Relative Cohort Size and Unemployment in the United States

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Abstract

Since the early 1970s it was argued in different studies that shifts from relative smaller to larger age cohorts of the labor force lower the unemployment rate (cohort crowding hypothesis). However, Robert Shimer (2001) provoked a debate with his controversial result that the overall unemployment rate tends to be lower when many young people supply labor. In contrast to other studies, he uses regional (state level) data. In this study I apply different regional data sets for the USA (including Robert Shimers original data) to analyze how aging affects unemployment in a framework that considers spatial interactions. At the state level, I can neither confirm the findings of Robert Shimer nor the cohort crowding hypothesis. Using county level data, however, I find local effects that are compatible with the cohort crowding hypothesis but also with specific assumptions about the heterogeneity of older and younger workers that are to the advantage of older workers.

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

JEL classification: J60, R12, J10, C23

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1 Introduction

The literature on the effects on unemployment of differences in population age cohorts originated in a study by George Perry (1970), who, along with Richard Easterlin, pioneered the hypothesis of cohort crowding. Using this hypothesis, a number of authors have argued that an increase in the percentage of youth in the working-age population raises the unemployment rate since the level of the unemployment rate is generally higher for younger workers.[1] All these studies used macroeconomic data.

A different approach from that of the cohort crowding hypothesis is found in Robert Shimers (2001) article, who used regional data for 1973-1996 to estimate the impact on overall unemployment rate of changes in the percentage of youth aged 16-24 in the population. In his analysis of US local labor markets, Robert Shimer found that the overall unemployment rate tends to be lower when many young people supply labor and argued that a high proportion of young workers incents firms to create new jobs because younger workers undertake more search activities, which reduce the firms' recruitment costs.

However, Chris Foote (2007) extended the sample period 1973-2005 and found no significant relationship between the unemployment rate and the proportion of youth in the population. Carsten Ochsen and Pascal Hetze (2006) discussed two other problems: First, many talented young people are still pursuing their education at these ages, so the level of formal education of those in the labor market is lower in this cohort than in older age groups. Second, Shimer used percentage of overall population and did not control for the percentage of different age groups who were in the labor market. The correlation coefficient between the labor market participation rate for the 16-64 age group and 16-24 age group is -0.2. One of the important reasons for this non-conforming trend in labor market participation is that the average duration of education for young people has steadily increased over the last decades.

A further issue is the consideration of spatial correlation. Carsten Ochsen

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

(2009) used regional (county level) panel data for Germany in a spatial and time dynamic model. Using the age group 16-39 as the definition of the young, regional unemployment declines the more younger worker are in the surrounding regions. Ochsen argues that this is because of the higher mobility (in terms of commuting) of younger workers. At the local level, neither the cohort crowding nor the Shimer effect can be confirmed. However, although the results are different, overall they point in the same direction as Robert Shimers results.[2] The cohort crowding effects can be overlaid by age-related changes in matching efficiency, job creation, and job destruction.

The present study contributes to the literature by using different regional data sets (at the state level and the county level) for the US and a new estimator to analyze the effects of smaller cohorts on the labor market, in particular, the issues of spatially dependent local labor markets. In addition, I consider different cut offs for the delineation between young and old. Finally, I present a theoretical model that provides an explanation for the effects found. I argue that the two age groups differ in their employment-related attributes (e.g., productivity, matching efficiency, and labor turnover), apart from cohort size.

The analysis I offer, undertaken to identify the demographic effects on unemployment, provides theoretical implications and empirical findings for the US labor market. Using different regional data and spatial and time dynamic econometric models, I examine empirically the consequences of an aging working-age population for the local labor markets. According to the estimates using county level data, ongoing aging in the local labor market causes a fall in local unemployment. In addition, aging in the surrounding areas has a positive effect on unemployment in the local district. My interpretation is that firms prefer older workers, but this age group also has less spatial mobility (in terms of commuting), which declines the matching efficiency and reduces job creation. Using state level data, I find neither the cohort crowding effect nor the Shimer effect.

[2] Using Shimer's data, Foote (2007) also showed that the consideration of spatial correlation at the state level reveals that the youth share effect is no longer significant. However, he considers "only" the Driscoll and Kraay standard errors, which is not sufficient to consider spatial correlation.

2 Theoretical Model

In most cases, the literature that has dealt with age and employment or matching is related to specific issues. Christopher Pissarides and Jonathan Wadsworth (1994) and Simon Burgess (1993) found evidence for Great Britain that the rates of job separation are higher for young workers because they are more likely to conduct job searches while they are employed.[3] Hence, as Melvyn Coles and Eric Smith (1996) argued in their study on England and Wales, matching may decrease with an older working population. Job separations and low hiring rates for older workers could also be the result of imagined or actual differences in productivity (Haltiwanger et al. 1999, Daniel and Heywood 2007); productivity may increase with age if job experience is important (Autor et al., 2003) and decline if human capital depreciates over a lifetime, as it may 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 changes in mobility in an aging labor force. According to Herbert Brücker and Parvati Trübswetter (2007) and Jennifer Hunt (2000), regional mobility decreases as age increases for both high- and low-skilled workers as well as for 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.[4]

Another important issue in the context of mobility is that of spatial dependencies of the 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 age structure of the labor force in the neighbor districts since 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. René Fahr and Uwe Sunde (2005) used data at the regional level for West Germany to

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

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

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, Michael Burda and Stefan Profit (1996) also considered the spatial dimension in the matching function for the Czech Republic, as Barbara Petrongolo and Etienne Wasmer (1999) did for France and the UK, Simon Burgess and Stefan Profit (2001) for the UK, and Reinhard Hujer et al. (2009) for Germany. These studies found significant spatial interactions in regional search activities or unemployment rates.

