Demographic Change and Regional Labour Markets

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Abstract

Like many other countries, Germany has experienced rapid population and workforce ageing, yet with substantial variation across regions. In this paper we first use this spatial variation between 1975 and 2014 to estimate quasi-causal supply effects of ageing on regional labour market outcomes, drawing on the identification strategy of Böhm and Siegel (2020). We find in our panel of German labour market regions that workforce mean age has considerable negative effects on the wage returns to age. We also obtain suggestive evidence that relative employment rates of older workers decline when mean age rises. A decomposition of the heterogeneous regional trends using our estimates shows that ageing of rural regions is mainly driven by supply (reflecting local population dynamics) whereas urban ageing is driven by demand (reflecting responses to economic conditions). We discuss the differential implications of these drivers for regional policy.

Keywords: ageing, demographic change, regional differences, wage returns to age
JEL Codes: J11, J31, R23

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I. Introduction

Many Western countries have been ageing quite rapidly over the past four decades. Societal changes, such as declining fertility rates, have shifted the age distribution of the population. This demographic change might have important causal effects on labour markets and on society more broadly. For instance we see that the age of the average worker has been increasing considerably. This raises the amount of experience supplied to labour markets and if this skill is valued in the market it is likely to have effects on wages, and potentially other outcomes too. Previous literature, including Katz and Murphy (1992) and Jeong, Kim, and Manovskii (2015), has established in aggregate data that an increase in the supply of labour market experience leads to a fall in relative wages of experienced compared to inexperienced workers. Böhm and Siegel (2020) show that this mechanism also upholds at the local labour market level in the United States. However, very little work has been done on the effects of ageing in the European context taking regions into account. A particularly interesting economy to study is Germany as it experiences one of the fastest rates of population ageing.

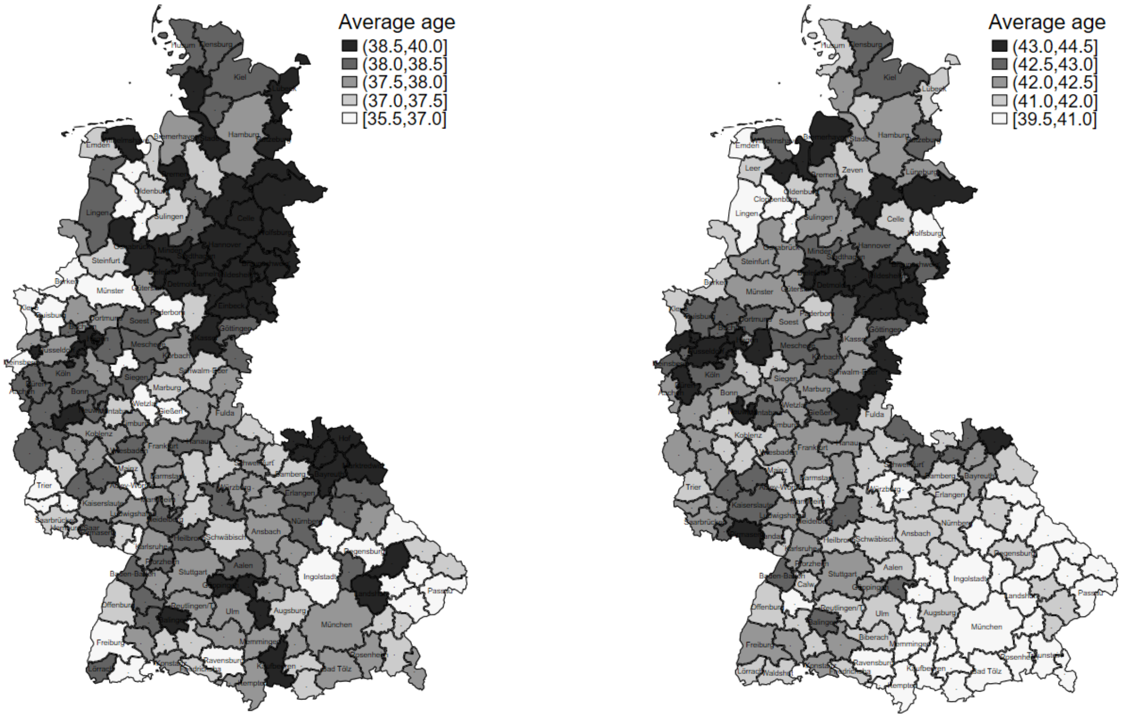
Yet changes in workforce mean age are not driven by population ageing alone but also by changes in the employment rates of older compared to younger individuals. In the regional context, workforce mean ages are also substantially affected by migration patterns of older workers relative to young ones. In fact, workforce ageing within countries like Germany is very heterogeneous. Figure I displays vast differences across West German local labour markets (henceforth also referred to as regions, see Section III for details on the underlying data and definitions). While the workforce aged everywhere, there is substantial spatial variation (see also Gregory and Patuelli, 2015). For example, there exist several regions, especially in the centre of West Germany, where mean age increased by a striking 5 to 7 years, whereas other regions, in Bavaria especially, saw increases of only 1 to 3 years.

In this paper we analyse the drivers and some of the consequences of workforce ageing in German regions. Ageing can be a causal force for economic changes if it is determined by societal factors, some of which appeared decades in the past such as changes in fertility preferences.[1] But ageing can also be a response to economic transitions via employment rates and migration flows. We therefore distinguish between two aspects of regional ageing: the effects of demographic change due to population dynamics (a supply effect) as well as economic responses to changing economic conditions (a demand effect). When viewing the workforce mean age as an indicator for the amount of experience per worker in a market, an increase due to supply forces should lower the valuation of experience skill and thereby the relative wages of older workers. In contrast, a larger demand effect should increase the observed workforce age and the relative wages of older workers at the same time. To understand the impact of workforce ageing on regional inequality across generations it is therefore imperative to disentangle supply and demand factors.

[1] We argue below that also preferences for locating in different regions have changed.

Figure I – Average workforce age in West German regional labour markets

(a) Workforce mean age in 1975 (b) Workforce mean age in 2014



Inspecting Figure I suggests that workforce ageing has occurred fastest in regions that experienced economic decline, such as the Saarland and the Rhine-Ruhr area in Germany's far West. The change in workforce age might therefore reflect a demand effect with high out-migration rates of younger workers and bad employment prospects for those who stay. On the other hand, most of Bavaria has seen much smaller increases in workforce mean age. This might be due to families (historically) having more children as well as rising preferences for locating in the South, which are aspects of the supply side. Disentangling the supply and demand forces in ageing is important for deriving policy implications. The supply effect is directly related to population dynamics and traditional economic policy can do rather little about it, whereas policies aimed at fostering fertility rates or attracting (young) people to the region might be effective. In contrast demand effects are directly related to regional incentives for job creation. We discuss specific policy options in Section VI.

This distinction between supply and demand reasons for regional workforce ageing is closely traced to our empirical analysis. Drawing on the Sample of Integrated Employment Biographies over 1975-2014, we first use spatial variation in predicted ageing, as *a directly measurable component of supply,* to establish the strength of its effect. Our methodology here largely follows Böhm and Siegel (2020), which is an adaption of Jeong, Kim, and Manovskii (2015) to the regional context, with a few modifications due to differences in the German data. We construct an instrumental variable using the age structure of the overall regional population decades earlier in order to estimate the causal effect of ageing on regional labour markets.[2] Within the regional labour market, this causal effect on ageing is a supply shock to the experience composition of the local workforce, which impacts relative scarcities of younger versus older workers. In contrast, ageing via unemployment or outmigration of

[2] We discuss the validity of this instrument in Section IV.

young workers *due to economic conditions* can be seen as a response to changes in local labour demand.

