | |
| | | | | | | | (0.049) | (0.038) | (0.032) | | | |
| W(ln share 25-49) | | | | | | | 0.033 | -0.035 | 0.143 | | | |
| | | | | | | | (0.074) | (0.055) | (0.045) | | | |
| ln share 25-54 | | | | | | | | | | 0.241 | 0.282 | 0.234 |
| | | | | | | | | | | (0.068) | (0.052) | (0.044) |
| W(ln share 25-54) | | | | | | | | | | 0.048 | 0.393 | 0.240 |
| | | | | | | | | | | (0.104) | (0.077) | (0.063) |
| W(ln $u_t$) | 0.812 | 0.778 | 0.763 | 0.820 | 0.745 | 0.761 | 0.817 | 0.958 | 0.759 | 0.818 | 0.710 | 0.760 |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) |
| ln $u_{t-1}$ | no | 0.469 | 0.613 | no | 0.444 | 0.611 | no | 0.515 | 0.610 | no | 0.414 | 0.610 |
| | | (0.005) | (0.007) | | (0.006) | (0.007) | | (0.006) | (0.007) | | (0.006) | (0.007) |
| W(ln $u_{t-1}$) | no | no | -0.411 | no | no | -0.413 | no | no | -0.421 | no | no | -0.423 |
| | | | (0.009) | | | (0.009) | | | (0.009) | | | (0.009) |
| within $R^2$ | 0.122 | 0.497 | 0.528 | 0.053 | 0.497 | 0.474 | 0.247 | 0.553 | 0.479 | 0.237 | 0.559 | 0.487 |
| BIC | -88,936 | -97,633 | -101,112 | -88,806 | -97,695 | -101,182 | -88,855 | -97,589 | -101,158 | -88,846 | -97,565 | -101,136 |
| observations | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 |

Notes: Dependent variable: ln of unemployment rate; BIC: Bayesian information criterion; all regressions include: fixed and time effects, local and spatial lagged working age population growth factor; county-cluster-robust standard errors are in parentheses; period: annual data for 2000-2014; balanced county level data.