With respect to aging of the labor force, I follow Carsten Ochsen (2009) and extend the framework of search and equilibrium unemployment by distinguishing between younger and older workers and between the age-related effects.[5] By considering age-sensitive differences in separation risks, mobility, labor productivity, and wages, I differentiate between younger and older workers who may generate different levels of surplus for firms if they fill a vacancy.

To retain simplicity, I treat on-the-job searches differently from the way they are treated in the standard framework (see Pissarides, 2000) in that I do not consider the two usual reservation productivity parameters that allow differentiation between productivity-related job destruction and on-the-job search.[6] In general, this approach helps to explain why employed people decide in favor of on-the-job search. The focus in this paper, however, is on the consequences of spatial search activities on matching, job creation and job destruction.

I consider two types of agents: workers and firms. All agents are risk neutral and discount the future at rate r. The labor force is divided into two age groups—younger workers y and the 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 average rate of unemployment u in a continuum of workers, normalized to 1, consists

[5] We analyze the effects of aging of the labor force but ignore the effects of a decline in population because most empirical studies find constant returns to scale of matching functions. Petrongolo and Pissarides (2001) provided an overview of the related literature. Therefore, the pure population size has no effect on matching and search equilibrium in the labor market.

[6] 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).

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 number of vacancies. That is, 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, I 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. In addition, the bulk of these commuting dependencies apply to regions that are adjacent. Thus, I refer to commuting and inter-regional searches as mobility. However, this definition of mobility does not include moves from 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 it is that tightness that 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 the age structure of the job seekers because younger workers are more mobile. Hence, only a part of the older job seekers from neighbor regions apply for jobs in the local region. I refer to $\sigma^l = p^l \sigma^l_y + \left(1 - p^l\right) \sigma^l_o$ 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 σ^l. There are two differences between $\tilde{\sigma}^n$ and σ^n: First, they are related to different labor force sizes—$\tilde{\sigma}^n$ to the local labor force and σ^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 α, with $0 \leq \alpha < 1$, accommodates the limited spatial mobility of older workers. The differences between $\tilde{\sigma}^l$ and σ^l are analog to those between $\tilde{\sigma}^n$ and σ^n.

The age distribution of the job seekers who are 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, the age structure of the job seekers depends on the age structure of the labor force.

To introduce a nonstandard matching technology that reflects the age composition of the job seekers, I consider job seekers in efficiency units identified by π, 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 $\pi\left(\bar{p}^l\right)\left(\sigma^l + \tilde{\sigma}^n\right)$ 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 $\pi'' < 0$.

Thus, I have the local matching function $m^l = m^l(\pi\left(\bar{p}^l\right)\left(\sigma^l + \tilde{\sigma}^n\right), v^l)$ as the local labor market flow rate of matches (in efficiency units) formed. 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. It follows, then, that the spatial correlation of unemployment rates are positive. In addition, 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 τ_o and τ_y denote the rates of the added risk 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 perspective of the local region, I add the probability that a mobile worker loses his or her 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 $i = [y, o]$:[7]

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

The first term on the right-hand side is the age-related flow into unemployment from local employment. The second term on the right-hand side

[7] However, the simplifying assumption is that the spatial flows are of equal size.

is the age-related flow into local unemployment from jobs in the neighbor region; thus, the positive flow of newly local unemployed from the surrounding region increases the higher the separation rates in this region. This is the second channel that generates positive correlated 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 Beveridge curve (BC):

$$u^l = \frac{\left(s^l + \tau_o^l\right) + \left(s^n - s^l + \tau_o^n - \tau_o^l\right)\omega_o^{l,n}}{s^l + \tau_o^l + \theta^l q^l(\theta^l, \bar{p}^l) + \theta^n q^n(\theta^n, \bar{p}^n)} + p^l\left(u_y^l - u_o^l\right). \tag{2}$$

The local BC includes spatial and (spatial) aging effects. The second term on the fraction line indicates that local unemployment increases as the number of spatially mobile workers increase and $s^n > s^l$ and $\tau_i^n > \tau_i^l$. With respect to the age-related effects, there are two channels: 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 the separation rate is identical for younger and older workers; otherwise, an increasing proportion of younger workers increases job destruction and unemployment since younger workers usually have higher turnover rates. Hence, 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 θ's in BC determine equilibrium unemployment and are explained by the willingness of firms to create vacancies.

Firms: Vacancies are open equally to younger and older workers. Whether local firms create new jobs or remain inactive is subject to the benefits they receive 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

$$rJ_o^l = \mu - w_o^l - \left(s^l + \tau_o^l\right)\left(J_o^l - V^l\right), \tag{3}$$

$$rJ_y^l = \mu + \delta - w_y^l - \left(s^l + \tau_y^l\right)\left(J_y^l - V^l\right), \tag{4}$$

$$rV^l = -\gamma + q^l(\theta^l, \bar{p}^l)\left(J^l - V^l\right). \tag{5}$$

Local firms receive revenues μ 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 a lower depreciation of human capital is an argument for the higher productivity of younger workers. Hence, I do not fix the sign of the output differential, so $\delta \gtreqless 0$.[8] The job-worker match ends at the probability $s^l + \tau_i^l$, in which case the value of the match is replaced by the value of an unfilled vacancy.