Estimating the causal supply effect provides key information about the importance of demographic ageing across otherwise equally-performing local labour markets. We also compare this causal effect to the overall relationship between ageing and local labour market outcomes (i.e. in the raw data and in the OLS coefficients of our regression analyses). These contain the supply as well as demand factors and are by no means comparisons between otherwise equally-performing local labour markets. In the raw data, we see that ageing is strongly related to suppressed employment rates of younger workers in comparison to older individuals. However when using our instrumental variable to get to the causal supply effect of ageing, these relationships vanish or turn around. Causal ageing in fact improves younger workers' relative local labour market outcomes as their declining supply makes them relatively scarce. Most notably their wages strongly rise compared to older workers. To put it differently, holding demand constant, an increase in workforce mean age reduces the relative wage of older workers.

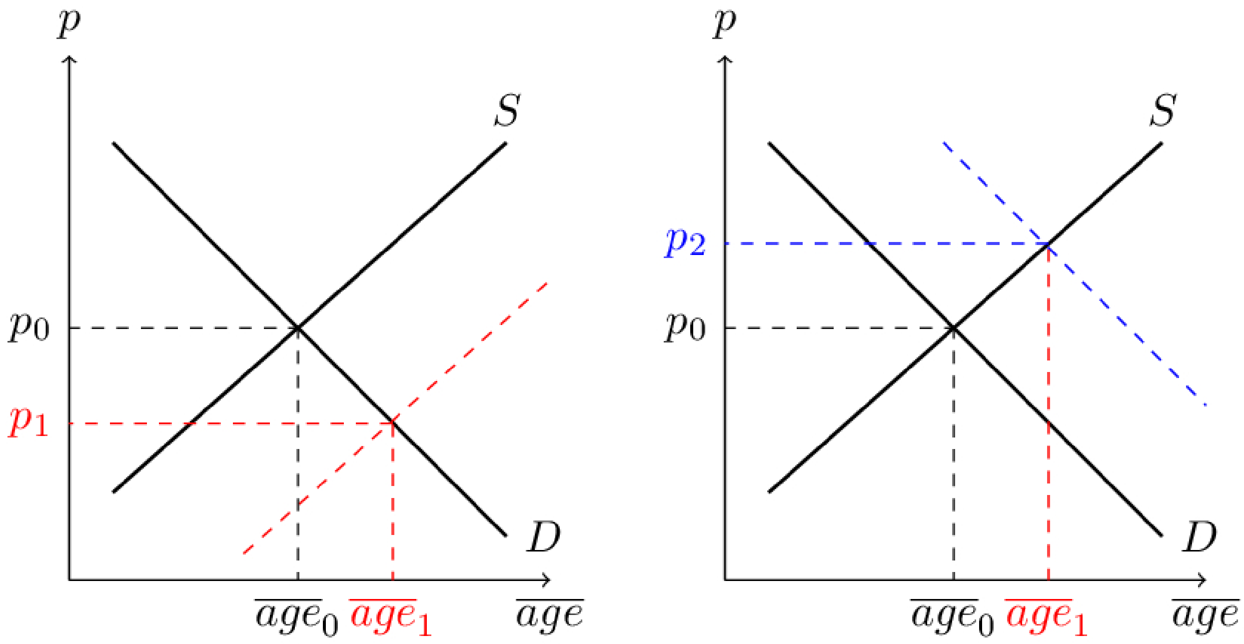
Finally, based on our estimates, we decompose changes in workforce age into contributions due to supply and demand effects. We find a role for supply as well as for demand changes as drivers of differential regional ageing. We further investigate what characteristics make regions more likely to have aged due to supply or demand factors. There is a strong urban-rural divide, with urban regions ageing mainly due to demand but rural regions mainly for supply reasons. The lack of supply of young workers in these rural regions suggests that policies aimed at rejuvenating the population through attracting more young people and incentivising larger family sizes would be more effective than traditional economic policies.

The paper proceeds as follows: In Section II we outline an economic framework that shows the role of supply and demand shifts. In Section III we give details on the data we use and report various descriptive statistics about the regional labour markets in Germany. In Section IV we explain the methodology for our empirical strategy. Section V reports the results of our estimation of the supply effect. Section VI decomposes regional ageing into supply and demand driven components. A final section concludes.

II. An Economic Framework

In our analysis we want to disentangle supply and demand forces behind regional workforce ageing. The key challenge is that in the data we observe outcomes are driven by both supply and demand forces. As older workers have relatively more experience and we view this as a skill that is priced in the market, a standard demand and supply framework as illustrated in Figure II applies. The relevant quantities demanded and supplied in the market is the average experience skill per worker as approximated by workforce mean age (on the horizontal axis), and its price is the valuation of experience skill, which in this paper we equate to the wage return to age (vertical axis). As in Böhm and Siegel (2020), supply is upward sloping because a higher wage return to age increases the desired relative employment rates of older workers as well as increases the relative in-migration of older workers from other regions. Demand is downward sloping since higher wage return to age reduces the relative labour demand for older workers. Our empirical results in Section V validate the assumptions made here.

Figure II – Supply and demand changes in workforce mean age



In the left panel of Figure II we illustrate the implication of a rightward shift in the supply curve due to ageing of the local population. It increases the workforce mean age and lowers the experience price. In the right panel of the Figure we illustrate the effect of a positive shift in demand. This also increases the workforce mean age but increases the price. These two graphs highlight two important issues. First, observing changes in this outcome alone does not shed light on the underlying causes. Second, the implications for the experience price, i.e. the relative wages of older workers, however differ across supply and demand induced changes in mean age. Understanding the drivers of regional workforce ageing is therefore important for relative wage outcomes, and changes in these by are informative about whether workforce age changes stem from supply or demand factors. Note, as ageing occurs at low frequency we are analysing its effects over long periods of time and therefore it is plausible that markets indeed adjust to new equilibria as assumed in the above figure.

The *shift* of the supply curve we illustrated in the left panel is what we refer to as the causal effect of ageing. In contrast, the right panel shows the effect of a demand shock that by altering the experience price induces –to restore equilibrium- also an increase in supply *along* the supply curve. But that in the right panel workforce mean age increases as the experience price increases (from p_0 to p_2) is a response to a demand change, it is not a causal change in age. In our empirical analysis, whose methodology we explain in Section IV, we use an instrumental variable strategy to identify causal changes in workforce mean age that correspond to shifts in the supply curve. This is what allows us to disentangle supply from demand changes in workforce mean age which is one of the main objectives of this work. In contrast, a simple OLS regression, which uses all changes in age, does not give a proper estimate of the causal effect of supply shifts but is upward-biased if demand shocks exist, as these lead to a positive co-movement between workforce age and the experience price, as shown in the right panel of Figure II.

Note, also in the left panel of Figure II there are adjustments in supply induced by the changing experience price. Following the outward shift of the supply curve, the experience price falls to reach equilibrium, resulting in a left-ward movement along the new supply curve. This reflects that when the mean workforce age increased, due to population ageing, experience is more abundant and valued less, thus reducing the relative incentives for older workers to participate and making it more attractive for the young to migrate into this region. For this reason, the relationship between ageing of the population that dictates the rightward shift of the supply curve and the actual change in workforce mean age is less than one to one.

III. Data and Descriptives

Data

We calculate regional employment and wage information using the Sample of Integrated Employment Biographies (SIAB) Regional File 1975-2014, which is provided by the Institute for Employment Research (IAB). The SIAB micro data include employment records for a 2 percent random sample of all workers between 17 and 62 years of age subject to social security contributions, i.e. excluding civil servants, self-employed and students. In order to obtain a consistent measure of the wage return to age throughout, we restrict our analysis sample to full-time (as reported by the employer) workers aged 20 and above as well as on workers' main annual employment spell that overlaps June 30th. We do not consider minor employment spells as they are only recorded in the data from 1999 onwards. We refer to the individuals selected in our analysis for each region and year, i.e. full-time employees aged 20–62, as the regions' workforce throughout this paper.

For all workers, the data contains, among others, information on daily wages, gender, foreigner status, age, education[3] occupation and place of work. Since wages are right-censored above the social security contribution threshold, we follow the imputation approach by Gartner (2005) to predict wages above that threshold.[4] From the microdata, we further calculate a wage return to age measure, as we explain in Section IV.