Table 5: Results for US County Level Data - Four Age Cohorts

| | Dependent variable: ln unemployment rate | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | reference: cohort 50-64 | | | | | | reference:cohort 55-64 | | | | | |
| age cohort | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| ln youth share | 0.122 | 0.123 | 0.120 | 0.130 | 0.156 | 0.126 | 0.130 | 0.161 | 0.126 | 0.144 | 0.178 | 0.137 |
| | (0.030) | (0.023) | (0.020) | (0.030) | (0.023) | (0.019) | (0.032) | (0.024) | (0.021) | (0.032) | (0.024) | (0.020) |
| W(ln youth share) | 0.057 | 0.092 | 0.142 | 0.056 | 0.270 | 0.135 | 0.058 | 0.361 | 0.168 | 0.078 | 0.373 | 0.167 |
| | (0.049) | (0.037) | (0.031) | (0.047) | (0.035) | (0.030) | (0.051) | (0.039) | (0.032) | (0.050) | (0.038) | (0.031) |
| ln share 25-34 | -0.008 | 0.167 | 0.077 | | | | -0.004 | 0.155 | 0.083 | | | |
| | (0.024) | (0.019) | (0.017) | | | | (0.025) | (0.020) | (0.018) | | | |
| W(ln share 25-34) | -0.147 | 0.773 | 0.116 | | | | -0.150 | 0.708 | 0.143 | | | |
| | (0.039) | (0.030) | (0.026) | | | | (0.042) | (0.032) | (0.027) | | | |
| ln share 25-39 | | | | 0.045 | 0.206 | 0.123 | | | | 0.059 | 0.245 | 0.140 |
| | | | | (0.032) | (0.024) | (0.020) | | | | (0.035) | (0.026) | (0.023) |
| W(ln share 25-39) | | | | -0.152 | 0.698 | 0.129 | | | | -0.146 | 0.889 | 0.184 |
| | | | | (0.049) | (0.037) | (0.031) | | | | (0.055) | (0.041) | (0.034) |
| ln share 35-49 | 0.129 | 0.121 | 0.088 | | | | | | | | | |
| | (0.038) | (0.029) | (0.024) | | | | | | | | | |
| W(ln share 35-49) | 0.013 | 0.088 | 0.134 | | | | | | | | | |
| | (0.054) | (0.040) | (0.033) | | | | | | | | | |
| ln share 40-49 | | | | 0.097 | 0.051 | 0.036 | | | | | | |
| | | | | (0.029) | (0.022) | (0.018) | | | | | | |
| W(ln share 40-49) | | | | 0.090 | -0.003 | 0.084 | | | | | | |
| | | | | (0.040) | (0.030) | (0.025) | | | | | | |
| ln share 35-54 | | | | | | | 0.153 | 0.200 | 0.116 | | | |
| | | | | | | | (0.053) | (0.040) | (0.034) | | | |
| W(ln share 35-54) | | | | | | | 0.043 | -0.600 | 0.256 | | | |
| | | | | | | | (0.079) | (0.060) | (0.049) | | | |
| ln share 40-54 | | | | | | | | | | 0.123 | 0.117 | 0.068 |
| | | | | | | | | | | (0.043) | (0.032) | (0.027) |
| W(ln share 40-54) | | | | | | | | | | 0.117 | 0.319 | 0.176 |
| | | | | | | | | | | (0.062) | (0.047) | (0.038) |
| W(ln $u_t$) | 0.806 | 0.958 | 0.759 | 0.806 | 0.797 | 0.760 | 0.806 | 0.775 | 0.761 | 0.809 | 0.777 | 0.761 |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.005) |
| ln $u_{t-1}$ | no | 0.557 | 0.611 | no | 0.478 | 0.612 | no | 0.462 | 0.611 | no | 0.466 | 0.612 |
| | | (0.005) | (0.007) | | (0.005) | (0.007) | | (0.005) | (0.007) | | (0.005) | (0.007) |
| W(ln $u_{t-1}$) | no | no | -0.416 | no | no | -0.416 | no | no | -0.418 | no | no | -0.415 |
| | | | (0.009) | | | (0.009) | | | (0.009) | | | (0.009) |
| within $R^2$ | 0.110 | 0.502 | 0.457 | 0.080 | 0.490 | 0.463 | 0.081 | 0.486 | 0.464 | 0.035 | 0.437 | 0.451 |
| BIC | -89,149 | -97,588 | -101,109 | -89,128 | -97,631 | -101,125 | -89,119 | -97,560 | -101,085 | -89,052 | -97,630 | -101,112 |
| observations | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 | 46,110 | 43,036 | 43,036 |

