Peer signals on local labor markets and the migration response along the work-life cycle

AUTHORS[1]: Timo Mitze, Amber Naz, Nils Karl Sørensen

ABSTRACT: We analyse the role of peer signals in explaining internal migration along the work-life cycle. In this context, peer signals are defined as age-specific labor disparities between alternative migration locations. While there is a large body of empirical research that has studied the migration response to aggregate local labor market disparities, the distinct novelty of this work is that we adopt an explicit work-life cycle perspective by testing for the strength of migration responses to these peer signals across age groups. Using data for internal migration flows and local labor market indicators in Denmark, our results show that peer signals are a significant factor in determining in the net in-migration rate of Danish municipalities in 2007-2015. In comparison, we do not observe significant effects when replicating the estimations with aggregate local labor market disparities instead of age group-specific peer signals. Moreover, while the estimation results generally support the neoclassical migration theory, we also detect significant alterations in the magnitude of the migration response across age groups. Similarly, rural-urban differences are found to be another key conditioning factor for the link between local labor market disparities and internal migration.

Keywords: Internal migration, life cycle, peer signals, local labor markets, rural-urban differences

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[1] Contact for correspondence: Timo Mitze, Department of Business and Economics, University of Southern Denmark, Alsion 2, DK-6400 Sønderborg. Tel.: +45/6550/1770, Fax: +45/6550/1779, Email: tmitze@sam.sdu.dk.

1. Introduction

A central research focus in regional and labor economics relates to the question(s) how factor mobility is driven by locational characteristics and how it consequently shapes the spatial structure of an economic system. In this paper, we address this issue by analyzing the determinants of migration flows between cities and regions within such a system and make predictions on how the migration response feeds back to these cities and regions. With relatively stable birth and death rates in most European countries, internal migration has become the key driver of spatial shifts in population, labor supply and human capital endowment. Here, a focus is set on identifying the role played by peer signals in determining a region's net in-migration rate. For the purpose of this study, peer signals are thereby defined as age-group specific local labor market disparities (e.g. in the unemployment rate), which are then linked to the observed migration patterns for the different age groups in focus. In doing so, we differ from most prior studies which have mainly looked at aggregated adjustment mechanisms related to local labor market disparities and regional amenities among other factors. This allows us to adopt an explicit work-life cycle perspective and to test for heterogeneous migration responses across different age groups to these peer signals.

Our focus on the heterogeneity of migration decisions along the work-life cycle has important policy implications, for instance, with regard to regional "brain gain-brain drain" processes stemming from selective interregional migration flows of (highly skilled) young population cohorts entering into specific labor market segments (Saxenian, 2002, Brücker and Trübswetter, 2007, Arntz, 2010, Piras, 2013). Similarly, investigating the specific regional determinants of migration at latter stages of a person's work-life cycle can help policy makers to identify "greying" regions and thus better address local needs in these regions linked to public infrastructure, affordable housing etc. (Dorfman and Mandich, 2016, Schaffar et al., 2018). In this context, we also investigate whether age group–specific migration rates are driven by different factors in an urban vis-à-vis rural context, which may help to address concerns related to depopulation trends in rural areas and thus discuss effective policy solutions that are able to (re)direct migration flows (Martinez-Fernandez et al., 2012, Buch et al., 2013). All in all, our analysis contributes to the attempt of mapping migration decisions along the work-life cycle acknowledging to complexity of these decisions (Kennan and Walker, 2015).

For the conduct of our empirical analysis, we use detailed data on age-specific internal migration flows and regional socio-economic indicators for Danish municipalities during the period 2007 to 2015. Our outcome variable of interest is the (age-specific) migration-induced population growth rate of each Danish municipality, which is specified as a function of peer signals on local labor markets and further overall socio-economic determinants (e.g. crime rates, social inequality etc.). By using not only data on age-specific migration flows but also the (relative) local labor market context such as the age-specific regional unemployment rate, average income and human capital endowment, we can test i) whether peer signals work differently from aggregate local labor market signals in driving internal migration or not and ii) whether the strength of peer signals differs across age groups and between rural and urban areas or not. A further motivation for using peer signals is that they may be seen as a close proxy for subjective measures of satisfaction with local employment opportunities, which have been shown to have a strong effect on interregional migration flows (Carlsen and Johansen, 2004).