Our microdata allows to distinguish between 326 German districts (NUTS-3) based on the place of work. We focus on West German districts, as we are interested in long-run effects of demographic ageing and since the SIAB data is available for East German districts only from reunification onwards. We further aggregate these districts to labour market regions defined by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).[5] Our regions, or local labour markets, are thus defined in our analyses as places where people live and work. This

[3] Missing values and inconsistencies with education variable are corrected following Fitzenberger et al. (2005).

[4] The Mincer equation is estimated by year and includes female status, education (3 categories), age, age squared, industries (14), occupation (13 categories), potential experience, potential experience squared, region dummies, and interaction terms between female status and education groups. Note, there is a change in occupational coding in 2010 which might lead to errors in the time-consistent Kldb88 classification which we use to construct our 13 occupation categories in the wage imputation. Robustness checks leaving out the occupation dummies however suggest that our results are qualitatively not affected by this. A related imputation is conducted in Böhm et al. (2019).

[5] In principle, SIAB data is available at the level of districts ("Kreise", NUTS-3) and there exists a unique many to one matching of districts to labour market regions as defined by the BBSR. However, since smaller regions have been aggregated in the SIAB for data protection reasons, a clear assignment is not always possible. For these cases, we assume that workers and economic activity are distributed between regions according to their relative population sizes in order to identify the Kreis values of merged regions.

leaves us with 204 West German local labour markets, for which we construct a regional panel covering the years 1975 to 2014. For these regions and years, we then calculate workforce mean age, estimated wage returns to age, and employment rates.

To construct measures of routine tasks from the micro data, we use the 1979 wave of the German BIBB/BAuA Employment Survey. The survey collects detailed workplace information including work tasks for about 30.000 individuals. For this, we divide individuals' tasks into routine and non-routine following Rohrbach-Schmidt and Tiemann (2013). We then determine whether a worker mainly conducts routine (as opposed to manual or abstract) tasks and declare an occupation as mainly routine if conducted most frequently within an occupation. This way we receive a time-constant occupation-specific task measure that we assign to our 120 occupations in the SIAB data.

Since the SIAB is administrative data on employees, we observe in this dataset only those who are currently in employment. For the construction of age-group specific employment rates and the instrument for mean workforce age, we exploit regional population age data from the Federal Statistical Office that is available at the level of German districts. The data includes information on the total number of regions' inhabitants by detailed age bins for the years 1961-2014.[6] We aggregate this data to the same 204 West German local labour markets as described above and merge it to our regional panel. We then calculate the local employment rate by younger (<42) and older workers (>=42) as the number of workers (from SIAB) divided by the number of inhabitants in these working age groups (from the population data).

Descriptives

Based on the regional panel described above Table I reports the means and standard deviations of regional characteristics in our first and last observation period. The statistics are shown for all regions (columns I and II) as well as for regions with the 25% slowest (columns III and IV) and fastest (columns V and VI) growth in workforce mean age between 1975 and 2014. According to panel A, regions with the strongest growth in mean age had a significantly lower mean age (0.91 years) in 1975, lower share of females[7], were significantly more often urban regions, and had a significantly lower employment rate among older workers. They also had a significantly lower ratio of old to young workers' employment rate, which is one of the outcome variables that may be affected by workforce ageing and is investigated in Section V. Table I further suggests that fast ageing regions were initially (and still are) regions that experienced more negative net migration (i.e. more out-minus in-migration) relative to slow-ageing regions. Much of this was driven by a net loss of young workers in these regions. Note, in terms of the wage return to age (our main outcome), education structure, share of foreigners, industry and occupational structure, the slowest and fastest ageing regions seem quite balanced.

[6] The data has gaps during 1962-1973 and 1975-1976. For these years, we fill in the data using linear interpolation.

[7] It may come as a surprise that the female share is not higher in 2014 than 1975 (it is the same in both years when weighing local labour markets by employment size instead of the unweighted statistics in Table I). This is due to the fact that we only report statistics for full-time workers, whereas the unreported share of females among part-time workers has strongly increased over time.

Table I – Regional characteristics by regional labour markets with different speed of ageing

	All regions		25 % slowest ageing regions		25 % fastest ageing regions		Fastest minus slowest
	mean	sd	mean	sd	mean	sd	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
A: In 1975:							
Wage return to age	0.40	0.15	0.37	0.16	0.39	0.16	0.02
Workforce mean age	37.90	0.80	38.25	0.69	37.34	0.73	-0.91***
Employment rate of older workers	0.30	0.07	0.31	0.08	0.27	0.07	-0.04**
Employment rate of younger workers	0.51	0.11	0.50	0.11	0.49	0.11	-0.01
Old / young employment rate	0.59	0.07	0.62	0.06	0.54	0.07	-0.08***
Share of female workers	0.32	0.04	0.33	0.04	0.30	0.04	-0.04***
Share of foreign workers	0.09	0.05	0.07	0.04	0.08	0.04	0.01
Share of workers by education							
without apprenticeship	0.26	0.05	0.25	0.05	0.25	0.04	0.00
with apprenticeship	0.71	0.05	0.72	0.05	0.72	0.04	-0.01
with university degree	0.03	0.01	0.03	0.01	0.03	0.01	0.00
Share of workers by job task content							
routine tasks	0.66	0.03	0.65	0.03	0.66	0.02	0.00
manual tasks	0.13	0.02	0.14	0.02	0.13	0.01	-0.01*
abstract tasks	0.20	0.02	0.20	0.02	0.20	0.02	0.00
Share of workforce in manufacturing	0.40	0.11	0.37	0.09	0.41	0.11	0.04
Net migration rate	-0.15	1.35	0.22	1.34	-0.14	1.28	-0.37
Net migration rate of younger workers	-0.11	1.09	0.21	0.97	-0.19	0.95	-0.40*
Net migration rate of older workers	-0.04	0.57	0.01	0.68	0.04	0.49	0.03
Urban status (time-constant)	0.50	0.50	0.29	0.46	0.59	0.50	0.29**
B: In 2014							
Wage return to age	0.71	0.18	0.67	0.14	0.74	0.19	0.07*
Workforce mean age	41.97	0.97	41.01	0.83	42.61	0.70	1.60***
Employment rate of older workers	0.32	0.06	0.32	0.07	0.32	0.06	-0.00
Employment rate of younger workers	0.44	0.09	0.49	0.10	0.40	0.07	-0.09***
Old / young employment rate	0.75	0.12	0.66	0.09	0.80	0.10	0.14***
Share of female workers	0.29	0.03	0.30	0.03	0.29	0.03	-0.00
Share of foreign workers	0.09	0.03	0.09	0.03	0.08	0.03	-0.01
without apprenticeship	0.08	0.02	0.07	0.02	0.08	0.02	0.01**
with apprenticeship	0.78	0.05	0.80	0.03	0.78	0.04	-0.01
with university degree	0.14	0.04	0.13	0.03	0.14	0.04	0.00
Share of workers by job task content							
routine tasks	0.59	0.03	0.58	0.03	0.59	0.02	0.01
manual tasks	0.14	0.02	0.14	0.02	0.14	0.01	-0.00
abstract tasks	0.27	0.02	0.27	0.02	0.26	0.02	-0.00
Share of workforce in manufacturing	0.35	0.09	0.35	0.09	0.35	0.09	-0.00
Net migration rate	-0.06	1.72	0.20	1.77	-0.21	1.72	-0.41
Net migration rate of younger workers	0.04	1.13	0.16	1.22	-0.08	1.14	-0.24
Net migration rate of older workers	0.24	1.86	0.07	1.89	0.26	1.97	0.19
Number of regions	204		51		51		102

This table reports the averages and standard deviations of regions' full-time workforce characteristics. These characteristics include mean age; estimated wage return to age; employment rates by age group; female, foreigner, and education shares; the share of routine workers; and urban status. The latter is time-constant and therefore only shown in Panel A. Net migration rates are calculated as (number of in-migrants – number of out-migrants) x 100/number of workers in the region.