Table 6: Elasticities of Age Cohort Effects on Unemployment Rate

| | short-run elasticities | | | long-run elasticities | | |
|---|---|---|---|---|---|---|
| age cohort | direct | indirect | total | direct | indirect | total |
| dependent variable: log unemployment rate | | | | | | |
| Table 4: Regression (3): reference cohort 40-64 | | | | | | |
| log youth share | 0.177 | 0.858 | 1.035 | 0.597 | 6.427 | 7.024 |
| | (0.020) | (0.105) | (0.116) | (0.067) | (1.193) | (1.240) |
| log share 25-39 | 0.139 | 0.568 | 0.707 | 0.457 | 4.355 | 4.812 |
| | (0.020) | (0.100) | (0.109) | (0.063) | (1.014) | (1.055) |
| Table 4: Regression (6): reference cohort 45-64 | | | | | | |
| log youth share | 0.171 | 0.777 | 0.948 | 0.552 | 5.103 | 5.655 |
| | (0.021) | (0.093) | (0.103) | (0.064) | (0.838) | (0.880) |
| log share 25-44 | 0.223 | 0.916 | 1.139 | 0.708 | 6.092 | 6.800 |
| | (0.026) | (0.127) | (0.137) | (0.081) | (1.129) | (1.182) |
| Table 4: Regression (9): reference cohort 50-64 | | | | | | |
| log youth share | 0.156 | 0.666 | 0.822 | 0.468 | 3.388 | 3.857 |
| | (0.019) | (0.089) | (0.097) | (0.055) | (0.513) | (0.546) |
| log share 25-49 | 0.242 | 1.072 | 1.314 | 0.729 | 5.439 | 6.168 |
| | (0.033) | (0.149) | (0.161) | (0.094) | (0.883) | (0.935) |
| Table 4: Regression (12): reference cohort 55-64 | | | | | | |
| log youth share | 0.172 | 0.754 | 0.925 | 0.512 | 3.717 | 4.229 |
| | (0.021) | (0.093) | (0.101) | (0.059) | (0.531) | (0.564) |
| log share 25-54 | 0.340 | 1.643 | 1.984 | 1.027 | 8.043 | 9.070 |
| | (0.046) | (0.207) | (0.223) | (0.131) | (1.215) | (1.283) |
| Table 5: Regression (6): reference cohort 50-64 | | | | | | |
| log youth share | 0.186 | 0.904 | 1.090 | 0.591 | 5.347 | 5.939 |
| | (0.021) | (0.109) | (0.120) | (0.065) | (0.818) | (0.865) |
| log share 25-39 | 0.179 | 0.868 | 1.047 | 0.569 | 5.142 | 5.711 |
| | (0.022) | (0.115) | (0.124) | (0.067) | (0.867) | (0.909) |
| log share 40-49 | 0.065 | 0.441 | 0.506 | 0.218 | 2.538 | 2.756 |
| | (0.018) | (0.074) | (0.077) | (0.050) | (0.473) | (0.493) |
| Table 5: Regression (12): reference cohort 55-64 | | | | | | |
| log youth share | 0.206 | 1.062 | 1.268 | 0.665 | 6.400 | 7.066 |
| | (0.022) | (0.114) | (0.125) | (0.069) | (0.935) | (0.985) |
| log share 25-39 | 0.213 | 1.138 | 1.351 | 0.692 | 6.840 | 7.532 |
| | (0.024) | (0.131) | (0.142) | (0.076) | (1.081) | (1.130) |
| log share 40-54 | 0.126 | 0.898 | 1.023 | 0.431 | 5.269 | 5.700 |
| | (0.027) | (0.120) | (0.127) | (0.077) | (0.866) | (0.900) |

Notes: Direct effects come from the local region and indirect effects come from the neighbor regions. Long-run effects cumulate feedbacks over the period considered. Results based on regressions reported in Tables 4 & 5; county-cluster-robust standard errors are in parentheses.