The vacant job costs γ per unit time and changes state according to the rate $q^l(\theta^l, \bar{p}^l)$. Hence, 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

$$J^l = \bar{p}^l J_y^l + \left(1 - \bar{p}^l\right) J_o^l. \tag{6}$$

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. This expectation holds true if $J^l = \gamma / q^l(\theta^l, \bar{p}^l)$; with eq. (6), the equation for the expected J^l, we have:

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

$$\frac{1}{q^l(\theta^l,\bar{p}^l)} = \frac{1}{\gamma}\left[\bar{p}^l J_y^l + \left(1-\bar{p}^l\right) J_o^l\right]. \tag{7}$$

the second important equation, the local job creation condition (JC). Market tightness is the only variable parameter, and it guarantees the identity of eq. (7). Firms open more vacancies if $1/q^l(\theta^l,\bar{p}^l)$ increases. Clearly, easy search conditions and high profits foster job creation.

Effects of Aging: Next, I analyze the effects of a change in the age structure and in the Appendix I provide the comparative static effects. A decline in the local share of the young reduces the average flows in the labor market if younger workers separate from jobs more often, while a lower total separation risk corresponds to less equilibrium unemployment. Thus, a higher percentage of older workers reduces the labor turnover such that fewer job-worker pairs must be matched: the BC shifts inwards. The (spatial) effect of the change in matching efficiency is negative because a decline in the local share of the young increases the average duration of the search on either side; hence, this aging effect shifts the local BC outwards. With respect to a new equilibrium in the local BC, it follows that aging has ambiguous effects.

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

With respect to job creation, aging influences local job creation by two means. The first comes from a possible difference between the value of a match with a younger and one with an older worker. If firms value young workers more highly than they do older 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. As we have a negative effect of aging on matching, job creation suffers from aging. However, the total effect is ambiguous. For example, when firms favor older workers, but the overall effect of aging is still negative, the positive effect of the employment characteristics of older workers are outweighed by the effect of decreasing matching efficiency. 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 the age structure in both regions.

Figure 1 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 and job creation. 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: unemployment is low if the vacancy rate is high because job seekers find new employment easily. The local JC, the curve that maps the job creation condition, has a positive intercept $\left(e^l + \tilde{\sigma}^n\right)\theta^l$ and shifts when the number of local 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 1 about here

I found three 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.

Spatial interactions of regional labor markets can cause these effects on the local labor market as well. 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.[9] 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.

[9] The intercept also decreases in this case.

3 Empirical Analysis

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 macro economic and regional data for the US. Following the cohort crowding literature the share of the young in the working age population is positively correlated with the overall unemployment rate. Figure 2 shows the share of the 15-24 years old in the working age population and the five years smoothed overall unemployment rate for the US. As expected, both series are positively correlated but at a moderate level (correlation is 0.2). Overall it does not seem that both series are "synchronized".

Figure 2 about here

Using the share of the 15-39 years old as the young the pattern changes a little. Figure 3 shows the relation between the share of this age cohort and the smoothed overall unemployment rate. Here, the correlation is 0.67. Using data at the national level one can at least conclude that there is some considerable correlation. However, using regional data allows to consider a more differentiated pattern.

Figure 3 about here

First, we start with state level data and the econometric model considered in the 2001 article of Robert Shimer:

$$\ln u_{it} = \alpha \ln young_{it} + c_i + \theta_t + \epsilon_{it} \tag{8}$$

where $\ln u_{it}$ is the logarithm of the overall unemployment rate in region i and year t, $\ln young_{it}$ is the share of the young (share of the working-age population who are aged 16-24) in region i and year t, c_i are regional and θ_t are time effects, and ϵ_{nt} is an error term. The parameter α is positive in Robert Shimers analysis of US state level data, which means that a larger share of the young in state i and year t correspond to a lower unemployment rate in this year and state. This result contradicts the cohort crowding hypothesis and related to the current demographic change this means that unemployment is positively correlated with aging. The main result in his article is provided in table 1.

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

Chris Foote (2007) extends the data used in the Shimer paper by nine years and uses the same estimation strategy. However, he does not found a significant relationship between local unemployment and the share of the young in this region. He also considers the same instrumental variable (IV) procedure as Robert Shimer does, but the results do not change. In addition, Chris Foote uses corrected standard errors as suggested by John Driscoll and Aart Kraay (1998). They provide a method that additionally to heteroskedasticity and autocorrelation considers spatial correlation. However, since for each year only one average value across all regions is considered to account for spatial correlation, this approach does not account adequate for neighborhood correlations. Chris Foote comes to the conclusion that the consideration of spatial correlation (by using Driscoll and Kraay standard errors) is a further argument why the effects in Robert Shimers data are in fact not significant. The main result in his article is provided in table 1.

Table 1 about here

I argue that, in principle, the local share of the young should capture changes in the 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. To consider additional spatial effects, I enlarge the specification of eq. (8). First, I will consider spatial and time lagged effects of the dependent variable, and second, and this is what I am primarily interested in, I also want to capture the effect of the share of the young in the neighbor region on local unemployment.

I argue that the young in both regions are homogeneous. However, the young in the local region do not need to be mobile to accept a job offer in their home region. The young in the neighbor region, however, need to be spatial mobile, in terms of commuting, to work in the local region. I distinguish this from the fact that they could move to the region where they work. Because in this case, they are living and working in the same region (after they have moved) and I do not consider them as spatial mobile. In the theoretical section I have argued that younger workers are more mobile than older workers are. If this is true, I need to consider an effect of the share of the young in the neighbor region on local unemployment. Since the young in both regions hold, on average, the same job relevant characteristics, I do not argue that, e.g., the young in neighbor regions are more productive that the young in the local region. In fact, this is not possible, because in my model every share will be considered for the local region and for the neighbor region (I am the neighbor of my neighbor).