Another noteworthy feature of our data is that the sample period covers the global economic crisis with a significant weakening of the Danish labor market. While this surely poses a challenge for empirical estimation (e.g. related to the issue of cross-sectional correlation stemming from latent common shocks), it also supports our identification strategy given that interregional disparities have widened significantly during the crisis. Accordingly, we argue that the global economic crisis can be viewed as an exogenous shock to the Danish economy and we apply robust panel data estimators with an unobserved common factor structure to account for this shock when identifying the age-specific migration response to interregional disparities. Previous research on modeling migration during times of crisis has shown that this is a viable empirical strategy (Mitze, 2018).

The remainder of the paper is organized as follows: Section 2 outlines the neoclassical migration model as theoretical underpinnings for our empirical model. A distinct focus is set on outlining life-cycle aspects of internal migration. Linked to the theoretical considerations, section 2 also discusses the alternative econometric specifications used for estimation. While section 3 presents the data and some stylized facts related to internal migration and interregional labor market disparities across Danish municipalities, section 4 presents the empirical results. Section 5 finally concludes the paper.

2. Modelling internal migration along the life cycle

2.1. Neoclassical migration theory

Studying the spatial mobility of people should be seen as multi-disciplinary and multi-level analytical construct that involves economics, demography, geography, sociology, law, political science, psychology and cultural studies (Brettel and Hollified, 2000). This paper starts from an economic perspective and analyses the spatial mobility of people in a labor market context through the lens of the neoclassical migration theory. The latter theory can be seen as a workhorse model for analysing migration processes under the premise of individual utility maximization and the assumption of perfect information available to the prospective migrant. Seminal contributions in the field of theoretical migration modelling include Lewis (1954), Ranis and Fei (1961), Sjaastad (1962), Lee (1966), Todaro (1969), Harris and Todaro (1970).

Lewis (1954) and subsequently Ranis and Fei (1961) have developed two-sector (agriculture, industry), two-region (rural, urban) models of migration on the assumption of perfect markets and labor surplus in the traditional agricultural sector. Workers from rural areas are attracted to move to industrialized urban areas because of the higher wages paid in the industrial sector. Hence, the wage differential takes the role of a pull factor in these models and migration between rural and urban areas continues until the surplus labor or disguised unemployment is absorbed by the industrial sector. The Todarian model of internal migration emphasizes the presence of unemployment and its link to internal migration. Todaro (1969) argued that urban-rural migration is due to disparities expected wages rather than observed wage levels in the urban manufacturing and rural agricultural sectors, respectively. By introducing the concept of expected wages, Todaro relaxes the assumption of perfect information of migrants with respect to the locational choice of migration decisions. According to this model, the individual's expected wage level is a function of observed wages and the probability of being employed.

The subsequent work of Harris and Todaro (1970) is considered to be a milestone in the formulation of the neoclassical migration theory as the authors formalize the basic ideas of the Todarian model. As for the latter, the individual's decision to migrate from an origin region i to a destination region j depends on the expected income (EY) in the two regions. The latter can be calculated as the actual income or wage level (W) in the regions weighted by the probability of being employed ($Prob[EMP]$), where the employment probability, in turn, is modelled as a function of the regional unemployment rate (U). Harris and Todaro (1970) assume that adjustments to labor market disparities are instantaneous. According to this model, migration from region i to region j will continue until the expected income in region j equals the expected income in region i.

Finally, costs of migration between two regions (C_{ij}) need to be considered, which can be social, economic and psychological in nature. The psychological costs of migration have already been emphasized by Sjaastad (1962) in his human capital model of migration. Rational individuals always discount their expected income with the cost of migration. Rational individuals always discount their expected income with the cost of migration. The migration flow between region *i* and *j* (denoted as M_{ij}) can then be defined as a function of

$$M_{ij} = \mathcal{F}(EY_{ii}, EY_{ij}, C_{ij}), \tag{1}$$

where EY_{ii} is the expected income of staying in region i, EY_{ij} is expected income by migrating from region *i* to region *j* and C_{ij} is the cost of moving from region *i* to region *j*. In turn, the probability of being employed is a function of the regional unemployment rate. Hence, expected income can be written as $EY_{ii} = Y_i \times Prob[EMP_i]$ with $Prob[EMP_i] = f(U_i)$ and likewise for region *j*. Then, under rational utility maximization an individual decides to migrate from region *i* to region *j* if the condition $EY_{ii} < EY_{ij} - C_{ij}$ holds.