Panel B of Table I shows that fast ageing regions, which were relatively young initially, have significantly older workers in 2014 (1.6 years higher mean age) compared to their slow ageing counterparts. This is not surprising as local labour markets that had a lot of young workers in 1975 should have a lot of older workers almost 40 years later. By contrast, in local labour markets that were relatively old in 1975, many of the workers responsible for this should have retired by 2014. Therefore, reversals in local labour markets' relative workforce ages can occur quite naturally.[8] A further reason is that these initially young and fast ageing regions experienced negative net migration particularly of young workers compared to slower ageing regions.

Panel B also shows that the wage return to age is significantly (at the ten percent level) higher in 2014 in fast compared to slower ageing regions; the differences have increased since 1974. This underscores the importance of our empirical strategy detailed below, as the relative rise of return to age in regions with fast increases in mean age may stem from factors that work in the opposite direction than the causal effect of ageing[9] Similarly, we see that in 2014 the ratio of old to young workers' employment rate is significantly higher in labour market regions that have aged fast than in regions that aged more slowly, which again raises the question of supply versus demand shifts. Section V will also use our empirical strategy to provide some evidence on the causal effect of ageing supply on older workers' relative employment rates.

IV. Empirical Strategy

In order to estimate the impact of regional workforce ageing on relative wages of older workers compared to younger workers, we proceed in the following steps. First, we estimate the wage return to age which will provide our measure for the relative wages of older workers. Then we build a regional panel, where we can relate the wage return to workforce mean age, and construct an instrumental variable following Böhm and Siegel (2020).

The idea of the first step is to use the SIAB micro data to control for potentially confounding effects when constructing a regional panel of wage return to age and of workforce mean age. That is, following Jeong, Kim, and Manovskii (2015), we construct at the micro level for each region-year wage return to age controlling for workers' other (non-age) productive characteristics. For this, we run the following log wage regression separately by region *l* and year *t*:

$$\log(\text{wage}_{ilt}) = \alpha_{lt} + \beta_{lt}\,\text{age}_{ilt} + Z_{ilt}\gamma_{lt} + \epsilon_{ilt} \qquad (1)$$

where the coefficient of worker i's age, β_{lt}, reflects our measure for the wage return to age. By controlling for observable characteristics, Z_{ilt}, we ensure that the return to age does not reflect confounding factors including gender, foreigner status, or education (3 categories).

The main regressor of interest in equation (1) is age_{ilt}. We interpret its coefficient β_{lt} as the wage return to age that prevails in region l at time t. That is, β_{lt} indicates by how much, on average, a worker's log wage rises with one additional year of age. In a parsimonious way it therefore captures the effect of workforce ageing on the relative wages of older compared to younger workers. We construct a regional panel of wage return to age and workforce mean age as a measure of workforce experience supply. We also collect, by region and year, workers' education (3 categories), gender,

[8] It is however not the case that urban local labour markets are older than rural local labour markets in 2014 (unreported in the Table for brevity). Fast-ageing markets were relatively more urban, as can be seen in Panel A, but this did not change the fact that urban markets are younger than rural markets in 2014. Part of the reason is that young workers increasingly migrate into urban markets.

[9] Changes in labour demand favouring older workers may include experienced-biased technical change (e.g., Caselli, 2017) or increases in demand for products intensive in experienced labour.

foreigner and urban status, and occupational routine content to complete this regional panel, which was summarized in of Table I.

The second step of the analysis is in the panel of labour markets regions. We estimate the effect of workforce mean age, capturing the supply of experience, on the wage return to age as:

$$\ln(\beta_{lt}) = \alpha_l + \alpha_t + \eta \ln(\overline{\text{age}}_{lt}) + \bar{Z}_{lt}\lambda + error_{lt} \qquad (2)$$

where $\overline{\text{age}}_{lt}$ is labour market region *l*'s average age in year *t*. In order to interpret $-1/\eta$ as the elasticity of substitution in regional production between experienced and inexperienced labour inputs, (2) has to be specified in logarithms (e.g. see Jeong, Kim, Manovskii, 2015, or the seminal paper of Katz and Murphy, 1992). As a robustness check, we explore a regression of the level of β_{lt} on the level of $\overline{\text{age}}_{lt}$. We also follow the underlying economic theory and use the average age of actual full-time employment (our 'workforce'), and not of the working age population, because this determines the relative marginal product and thus the wage return to age in the labour market region. The fixed effects α_l control for time-invariant differences in wage return to age across regions (e.g. due to urbanization that we showed in of Table I) and the year dummies α_t absorb aggregate changes in variables over time (e.g. due to technical change which may be experience-biased). Note, since workforce ageing occurs at slow frequency, we do not use a yearly panel, but one with one observation for each region per decade, i.e. 1975, 1985, 1995, 2005, 2014. In additional specifications, we add time-varying region-specific averages $\bar{Z}_{lt}\lambda$ such as share of females, foreigners, and middle- and high-educated workers as well as industry- and occupation shares to regression (2).

We devise an instrumental variable strategy to extract the arguably causal supply effect of ageing on the wage returns to age. In particular, we use the predicted regional workforce mean age constructed from population age structures in earlier years in that region, akin to Böhm and Siegel (2020). This is necessary because it is possible, and in fact likely given our empirical results below, that changes in the demand for experience persist which vary across region-years. In particular, in one labour market region the demand for experienced workers might rise, increasing the wage return and leading through market adjustments also to an increase in regional experience skill (e.g. via changes in participation or migration), as illustrated in the Figure II (b). To address this problem, our instrument makes use of the fact that current mean workforce age is strongly affected by the age structure of the residential population in earlier years.

In particular, we predict the mean age of (full-time) employees, our 'workforce', in labour market region *l* and year *t*. For this, we use our regional population age data, which includes information on the total number of regions' inhabitants by age bins for the years 1961-2014. We calculate the mean age in t-14 of all individuals in the population that enter workforce age 20-62 in t, which in our case are all residents in the 10 age bins [6-9], [10-14], [15-17], [18-19], [20-24], [25-29], [30-34], [35-39], [40-44] and [45-49]. We then add 14. Formally, we calculate:

$$\overline{\text{age}}_{lt}^{cf} = \left[Pop_{l,t-14}^{[6;9]}\left(6 + \frac{9-6}{2}\right) + \cdots + Pop_{l,t-14}^{[45;49]}\left(45 + \frac{49-45}{2}\right) \right] / \left[Pop_{l,t-14}^{[6;9]} + \cdots + Pop_{l,t-14}^{[45;49]} \right] + 14$$

where $P_{l,t-14}^{[6;9]}$ is the number of local inhabitants in age bin 6 to 9 in t-14 and region l. We choose 14 years for the lag, as this is the largest possible gap between our first observation point in the population data and the SIAB employment data. This way our instrument reflects the predicted mean age, had the workforce only aged according to the natural population ageing rate during the preceding 14 years (e.g. no migration between regions or differential changes in age-specific employment rates).

Our instrument is exogenous if, given the fixed effects capturing permanent differences across regions α_l and aggregate differences across years α_t, the age structure in a given region in *t-14* is not affected by the relative demand for experience in t.[10] As Böhm and Siegel (2020) explain, if it were to some extent affected by the demand for experience in t, the instrument would not fully succeed in extracting exogenous variations in workforce mean age. As a consequence the estimated η from equation (2) would be too large, i.e. smaller in absolute terms. In our results we find exactly such a bias between the OLS estimates and the estimates based on our IV, indicating that the IV is indeed necessary for extracting causal changes of regional experience supply. Instrument validity has two further requirements. First, a first stage needs to exist such that the instrument is relevant. This is the case, as we demonstrate below. Second, the exclusion restriction needs to hold, which requires that the age structure in *t−14* affects the wage return to age in *t* only through its effect on workforce age. Since changes in a region's age structure may come with changes of demographic groups which might have differing life-cycle wage profiles, such as females, foreigners, or middle and high educated workers, as a robustness check we control for their shares in the instrumented regression (2). We also provide a specification that controls for regions' contemporaneous employment by industry and occupation, which further probes the exogeneity and exclusion restriction assumptions.