To capture time invariant unobservables in the econometric model, a fixed effects specification is considered. To account for additional unobserved time variant effects at the local level, I also considered time lagged and spatial lagged effects. In order 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. First, the matrix has the entry 1 if two regions share 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. $W \ln u_{it}$ generates the average values of the regions adjacent to region i. This is the spatial lagged effect of the dependent variable. With $\ln u_{i,t-1}$ as the time lagged effect of the dependent variable, $W \ln u_{i,t-1}$ is the combined spatial and time lagged effect.

Starting from the Shimer Model, eq. (8), I consider a spatial and time dynamic model

$$
\begin{aligned}
\ln u_{nt} &= \gamma \ln u_{n,t-1} + \lambda W_n \ln u_{nt} + \pi W_n \ln u_{n,t-1} \\
&\quad + \alpha \ln young_{nt} + \beta W_n \ln young_{nt} \\
&\quad + c_n + \theta_t + \epsilon_{nt}
\end{aligned} \tag{9}
$$

where $\ln u_{nt}$, $\ln young_{nt}$ and ϵ_{nt} are stacked $Tn \times 1$ column vectors, W_n is a row normalized $n \times n$ spatial weights matrix that is nonstochastic and that generates the spatial dependence between cross sectional units, c_n are regional and θ_t are time effects.

In this specification I want to consider unobserved time varying effects in the local and neighbor region that are correlated with the time and spatial lag of the dependent variable. The parameter α should catch in principle the same effect as in the model proposed by Robert Shimer. With respect to the spatial effect of the share of the young I argue as outlined above: There is no reason to assume that young workers in the neighbor region differ in their job relevant characteristics from the young in the local region, with one exception: Mobility in terms of commuting. In the local region young and old workers apply for jobs in their home region and there is no restriction due to mobility. However, with respect to jobs in the neighbor region, not all older workers in the local region apply for this job because of their limited mobility in terms of commuting. Therefore, the spatial share of the young, $W_n \ln young_{nt}$, is used as a proxy variable for mobility in terms of commuting. The smaller the share of the young in the neighbor region, the less likely do local firms get applications from this region. This, in turn, increases search costs and reduces the vacancy rate. Hence, I expect that the parameter β has a negative sign. In contrast, α is positive if the cohort crowding hypothesis can be confirmed at the local level, and it is negative if Robert Shimers argumentation (which was restricted to the local region) can be empirically confirmed. According to the model in section 2, α is positive if, for example, younger workers are less attractive for firms. This explanation does not contradict the cohort crowding hypothesis. However, such issues affect the flow in the labor market and this, in turn, can lead to effects that are different from cohort crowding.

If the spatial effect of the age structure of the working age population is of importance, we have to consider the bias on α if we neglect β. Let ω be the parameter for the local effect, when the spatial effect is neglected. The standard result is then $\omega = \alpha + \beta\delta$, where δ is a measure for the covariance of the local and the spatial age structure. I expect the latter to be positive and β to be negative, which yields a negative bias on ω. This might be an explanation, why Robert Shimer has estimated a negative relationship between the unemployment rate and the share of the young.

In the analysis I will not discuss the effects of the lagged dependent variable, because these parameters are not important here. These lags serve as proxies for unobserved effects only.

3.1 Data

I use three different data sets. First, the original data used in Robert Shimers (2001) article. He uses 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 rate is taken from the CPS and shares are taken from Census. He uses annual data for 51 US states and the period 1973 - 1996. The second data set is taken from the paper by Chris Foote (2007), who extends the data of Robert Shimer to 2005 and uses the same sources.

The third data set is new. I use the unemployment rate and share of the young at the US county level. The latter group is considered in three different definitions: share of the working-age population (ages 15-64) who are aged 16-24, share of the working-age population who are aged 16-39, and share of the working-age population who are aged 16-49. With respect to the first share I follow the definition of Shimer and Foote and for the second share I consider the criticism of Carsten Ochsen and Pascal Hetze (2006). I use this broader definition of young and old workers than most other studies because I believe that many of the individual characteristics that are relevant to job creation and job destruction, such as quit rates and productivity changes, alter when workers reach middle age.[10] The last share

[10] 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.

serves as a control group to test if the results are plausible if I use such a definition. The unemployment rate is taken from the BLS and shares are taken from Census. The analysis considers annual data for 3074 counties and the period 1998 to 2007.

With respect to the percentages of younger and older people 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 6.3 percentage points (standard deviation of 2.04) and ranges from 1.9 to 17.4 percentage points. The data extended to 2005 do not differ much: the average unemployment rate is about 5.9 percentage points (standard deviation 1.98) and the range is not different from for former. The share of the young (aged 16-24) in the period 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 we have an average unemployment rate of 5.8 (standard error of 2.69) with a range between 0.7 and 30.6. With respect to the share of the age cohort 16-24 we get an average of 0.40 (standard error is 0.04) and minimum and maximum values of 0.23 and 0.71. Hence, at the county level we have much more variation in a shorter time period.