Table 7: Average Percentage Change in US Unemployment Rate

| | | | effects of continuously compounded rate of change | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | continuously | overall | short-run change | | | long-run change | | | overall changes | |
| | compounded rate of change | change rate | direct | indirect | total | direct | indirect | total | short-run | long-run |
| age cohort | (a) | (b) | (c) | (d) | (e) | (f) | (g) | (h) | (i) | (j) |
| Table 4: Regression (3): reference cohort 40-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.043 | -0.206 | -0.249 | -0.146 | -1.540 | -1.686 | | |
| log share 25-39 | -0.819 | -10.686 | -0.115 | -0.458 | -0.573 | -0.374 | -3.515 | -3.889 | -10.91 | -55.21 |
| Table 4: Regression (6): reference cohort 45-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.042 | -0.186 | -0.228 | -0.135 | -1.223 | -1.358 | | |
| log share 25-44 | -1.117 | -14.302 | -0.249 | -1.013 | -1.262 | -0.791 | -6.736 | -7.527 | -18.96 | -72.82 |
| Table 4: Regression (9): reference cohort 50-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.038 | -0.160 | -0.198 | -0.115 | -0.812 | -0.926 | | |
| log share 25-49 | -1.089 | -14.005 | -0.263 | -1.158 | -1.422 | -0.771 | -5.877 | -6.648 | -20.43 | -66.80 |
| Table 4: Regression (12): reference cohort 55-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.042 | -0.181 | -0.223 | -0.125 | -0.891 | -1.016 | | |
| log share 25-54 | -0.719 | -9.534 | -0.244 | -1.175 | -1.419 | -0.738 | -5.753 | -6.490 | -20.69 | -66.46 |
| Table 5: Regression (6): reference cohort 50-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.046 | -0,217 | -0.262 | -0.145 | -1.281 | -1.426 | | |
| log share 25-39 | -0.819 | -10.686 | -0.147 | -0.701 | -0.847 | -0.466 | -4.150 | -4.616 | | |
| log share 40-49 | -1.449 | -18.299 | -0.094 | -0.636 | -0.730 | -0.316 | -3.660 | -3.976 | -22.89 | -77.19 |
| Table 5: Regression (12): reference cohort 55-64 | | | | | | | | | | |
| log youth share | -0.245 | -3.435 | -0.050 | -0.254 | -0.305 | -0.163 | -1.534 | -1.696 | | |
| log share 25-39 | -0.819 | -10.686 | -0.174 | -0.918 | -1.093 | -0.567 | -5.520 | -6.087 | | |
| log share 40-54 | -0.632 | -8.492 | -0.080 | -.0565 | -0.644 | -0.273 | -3.313 | -3.586 | -29.09 | -81.54 |

Notes: Continuously Compounded Rate of Change is calculated as $(\ln(x_t)-\ln(x_{t-1}))*100$. Overall change is calculated as $((x_{t+15}-x_t)/x_t)*100$. Direct effects come from the local region and indirect effects come from the neighbor regions. Long-run effects cumulate feedbacks over the period considered. Results based on regressions reported in Table 4 & 5.

Table 8: Basic Statistics

| | obs | mean | se | min | max |
|---|---|---|---|---|---|
| A: State Level Data: 1973-1996 | | | | | |
| unemployment rate | 1,234 | 6.4279 | 2.0684 | 1.9 | 17.4 |
| youth share | 1,234 | 0.2391 | 0.0343 | 0.1638 | 0.3271 |
| B: State Level Data: 1973-2005 | | | | | |
| unemployment rate | 1,683 | 5.9670 | 2.0121 | 1.9 | 17.4 |
| youth share | 1,683 | 0.2277 | 0.0360 | 0.1623 | 0.3271 |
| C: County Level Data: 2000-2014 | | | | | |
| unemployment rate | 46,110 | 6.3668 | 2.7408 | 0.8168 | 29.6683 |
| youth share | 46,110 | 0.2055 | 0.0431 | 0.0612 | 0.6198 |
| share 25-34 | 46,110 | 0.1778 | 0.0273 | 0.0625 | 0.3696 |
| share 25-39 | 46,110 | 0.2747 | 0.0357 | 0.0781 | 0.4847 |
| share 25-44 | 46,110 | 0.3815 | 0.0421 | 0.2012 | 0.5823 |
| share 25-49 | 46,110 | 0.4942 | 0.0434 | 0.2665 | 0.6818 |
| share 25-54 | 46,110 | 0.6060 | 0.0393 | 0.3114 | 0.7714 |
| share 35-49 | 46,110 | 0.3164 | 0.0348 | 0.1352 | 0.5455 |
| share 35-54 | 46,110 | 0.4281 | 0.0374 | 0.1807 | 0.6136 |
| share 40-49 | 46,110 | 0.2195 | 0.0252 | 0.0865 | 0.3636 |
| share 40-54 | 46,110 | 0.3312 | 0.0318 | 0.1128 | 0.5090 |

Notes: State level data are taken from the studies of Robert Shimer (2001) and Chris Foote (2007). Unemployment rates at the county level are taken from Bureau of Labor Statistics and shares are taken from Census.