V. Estimation Results

First Stage of the Instrumental Variable

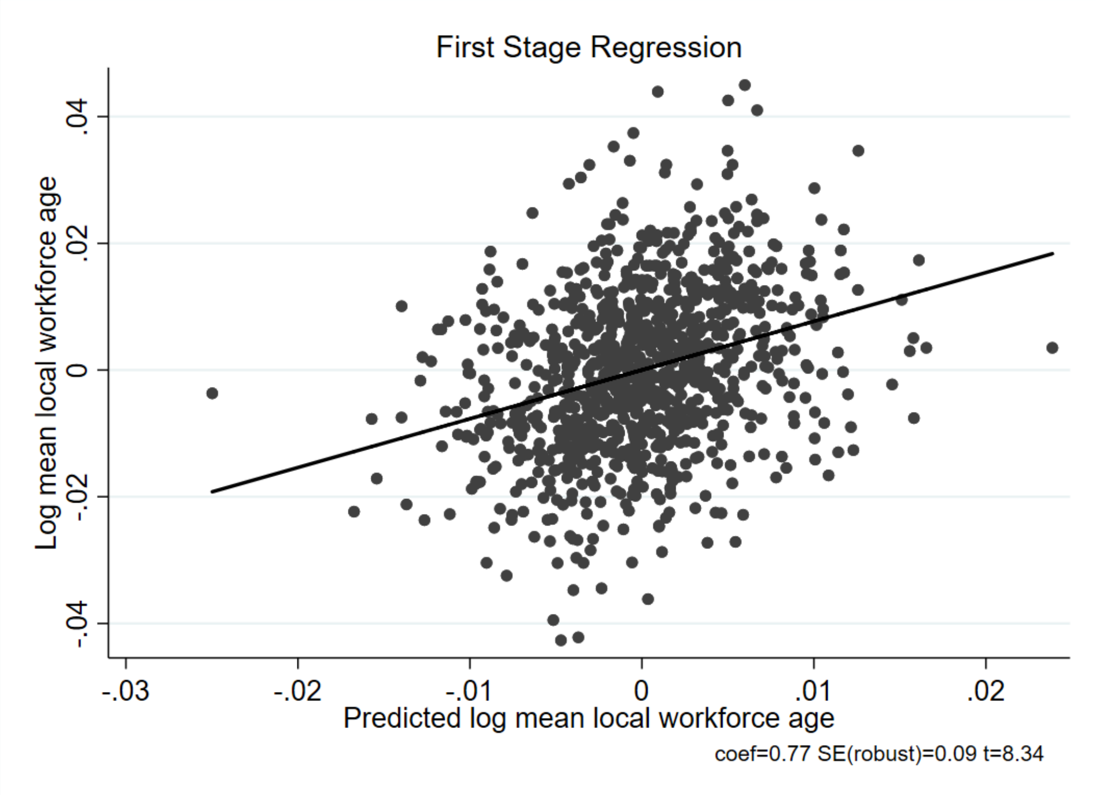
Before turning to our main results, we first provide evidence on the identification strategy. The success of our empirical strategy relies on a valid instrument for local workforce age. Figure III shows the association between the predicted (log) workforce mean age from population records 14 years earlier and actual (log) workforce mean age today. In particular, we plot the first stage after the IV first-stage regression:

$$\ln(\overline{\text{age}}_{lt}) \ = \tau_t + \delta_l + \phi \ln\left(\overline{\text{age}}_{lt}^{cf}\right) + u_{lt}, \qquad (3)$$

where $\overline{\text{age}}_{lt}$ is the mean local workforce age, $\overline{\text{age}}_{lt}^{cf}$ is the predicted mean workforce age constructed from population data 14 years prior, and τ_t and δ_l are time and region fixed effects. Note that the predicted mean age only captures the natural population growth, i.e. excluding changes in regional workforce age due to e.g. migration or changes in local participation rates. As expected, lagged population data is well able to predict the current workforce age structure. Conditional on the fixed effects, an increase in the predicted log mean age of 1 significantly increases the workforce log mean age by 0.77. That the coefficient is below one is in line with adjustments in relative employment rates and migration along the supply curve of Section II. It is also consistent with the (mild) direct evidence we find below for declining relative employment rates of old versus young workers when the regional workforce ages. The F-statistic of excluded instruments for the first stage is large at 70 and above any rules of thumb for instrument strength.

[10] It should also not be affected by an omitted third factor that at the same time influences the outcome. We probe this by adding control variables including region's demographics as well as industry and occupation structure.

Figure III – First stage: Actual over predicted log mean local workforce age



Notes: This figure shows the added value plot (or partial residuals plot) of $\ln\left(\overline{\text{age}}_{lt}^{cf}\right)$ after the first stage regression (3).

Main Second Stage Estimation Results

In Table II, we report our main regression results, establishing the effect of workforce (log) mean age on the (log) wage return to age. The number of observations in the first three columns is 1,018 and therefore below the overall number of 1,020 regions in our panel, which reflects the fact that, in very infrequent region-years, the estimated wage return to age can be zero or negative. This leads to missing values when taking logs (e.g., compare the column IV of the table, which is in levels and therefore no observations are missing). Column I of Table II

Table II shows the result from estimating the regional panel specification (2) by OLS, whereas subsequent columns show the results obtained using the predicted workforce (log) mean age as an instrumental variable. Comparing columns I and II highlights the importance of using this identification strategy. The OLS estimates suggest that (controlling for year and regional fixed effects) there is essentially no relationship between log workforce mean age and the log of the wage returns to age.

Table II - Local labour market effects of workforce ageing on the wage returns to age

	I	II	III	IV	V	VI
Log workforce mean age	-0.546	-4.825**		-3.510*	-3.450*	-3.588*
	(0.729)	(2.308)		(2.061)	(2.084)	(2.054)
Workforce mean age			0.079**			
			(0.035)			
Share of female workers				-0.495	-0.749	-0.944
				(0.656)	(0.688)	(0.672)
Share of foreign workers				-0.069	0.074	-0.075
				(0.823)	(0.844)	(0.835)
Share of workers with apprenticeship				0.284	0.385	-0.038
				(0.669)	(0.678)	(0.715)
Share of workers with university degree				2.468**	2.259**	1.407
				(1.041)	(1.051)	(1.146)
Share of workers in manufacturing					-0.398	-0.313
					(0.285)	(0.309)
Share of workers in routine tasks						-1.715
						(1.599)
Share of workers in abstract tasks						0.318
						(1.879)
LMR FE	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X
Estimator	OLS	IV	IV	IV	IV	IV
Observations	1018	1018	1020	1018	1018	1018
R2	0.542	0.517	0.496	0.538	0.540	0.541
F-stat		70	56	97	97	96

Notes: This table shows results from estimating (2) with the log wage returns to age $\ln(\beta_{lt})$ as the dependent variable in column I-II, IV-VI and 100 x returns to age (100x β_{lt}) in column III. The last row shows the F-statistic of the IV 1st stage. Robust standard errors (in parentheses) are clustered by region. * p<0.1, **p<0.05, *** p<0.01.

By contrast, the IV estimates for the same specification in column II show a substantially larger negative effect that is statistically significant at the 5 percent level. This is because the IV strategy is designed to identify a causal effect that stems from changes in the supply of experience (as captured by workforce mean age), whereas the OLS documents a (partial) correlation that could stem from supply or demand changes.[11] According to column II, an increase in regional workforce mean age by 1 percent reduces the wage return to age by 4.8 percent. This is quantitatively a relatively large effect; it indicates that experienced and inexperienced inputs are not very substitutable within local labour markets in Germany. The implied elasticity of substitution between experienced and inexperienced labour inputs in the regional production function is $-1/\widehat{\eta_{lt}} \approx 0.21$.[12]

Column III is akin to the previous two but specified in the levels of workforce mean age and wage return to experience (i.e. equation (2) with β_{lt} on the left-hand-side and $\overline{\text{age}}_{lt}$ on the right-hand-

[11] In fact, Böhm and Siegel (2020) argue (and find in a panel of US local labour markets) that ignoring the endogeneity of experience supply to demand shifters biases the estimated effects in specification (2) upwards. Our findings in columns I and II here are in line with this conclusion.