3.2 Econometric Model

Age effects on the unemployment rate are analyzed using mostly macroeconomic data. In this section I provide alternative estimates that allow spatial effects to be considered using regional data. In order to draw conclusions on the basis of different approaches, which should serve as a kind of robustness check, I estimate the model in three different ways. First, I apply the usual within panel estimator with fixed and time effects and robust standard errors. Second, I use the same estimator and calculate standard errors according the method provided by John Driscoll and Aart Kraay (1998).[11] In addition

[11] When the assumption of cross-sectional independence is violated, estimates of standard errors are inconsistent, so they are not useful for inference. Driscoll and Kraay (1998) argued that spatial correlations among cross-sections may arise for a number of reasons, ranging from observed common shocks, such as terms of trade or oil shocks, to unobserved

to heteroskedasticity this procedure also controls for (serial) autocorrelation and spatial correlation. In the latter case, however, they use annual averages over all regions. This does not consider adequate regional correlation, e.g., of neighbor regions.

Third, I use an estimator provided by Lung-fei Lee and Jihai Yu (2010). In this case, the parameters for the time lagged, spatial lagged, and space-time lagged values of the dependent variables are estimated using a quasi-maximum likelihood estimator that is extended by a bias correction. To avoid biased estimates for the lagged effects of the dependent variables, the authors developed a data transformation approach that has the same asymptotic efficiency as the quasi-maximum likelihood estimator when n is not relatively smaller than T. The reason why I use three different approaches is that no one of them is free of criticism. In the first and second case I have better standard errors but biased coefficients with respect to the time and spatial lagged effects of the dependent.[12] In the third case the coefficients are unbiased but the standard errors are probably nor correct.

What about IV estimation? With respect to the causal relationship of 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. With respect to migration, one could argue that there are two opposing effects that 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. For Robert Shimers and Chris Footes data I also estimate the model with an IV estimator using

contagion or neighborhood effects. Building on the non-parametric heteroskedasticity and autocorrelation consistent covariance matrix estimation technique, they showed how this approach can be extended to a panel setting with cross-sectional dependence.

[12] See, for example, Nickell (1981) with respect to 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.

the same instrument as they do; the local lagged birth rates. For the county data, however, I do not estimate the model with an IV estimator because appropriate instruments are not available at the county level. In addition, birth rates are probably not a suitable instrument at the county level because family movements can affect this variable much more than at the state level. Without additional IV estimates at the county level, however, we have to be careful when interpreting the results.

3.3 Results

Table 2 provides the results of the three preferred estimators—robust, D&K, and L&Y— using the original data from Robert Shimers article. With respect to the specification without the spatial effect of the young, I find that the local younger labor force is negatively related to the local unemployment rate, when the specification "robust" is considered. Hence, using this estimator I get results that are comparable to those of Robert Shimer. However, the effect is not statistical significant for the second and third estimator. When I consider the spatial share of the young, the effects for the local share of the young are insignificant in all cases. I find a similar effect for the percentage of younger workers in the surrounding labor market. Given that younger workers are more mobile than older workers, aging reduces the share of regional mobile workers, and this reduction, in turn, increases the local unemployment rate. However, this effect is not significant.

Table 2 about here

The original data used in the paper by Chris Foote are used in the estimates provided in table 3. In contrast to the results in table 2 no effect is significant. This is surprising to some extend, since the only difference is the extension of the considered period. However, the results are in line with Chris Footes conclusion whereby overall there is no significant relationship between the local unemployment rate and the local share of the young. That this applies to the spatial share of the young as well.

Table 3 about here

The results in the tables 2 and 3 can be interpreted in different ways. Of course, it is possible that the difference between younger and older workers is too small to be significant. However, 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 and insignificant. A third explanation is related to the size of the regions. Within a state are also a lot of spatial mobile workers that are measured as local workers. As mentioned above, neglecting the share of the young in the neighbor region yield a negative bias on the share of the young in the local region. At the state level, however, I cannot distinguish these two groups within a state. Hence, the true local effect can also be positive. In addition, 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 the explanation related to the wrong regional size is relevant, the results are expected to be different when county level data are considered. In the next step I therefore focus on counties as regions and use in the first case the same definition of the young as Robert Shimer and Chris Foote.

The results in table 4 are related US county level data. Now, the first and third specification yield significant positive effects. The second effect is significant only at the 10 percent level, but with only ten years the correction for spatial correlation in the variance covariance matrix could be misleading. When I now consider the spatial share of the young as additional variable, the effects of the local share remain practically unchanged. In contrast, the spatial effect is not significant. The results in table 4 are now compatible with the cohort crowding hypothesis. However, is it also possible, that the results reflect differences in characteristics of younger and older workers. As discussed above, young workers are more mobile, have higher turnover rates, and could be less productive.

Table 4 about here

I now want to consider another definition of younger workers. As argued above, many talented young people do not have finished their education when 24 years old and do not have some basic job experiences. Hence, I define the young as those between 16 and 39 years old. Table 5 provides the results for the US county data. The results for the local share of the young are similar to those provided in table 4. However, in this case all estimated effects are significant at the 1 percent level. The spatial effect of the young is now significant negative. The first result is an indication of higher productivity among older workers and the second an indication that, the higher the number of younger job seekers in the neighbor district, the more jobs will be created in the local labor market.[13] With respect to the latter effect I conclude that spatial mobility in terms of commuting is of importance for the local unemployment rate. The larger the share of young workers in the neighbor regions, the lower the local unemployment rate. One reason why I yield this significant effect here but not in the former specification is that the match quality with experienced younger workers is higher than with unexperienced ones. This makes the spatial effect stronger.

Table 5 about here

As discussed above, this second spatial age effect does not mean that the productivity differential between younger and older workers is reversed since it is not possible that a worker from the spatial region will always have higher productivity because every region is both a neighbor and a local district in the estimates; instead, it appears that the estimated effect reflects the spatial mobility of workers in the surrounding area. The outcome of this effect is comparable to the standard effect of on-the-job searches on job creation; that is, the more people demanding new jobs, the lower the search costs for firms and this lower cost increases job creation.

However, if this is the case, why does the local labor supply yield to an opposing effect? One explanation is that both younger and older job seekers in the local labor market apply for vacant jobs in the region, as the theoretical model assumed. Hence, if aging is restricted to the local area, regional mobility no longer influences job creation and, if aging occurs in the local and neighbor regions in a similar way, the overall number of job

[13] These findings may improve our understanding of the differences between regional and national level findings. As Robert 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 levels of aggregation is puzzling. Our results may provide a key to the puzzle.

seekers is reduced; thus, search costs increase and job creation declines in both regions because of their spatial interaction.

As a robustness check I now consider a cut off for younger and older people that is at an even higher age than before. Here, the young are defined as those between 16 and 49 years old. I expect that both the local and the spatial effect will be less strong and less or not significant. Table 6 provides the results. Only the local effect when using the estimator suggested by Lee and Yu is significant. However, as discussed earlier, the corresponding standard errors are misleading if the residuals exhibit a specific pattern.[14] That is, we should be careful when interpreting the results when no other estimator yields significant results. To sum up, the results provided in table 6 indicate that both the local and the spatial effect diminish when I increase the cut off between young and old.

Table 6 about here

3.4 Further Estimates

This section provides some IV results that are comparable to tables 2 and 3. Since it is plausible that the parameters that correspond to aging suffer from a simultaneous equation bias, I ran additional regressions and instrument the percentage of young people in the local and surrounding region by (time) lagged birth rates and by the spatial lag of (time) lagged birth rates. I estimate the equations with a fixed effects instrumental variable (IV) estimator. Table 7 provides the estimates. According to the estimates, the simultaneous equation bias seems to have a negligible effect on the size of the parameters. With respect to the shorter period, I derive the same result for the specification without a spatial age effect, and the effect is still significant at the 5% level. All other effects are not significant. Overall, my IV estimates for the US at the state level, using Robert Shimers and Chris Footes data, lead not to conclusions that do deviate from the findings above. This is in accordance with Robert Shimers findings.

Table 7 about here

[14] The variance covariance matrix is estimated under the null of white noise in the residuals.

According to the results at the state level, I conclude that IV estimates are not necessary to improve the estimates. Unfortunately, I cannot do the same regression exercise with the county level data. If this conclusion holds for this level of aggregation as well, the results presented in this paper are robust. However, this is speculative and we have to be carefully when interpreting the results at the county level.

4 Conclusions

In this paper, I examined the relationship between the change in the (spatial) age structure of the working age population and unemployment at the regional level using both a theoretical and an empirical model. In the empirical part I consider different data for the US at the regional level. Based on my proxy for aging—the percentage of younger people in the working age population—ongoing aging will cause two opposing effects when I use US county level data and a broader definition of the young. First, aging in the local labor market decreases unemployment, while aging in the surrounding areas has a positive effect on the unemployment rate in the local district. My interpretation is that an aging labor force decreases the matching efficiency but local firms respond positively to the local percentage of older workers because of productivity differences between older and younger workers. However, the results are also compatible with the cohort crowding hypothesis, which I do not call into question. The effect of aging in the surrounding area differs from the local effect because younger workers are more mobile (in terms of commuting) than older workers are.

My results also suggest that regions with a larger percentage of older workers have to attract younger ones, and this can have two effects—the matching efficiency increases and firms become more willing to create jobs—both of which decrease the regional unemployment rate. In addition, it appears to be necessary for the regional mobility of older people in the labor market to increase in order to mitigate the estimated effects of aging on unemployment.

Using state level data like Robert Shimer and Chris Foote yield no support for an effect of aging on unemployment. My interpretation is that this level of disaggregation is too high to differentiate the two opposing effects of productivity and mobility. In addition, the results at the county level underline that commuting is important to reduce local unemployment. However, the results (may) depend on the definition of the young.

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:

$$\begin{aligned}
\left.\frac{\partial u^l}{\partial p^l}\right|_{\partial\theta^l=0} &= \left(u^l_y - u^l_o\right) \qquad (10) \\
&+ p^l \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma^l_y}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma^l_y}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \begin{pmatrix} \frac{-u^l_y}{s^l+\tau^l_y+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \\ -\frac{-u^l_o}{s^l+\tau^l_o+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)} \end{pmatrix} \\
&+ \begin{pmatrix} \theta^l \frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial \bar{p}^l} \frac{\sigma^l_y}{\sigma^l+\tilde{\sigma}^n} \\ +\theta^n \frac{\partial q^n(\theta^n,\bar{p}^n)}{\partial \bar{p}^n} \frac{\sigma^l_y}{\sigma^n+\tilde{\sigma}^l} \end{pmatrix} \frac{-u^l_o}{s^l+\tau^l_o+\theta^l q^l(\theta^l,\bar{p}^l)+\theta^n q^n(\theta^n,\bar{p}^n)}.
\end{aligned}$$

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:

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

Both terms on the right-hand side are similar to the second and third term in eq. (10), 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 (7), we reorganize (7) and make use of an implicit differentiation. The two arguments in q^l are θ^l and $\bar{p}^l$. For $F\left(\theta^l, \bar{p}^l\right) = 0$, we differentiate θ^l with respect to $\bar{p}^l$ and make use of $-\frac{\partial F/\partial \bar{p}^l}{\partial F/\partial \theta^l}$:

$$\frac{\partial \theta^l}{\partial \bar{p}^l} = -\frac{\begin{matrix} q^l(\theta^l,\bar{p}^l)\left(J_y^l - J_o^l\right) \\ +\frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial p^l}\left[\begin{matrix} \bar{p}^l J_y^l\left(1-\frac{\partial J_y^l}{\partial q^l(\theta^l,\bar{p}^l)}\frac{q^l(\theta^l,\bar{p}^l)}{J_y^l}\right) \\ +\left(1-\bar{p}^l\right)J_o^l\left(1-\frac{\partial J_o^l}{\partial q^l(\theta^l,\bar{p}^l)}\frac{q^l(\theta^l,\bar{p}^l)}{J_o^l}\right)\end{matrix}\right]\end{matrix}}{\begin{matrix} \bar{p}^l\left(J_y^l\frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial\theta^l} + q^l(\theta^l,\bar{p}^l)\frac{\partial J_y^l}{\partial\theta^l}\right) \\ +\left(1-\bar{p}^l\right)\left(J_o^l\frac{\partial q^l(\theta^l,\bar{p}^l)}{\partial\theta^l} + q^l(\theta^l,\bar{p}^l)\frac{\partial J_o^l}{\partial\theta^l}\right)\end{matrix}}. \tag{12}$$

The denominator of (12) 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 (12) 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, (12) 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 (12) dominates the total effect.

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6 Figure and Tables

Table 1: Main Results in the Two Studies

	Rob Shimer	Chris Foote
share of the young	-1.246‡	-0.420

NOTE: ‡=1% level of significance

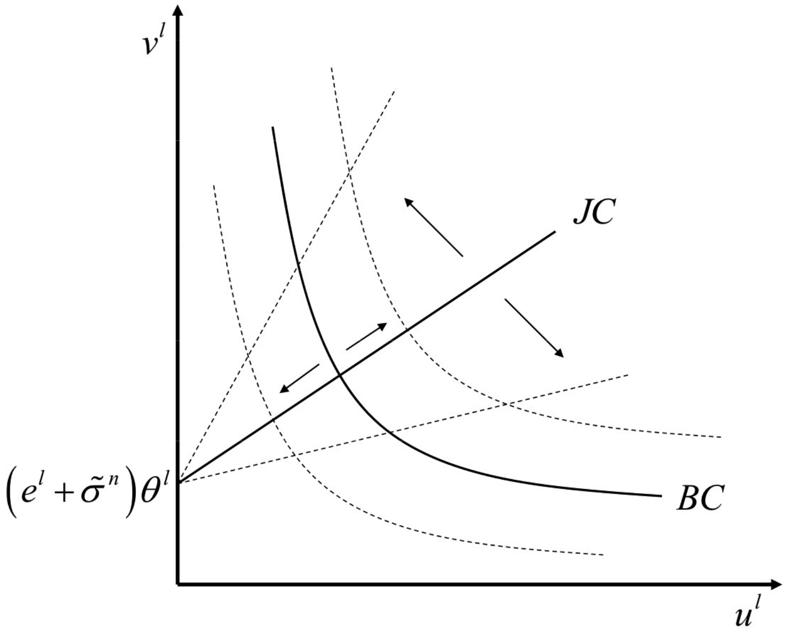

Figure 1: Effects of Aging on the Search Equilibrium

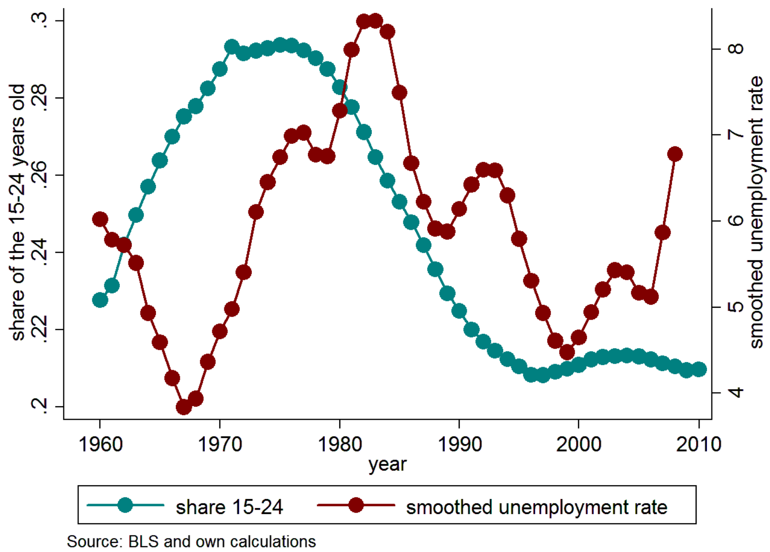

Figure 2: Share of the 15-24 Years Old and Smoothed Unemployment Rate, USA, 1960-2010