[12] Böhm and Siegel (2020) obtain a very similar implied elasticity of substitution between experience skill and raw labour in U.S. local labour markets.

side). The coefficient in this level-level regression is -0.079. That is, a one year higher regional workforce mean age (about one standard deviation across regions; see Table I) leads to a 0.079 log points lower wage return to age (about one half of a standard deviation).

In the Jeong, Kim, and Manovskii (2015) model, which underlies our empirical approach, controls for individual worker characteristics in the Mincer wage regression (1) are sufficient to ensure that the returns to age do not reflect such characteristics as confounding factors. This is why column II of

Table II is our preferred specification. Nonetheless, as discussed in the previous section, including workforce characteristics $\bar{Z}_{lt}\lambda$ to panel regression (2) may be considered an important robustness check of our exclusion restriction. In column IV we add as further controls the share of female and of foreign workers and –to capture non-experience skill supplies– the share of workers with a completed apprenticeship and with a university degree. In this specification, the share of workers with a degree is unsurprisingly strong and significant for the return to age as life-cycle wage profiles are known to be steeper among university graduates.[13] Nonetheless, the impact of ageing on the wage return is only moderately affected and it remains statistically significant at the 10% level.

Finally, we conduct specifications where we account for more fundamental structural changes in the local labour market that might influence the wage returns to age. For this, we add the share of workers in manufacturing industries to the regression to capture region-specific shifts away from manufacturing towards service sector industries (column V). In addition, we add the share of abstract jobs as well as the share of routine jobs (column VI).[14] In both additional estimates, the main results remain largely unchanged. This might not be all to surprising, given that fast and slow ageing regions do not seem to differ much in terms of their industry structure and job content, as suggested by Table I.

Effects of workforce ageing on the relative employment rates of older workers

We also investigate whether regional workforce ageing has an effect on the relative employment rates of older compared to younger workers. It is important to bear in mind that we do not directly observe employment rates, but can only proxy a region's age-specific employment rates by the number of people employed in that region according to the SIAB data relative to population estimates from the Federal Statistical Office. As such, there is bound to be some measurement error in the old-to-young-employment rates that we construct. Since we do not have micro data on the population, we cannot control for individuals' other productive characteristics such as gender, foreigner status, or education as in equation (1). However, in the panel regressions we can and do control for the share of such characteristics separately among the groups of older and younger workers.

[13] By contrast, the share of females only moderately associates with a lower return to age. In further robustness checks, we have also conducted all our analyses using the male workforce only and found qualitatively the same results.

[14] Qualitatively we find rather similar results when using the share of workers in manufacturing or in goods production instead of the share of routine workers. This is perhaps not that surprising given that Bárány and Siegel (2018, 2020) find a tight connection between trends in occupational and in sectoral employment.

Table III - Local labour market effects of workforce ageing on the old-to-young employment rate

Dependent variable: (log) old-to-young employment rate						
	I	II	III	IV	V	VI
Log workforce mean age	4.777***	-0.374		-0.387	-0.357	-0.361
	(0.176)	(0.882)		(0.747)	(0.745)	(0.729)
Workforce mean age			-0.020			
			(0.018)			
Share of young female workers				0.676***	0.637***	0.647***
				(0.149)	(0.151)	(0.156)
Share of older female workers				0.406***	0.373**	0.360**
				(0.156)	(0.164)	(0.160)
Share of young foreign workers				-0.335*	-0.312	-0.311
				(0.203)	(0.206)	(0.204)
Share of older foreign workers				0.209	0.223	0.225
				(0.265)	(0.261)	(0.263)
Share of young workers with apprenticeship				0.132	0.146	0.188
				(0.204)	(0.204)	(0.200)
Share of older workers with apprenticeship				0.010	0.026	0.092
				(0.136)	(0.135)	(0.142)
Share of young workers with university degree				0.174	0.140	0.338
				(0.299)	(0.298)	(0.294)
Share of older workers with university degree				-0.194	-0.227	-0.091
				(0.313)	(0.313)	(0.327)
Share of workers in manufacturing					-0.123	-0.098
					(0.114)	(0.119)
Share of workers in routine tasks						-0.625
						(0.555)
Share of workers in abstract tasks						-1.425**
						(0.717)
LMR FE	X	X	X	X	X	X
Year Dummies	X	X	X	X	X	X
Estimator	OLS	IV	IV	IV	IV	IV
Observations	1020	1020	1020	1020	1020	1020
R2	0.770	0.452	0.360	0.487	0.491	0.495
F-stat		70	56	93	92	92

Notes: This table shows results from estimating (2) with the log old-to-young employment rate as the dependant variable in column I-II, IV-VI and the level of this ratio in column III. The last row shows the F-statistic of the IV 1st stage. Robust standard errors (in parentheses) are clustered by region. * p<0.1, **p<0.05, *** p<0.01.

Table III shows the results from the panel regressions with the old-to-young employment rate as the outcome variable. The OLS estimates in column I suggest that higher (log) workforce mean age is associated with a higher (log) old-to-young employment rate. However, the subsequent columns, where the estimates are derived using our instrumental variable approach, all display negative coefficients. These results suggest that the causal effect of regional workforce ageing on the relative employment rate of older workers is negative. Admittedly, at conventional levels the effect is not statistically significant in any of these specifications. This is in contrast to Böhm and Siegel (2020) who document in US data a strong and significant effect. That the effect is not as strong and significant in our German data could be due to a variety of reasons, such as institutional differences (including in the retirement schemes) across the two countries, but also due to the lack of detailed population micro-data for Germany that prevent us from constructing a precise old-to-young employment rate.

The conclusion that we can draw from our IV estimates is that in Germany demographic ageing impacts local labour markets by affecting the wage return to age. This is consistent with existing evidence for the US and with economic theory; older labour market regions have larger supplies of experience and thus workers receive lower wage premia for being experienced. In the next section we use these estimates to disentangle the drivers of workforce ageing (and in the Appendix the wage returns to age) across German regions.

VI. Decomposing Regional Ageing

We have demonstrated substantial regional differences in workforce ageing together with some of its consequences for regional wages. For regional policy, it is important to understand the underlying causes of these age shifts. To shed light on the drivers of workforce ageing, we thus decompose total observed mean workforce ageing into a part that is demand-side driven (e.g. age-biased labour demand changes that alter relative employment rates) and a part that is supply-side driven (e.g. declining birth rates, non-economic outmigration of young workers) and then characterize regions that are more demand-side or supply-side driven.

Figure I showed that mean age strongly increased during the period 1975-2014 but it also hinted at substantial regional variation. Panel (a) of Figure IV focuses on the differential age changes across local labour markets over time. That is, the general ageing (which is not the focus of our paper) is removed and the average mean age change is zero in this figure. We now clearly see strong regional variation, with a difference of almost six years between the fastest and the slowest ageing markets. We also see, once again, that relative ageing was rather slow in the South (East) while it was faster in the Centre (West) of the country. We now aim to untangle the contributions of supply and demand shifts for relative age to the regional differences in ageing.

We need two ingredients in order to conduct this decomposition. First, we need to identify regions' elasticity of age demand. In Figure II, this elasticity is the (inverse) slope of the age demand curve in $\ln(\mathrm{p})$ - $\ln(\overline{\mathrm{age}})$ space and it was estimated in our main specification (Table II, Column II) as -1/4.825, based on arguably exogenous shifts (counterfactual average age conditional on region and year fixed effects) in age supply. Second, we assume that all measured regional ageing differences that are not due to demand must be due to supply.[15] This implies that we can use the first stage estimate from our IV strategy to infer regions' elasticity of age supply:[16] if average age increases by 0.77 of the counterfactual change in age due to supply and average returns to age decline by -4.825*0.77=-3.72, the implied slope of the labour supply curve in Figure II is 3.72/(1-077)=16.15 and the elasticity of age supply is 1/16.15. The implied supply curve is quite steeper than the estimated demand (i.e. shifts in

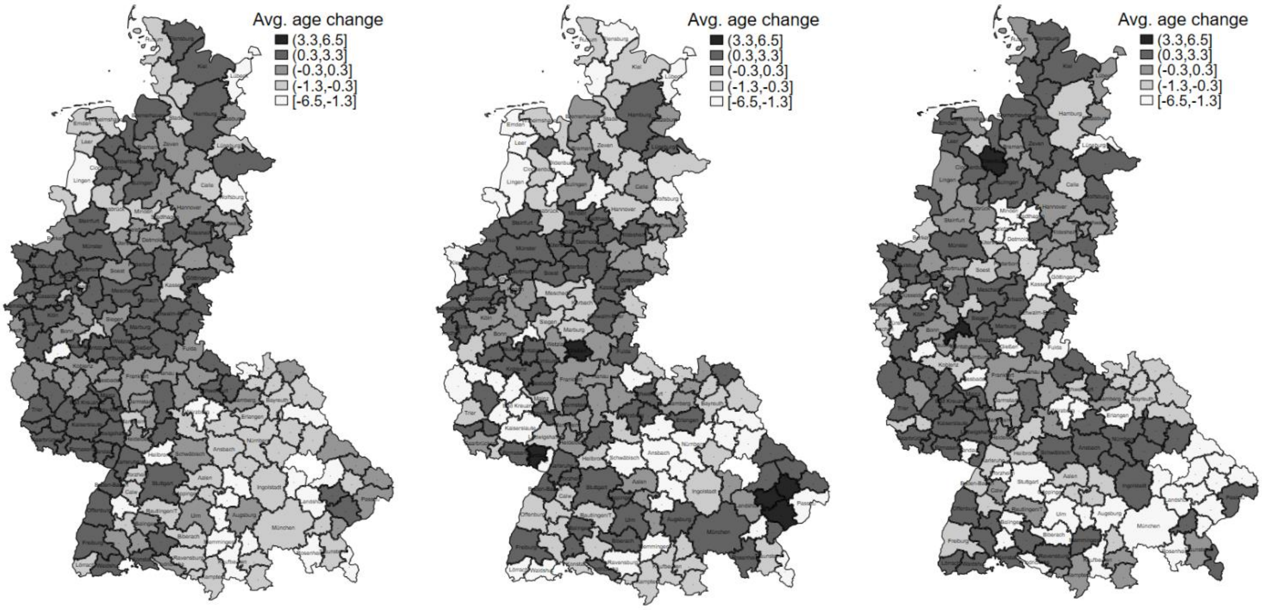
[15] Admittedly, some of the lower than one first-stage coefficient may also be measurement error due to sampling. But the coefficient size of 0.77 is quite substantial (i.e. we do not expect too much measurement error) and more generally we interpret our inferred age supply elasticity (which is already quite low) as an upper bound.

[16] This is under our maintained exogeneity assumption that those shifts in counterfactual age supply that we use for identification (i.e. in the IV first stage) are uncorrelated with shifts in age demand. Therefore, if the age supply curve were inelastic the first-stage coefficient would be exactly 1. As explained in Section II, that it is in fact somewhat elastic may be due to employment or migration responses to regional workforce ageing.

demand will have comparatively strong price effects on the return to age) but far from completely inelastic. Therefore, both supply and demand shifts can have a role to play in regional ageing. With these two key elasticities at hand, we can untangle all relative changes in returns to age and average age into differential supply and demand shifts for age across local labour markets. The detailed steps of this calculation together with the effects on relative returns to age (which align well with the changing relative average age shown here) are in Appendix A.

Figure IV - Change in mean workforce age (1975-2014) and decomposition

(a) Overall change in age (b) Demand-side driven (c) Supply-side driven



Panel (b) of Figure IV depicts the regional ageing that is due to differential shifts in the demand for older workers and Panel (c) shows the shifts in supply. While there exists substantial variation, we find comparatively large demand shifts in many urban regions, including the major cities of Hamburg, Munich, Stuttgart and the Rhine-Ruhr area. These are areas with strong economic and innovation activity that tend to have high demand for skills, which is consistent with the view that the demand for skills, including experience skills, has increased particularly fast in urban areas. Table A1 in the Appendix corroborates this interpretation as it shows that regions which experienced relatively strong demand shifts for age are often urban and have higher shares of high-skilled jobs, less medium-skilled jobs, and more foreigners.

At the same time, it is well known that many young individuals relocate to cities, which reduces urban areas' average age. This is reflected in panel (c) of Figure IV where indeed cities like Hamburg or Stuttgart would have become younger during 1975-2014 had it only been for ageing due to supply shifts. To be precise, we view supply shifts as changes occurring for reasons that are not directly related to labour market prospects, such as fertility or migration because of education or "life-style" factors. Young and well-educated workers in particular have increasingly valued the amenities of cities as places to live (see e.g. Couture and Handbury, 2017). With this in mind, it is indeed plausible that the supply of older workers in cities has relatively weakened (supply of young workers rather strengthened) compared to rural regions. In addition, relative fertility rates in the rural regions have declined quite drastically since the 1970s, which is the type of variation in ageing supply that we exploited in Section V. These factors have led to on average stronger ageing supply shifts (i.e. relative declines in the availability of young workers) in rural regions as depicted in Figure IV(c).[17]

As we emphasized before, overall there exists a Centre (West) to South (East) gradient of ageing that is also visible in Figure IV(a). However, once we consider the reasons for this ageing, they are better described by an urban-rural divide, whereby ageing demand shocks tend to be strong in cities while supply shocks are stronger in regions that are more rural.[18] This has important implications for policy makers who want to cushion the impact of ageing shocks on their communities. In particular, traditional regional policies (e.g. discussed in Moretti 2012, Kline and Moretti 2014) are designed to boost economic activity and might thus counteract negative demand shocks. One age-specific measure here may be to encourage transmission of cutting-edge technology, and thus of the skill- and experience-bias of technology, from the leading economic centres toward the periphery.[19]

In contrast, a lack of supply of young workers should rather be addressed using fertility and migration policies. One local measure is to attract young families into the region. In fact, several rural municipalities in Bavaria, Rhineland-Palatinate and other federal states have offered buildable land especially to young families. Another option is investing in improved transport links, which increases the attractiveness to live in an area but also enables "workplace migration" of young individuals from where they (prefer to) live into locations where they are scarce. In a recent paper, Heuermann and Schmieder (2019) find that public transport links raise employment, particularly of young and well-educated workers, in smaller cities as urban residents become more likely to commute there. As Heuermann and Schmieder further point out, several large and highly productive German companies are headquartered in smaller cities and towns together with numerous "Mittelstand" and "hidden champion" firms.[20] For this reason it seems important in countries with decentralized economic structures such as Germany to raise the labour supply of young workers in the peripheral regions.

VII. Concluding Remarks

There is an increased recognition that regional differences can be used as a laboratory for estimating equilibrium effects (e.g. Guren et al, 2020). In this paper, we apply an empirical strategy adopted from Böhm and Siegel (2020) to identify the causal supply effects of demographic ageing on regional labour markets in Germany. Our headline finding is that ageing leads to comparable declines in the wage returns to age as in earlier studies, which have however focused on the United States. We use our estimation results to decompose the heterogeneous trends in regions' workforce ageing into effects due to supply as opposed to demand. This is important for regional policy.

[17] In Table A1, rural regions are formally shown to be a strong correlate of supply shifts (i.e. urban regions a negative correlate of supply shifts). This is corroborated by the share of apprenticeship employment as positive and share of foreign workers as negative correlates. In 1975 (top panel of Table A1), net migration especially of young workers was negative (positive) in supply (demand) driven regions. This is consistent with our interpretation that preference-based location choices have been important. The South also had weaker ageing supply shifts.

[18] As we documented in Table I, the urban regions tended to experience faster workforce ageing despite the supply effect acting toward a younger workforce in urban regions.

[19] Some of this may be happening already with improved communication technology, the adoption of which has accelerated during the Covid-Crisis. In addition, the German government has initiated programmes to support the expansion of 5G mobile communication networks especially to rural areas.

[20] While they have benefitted tremendously from globalization over the past decades, there are perennially reports that many of these firms face difficulties attracting young talent to their locations.