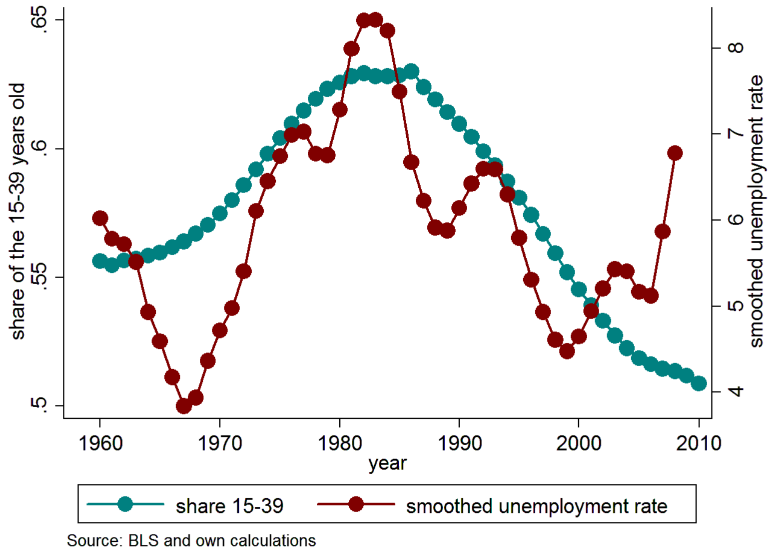

Figure 3: Share of the 15-39 Years Old and Smoothed Unemployment Rate, USA, 1960-2010

Table 2: Results for Robert Shimers US State Level Data

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	robust	D & K	L & Y	robust	D & K	L & Y
share of the young	-0.217†	-0.217	-0.123	-0.201$^{\sharp}$	-0.201	-0.122
spatial share of the young				-0.140	-0.140	-0.035

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; methods: robust = within fixed effects estimator with robust standard errors, D&K = within fixed effects estimator with Driscoll and Kraay standard errors, L&Y = quasi maximum likelihood estimator with bias correction according to Lee and Yu; observations: 1,290; significance: ‡=1%, †=5%, $^{\sharp}$=10%.

Table 3: Results for Chris Footes US State Level Data

	(7)	(8)	(9)	(10)	(11)	(12)
Variables	robust	D & K	L & Y	robust	D & K	L & Y
share of the young	-0.054	-0.054	0.001	-0.005	-0.005	0.008
spatial share of the young				-0.141	-0.141	-0.027

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; methods: robust = within fixed effects estimator with robust standard errors, D&K = within fixed effects estimator with Driscoll and Kraay standard errors, L&Y = quasi maximum likelihood estimator with bias correction according to Lee and Yu; observations: 1,749; significance: ‡=1%, †=5%, $^{\sharp}$=10%.

Table 4: Results for US County Level Data: Young aged 16 to 24

	(13)	(14)	(15)	(16)	(17)	(18)
Variables	robust	D & K	L & Y	robust	D & K	L & Y
share of the young	$0.131^{\ddagger}$	$0.131^{\sharp}$	$0.141^{\ddagger}$	$0.156^{\ddagger}$	$0.156^{\sharp}$	$0.135^{\ddagger}$
spatial share of the young				-0.032	-0.032	0.014

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; methods: robust = within fixed effects estimator with robust standard errors, D&K = within fixed effects estimator with Driscoll and Kraay standard errors, L&Y = quasi maximum likelihood estimator with bias correction according to Lee and Yu; observations: 27,666; significance: ‡=1%, †=5%, $^{\sharp}$=10%.

Table 5: Results for US County Level Data: Young aged 16 to 39

	(19)	(20)	(21)	(22)	(23)	(24)
Variables	robust	D & K	L & Y	robust	D & K	L & Y
share of the young	$0.171^{\ddagger}$	$0.171^{\ddagger}$	$0.197^{\ddagger}$	$0.230^{\ddagger}$	$0.230^{\ddagger}$	$0.228^{\ddagger}$
spatial share of the young				$-0.267^{\ddagger}$	$-0.267^{\ddagger}$	$-0.144^{\ddagger}$

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; methods: robust = within fixed effects estimator with robust standard errors, D&K = within fixed effects estimator with Driscoll and Kraay standard errors, L&Y = quasi maximum likelihood estimator with bias correction according to Lee and Yu; observations: 27,666; significance: ‡=1%, †=5%, $^{\sharp}$=10%.

Table 6: Results for US County Level Data: Young aged 16 to 49

	(25)	(26)	(27)	(28)	(29)	(30)
Variables	robust	D & K	L & Y	robust	D & K	L & Y
share of the young	$0.123^{\sharp}$	$0.123^{\sharp}$	$0.137^{\ddagger}$	0.115	0.115	$0.133^{\ddagger}$
spatial share of the young				-0.031	-0.031	0.010

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; methods: robust = within fixed effects estimator with robust standard errors, D&K = within fixed effects estimator with Driscoll and Kraay standard errors, L&Y = quasi maximum likelihood estimator with bias correction according to Lee and Yu; observations: 27,666; significance: ‡=1%, †=5%, $^{\sharp}$=10%.

Table 7: IV Results for US State Level Data

	(31)	(32)	(33)	(34)
Variables	1973 - 1996	1973 - 2005	1973 - 1996	1973 - 2005
share of the young	-0.373†	-0.063	-0.341	-0.059
spatial share of the young			-0.170	-0.159

NOTES: Dependent variable: log of unemployment rate; regression include: time lagged effect of the dependent, spatial lagged effect of the dependent, spatial and time lagged effect of the dependent and (regional) fixed and time effects; instruments: lagged birth rate and spatial-time lagged birth rate; observations: 1973 - 1996 = 1,290, 1973 - 2005 = 1,749; significance: ‡=1%, †=5%, $^{\sharp}$=10%.