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Online Appendix

Appendix A - Details on the Decomposition Analysis

We estimate the elasticity of regional age demand (η) and infer the elasticity of supply (γ) as described in the main text. Given the estimated $\alpha_l + \alpha_t$ and η we can infer the shocks to the local demand for age $error_{lt}$ that make the realized $\ln(\overline{\text{age}}_{lt})$ consistent with the returns $\ln(\beta_{lt})$ in equation (2). The relative demand and supply equations for age in long changes become

$$\Delta\ln(\beta_l) = \eta\,\Delta\ln(\overline{\text{age}}_l) + \Delta errorD_l \qquad \text{(A1)}$$

$$\Delta\ln(\beta_l) = \gamma\,\Delta\ln(\overline{\text{age}}_l) - \Delta errorS_l \qquad \text{(A2)}$$

where Δ is the long difference operator, e.g. $\Delta errorD_l = error_{l2014} - error_{l1975}$ and all the variables (A1) and (A2) are demeaned to remove general nationwide changes and focus on regional differences. Equations (A1) and (A2) are a system of simultaneous equations for the changes in the regional supplies and demands for age.

The supply shocks $\Delta errorS_l$ are immediately identified given inferred γ and the realized $\Delta\ln(\overline{\text{age}}_l)$, $\Delta\ln(\beta_l)$. Using (A1) and (A2) we can also solve for these changes of age (quantities)

$$\Delta\ln(\overline{\text{age}}_l) = \frac{\Delta errorD_l + \Delta errorS_l}{\gamma - \eta} \qquad \text{(A3)}$$

and returns (prices)

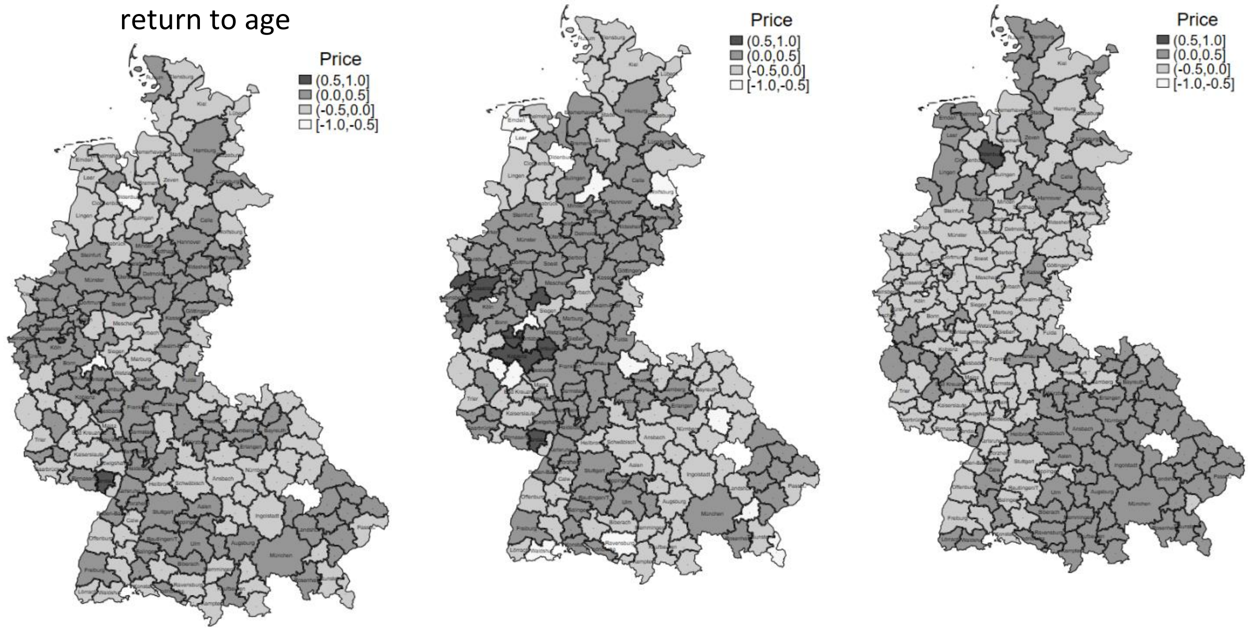
$$\Delta\ln(\beta_l) = \frac{\gamma\Delta errorD_l + \eta\Delta errorS_l}{\gamma - \eta} \qquad \text{(A4)}$$

From (A3), both supply and demand shocks raise quantities in a market ($\gamma - \eta > 0$ as our estimates $\gamma > 0 > \eta$). They work against each other on prices, since $\Delta errorD_l$ raises the returns to age in (A4) whereas $\Delta errorS_l$ lowers it.

Finally, we decompose the realized changes in prices and quantities. The contributions of demand shocks to changing regional age are $\frac{\Delta errorD_l}{\gamma-\eta}$ and to regional returns $\frac{\gamma\Delta errorD_l}{\gamma-\eta}$. The contributions of supply shocks are $\frac{\Delta errorS_l}{\gamma-\eta}$ and $\frac{\eta\Delta errorS_l}{\gamma-\eta}$, respectively. Together, the two contributions sum to the total of regions' differential changes in age and its return.

Figure A1 - Change in wage return to age (1975-2014) and decomposition

(a) Overall change in wage return to age | (b) Change due to demand | (c) Change due to supply



In the main text, we have shown the decomposition of differential changes in average age across regions. In Figure A1 we also show the corresponding changes in the returns to age. First, the overall returns to age have again increased quite strongly in the centre and West of the country and not increased as much in the rural North and South East (Panel A). Demand shocks had a large role for the increasing returns in the centre and West, notably the Rhine-Ruhr area whereas supply had a strong role in Bavaria. That is, the Bavarian population experienced relatively slow ageing due to supply factors and thus relatively large increases in the returns to age (as older workers became relatively scarce).

Comparing Figures IV and A1 highlights that the effects of demand on mean age and the returns to age align quite well, raising quantities and prices in broadly the same regions (i.e. darker vs brighter colours seem correlated regionally across the two figures' panels (b)). At the same, also supply effects appear well-aligned as average age rises in regions with positive supply shocks while returns decline (i.e. darker vs brighter colours correlate negatively across Figures IV(c) and A1(c)).

Appendix B – Decomposition

Table A1 – Correlations between supply/demands shifts and regional characteristics

Dependent variable:	Overall	Supply shifts	Demand shifts
A: In 1975:			
Share of female workers	-0.343***	-0.170**	-0.037
Share of foreign workers	0.076	-0.102	0.147**
Share of workers without apprenticeship	-0.083	-0.161**	0.109
Share of workers with apprenticeship	0.053	0.162**	-0.129*
Share of workers with university degree	0.119*	0.007	0.064
Urban region (time constant)	0.214***	-0.151**	0.279***
South region (time constant)	-0.270***	-0.139**	-0.024
Share of workforce in manufacturing	0.103	-0.083	0.144**
Share of workers in routine tasks	-0.015	-0.168**	0.158**
Share of workers in abstract tasks	0.109	0.106	-0.040
Share of workers in manual tasks	-0.109	0.142**	-0.207***
Net migration rate	-0.016	-0.128*	0.118*
Net migration rate of younger workers	-0.030	-0.200***	0.180**
Net migration rate of older workers	0.021	0.079	-0.066
B: In 2014:			
Share of female workers	-0.043	0.012	-0.038
Share of foreign workers	-0.093	-0.217***	0.160**
Share of workers without apprenticeship	0.187***	0.017	0.095
Share of workers with apprenticeship	-0.129*	0.139**	-0.216***
Share of workers with university degree	0.056	-0.176**	0.208***
Share of workforce in manufacturing	-0.048	-0.101	0.071
Share of workers in routine tasks	0.059	0.067	-0.030
Share of workers in abstract tasks	-0.056	-0.148**	0.113
Share of workers in manual tasks	-0.012	0.092	-0.098
Net migration rate	-0.101	0.021	-0.081
Net migration rate of younger workers	-0.058	0.045	-0.080
Net migration rate of older workers	-0.095	-0.014	-0.043

Notes: Net migration rates are calculated as (number of in-migrants – number of out-migrants) x 100/number of workers in the region.