While the basic neoclassical migration model focusses on the role of expected labor market returns, recent theoretical and empirical contributions have enriched the analysis of internal migration by controlling for further region-specific factors that cater to a more general utility maximizing approach of prospective migrants. These factors include regional human capital endowment (Borjas, 1987), house prices (Gabriel et al., 1992, Potepan, 1994, Bitter, 2008), commuting (Evers and van der Veen, 1985, Evers, 1989), economic freedom and equality (Cebula, 2014), mobility grants (Westerlund, 2003), public transfer payments (Angelucci, 2012, Schmidt, 2013), the regional age composition (Plane, 1993) and further region-specific amenities (Knapp and Graves, 1989, Biagi et al., 2011, Sarra and Del Signore, 2010). Although these locational characteristics are clearly helpful to address the complexity of internal migration decisions, the migration model becomes more eclectic with a priori unclear theoretical priors. While, for instance, the regional human capital stock is typically assumed to be positively correlated with increasing in-migration flows as a large stock of skilled employees in a region may increase the absorptive capacity of the (high-skilled) labor market (Fu and Gabriel, 2012), scholars have also argued that a large regional stock of skilled employees may increase local labor market tightness, which acts as an impediment to in-migration (Paidousis, 1986).

The lack of affordable residential properties is another important factor, which may drive down internal in-migration rates (Ghatak et al., 2008). Mulhern and Watson (2009) find that house prices are crucial for inter-provincial migration in Spain, thereby adding significant explanatory power to conventional labor market indicators such as wage and unemployment rate differences. House prices or rent prices of houses constitutes a large portion of the household expenditures and are likely to affect the migration decision of individuals negatively. Thus, high differences in house prices may serve as an impediment to migrate as found in Gabriel et al. (1992), Potepan, (1994), Bitter (2008) among others.

The same accounts for regional transfer payments as they might distort relative prices and labor market signals between different locations (Schmidt, 2013). Finally, regional amenities can be an important factor in analyzing regional migration (Greenwood et al., 1991). Quality of life prevailing in the region is also one of the non-economic factors that can influence the decision of migration. For instance crime rates are generally taken as the proxy to assess the quality of life in the region (Cebula, 2005). Moreover, some studies also incorporate industrial structures and the dynamics of structural change across regions to explain observed migration patterns (Saks and Wozniak 2011, Kubis, 2005).

2.2. Life-Cycle Considerations

The importance of life-cycle considerations stems from the assumption that the individual migrant's preferences, endowments and accordingly the demand for locational characteristics change over time. Interacting these individual-specific preferences and traits with location-specific characteristics related to the labor market, amenities, the social environment among other factors should may hence be seen as a fruitful starting point for modeling life-cycle migration (Graves and Knapp, 1988). There is now a growing body of –mainly empirical– research that studies the influence of the life-cycle position on individual migration propensities (see, e.g., Détang-Dessendre et al., 2002, Nivalainen, 2004) and the associated role played by locational characteristics in meeting the requirements of migrants of different age (e.g. Clark and Hunter, 1992, Millington, 2000, Whisler et al., 2008, Mitze and Reinkowski, 2011). As Détang-Dessendre et al. (2008), for instance, argue, in the early years of the individual's working life, professional motives far outweigh residential motives. Similarly, focusing on the role played by quality of life and quality of business environment indicators, Chen and Rosenthal (2008) find that young, highly educated households tend to move towards places with higher quality business environments. In contrast, the authors find that couples near retirement tend to move away from places with favorable business environments and towards places with highly valued consumer amenities.

Accordingly, we expect a stronger response of the migration flow between region *i* and *j* to a change in expected income for younger age groups compared to older age groups as

$$\frac{\partial M_{ij}^{young}}{\partial EY_{ij}^{young}} > \frac{\partial M_{ij}^{old}}{\partial EY_{ij}^{old}},$$

whereas the migration response to (interregional differences in) location-specific amenities ($\mathbf{Z}$), such as attractive consumer locations, a beautiful landscape, access to health services etc., can be expected to be stronger for older compared to younger age groups as

$$\frac{\partial M_{ij}^{young}}{\partial \mathbf{Z}_{ij}^{young}} < \frac{\partial M_{ij}^{old}}{\partial \mathbf{Z}_{ij}^{old}}$$

given that the utility associated with the use of these amenities varies over the life cycle. In general terms, we can thus extent eq.(1) to an age-specific, augmented neoclassical migration function $\mathcal{F}(\cdot)$ as

$$M_{a,ij} = \mathcal{F}(EY_{a,ii}, EY_{a,ij}, C_{a,ij}, \mathbf{Z}_{a,ii}, \mathbf{Z}_{a,ij}), \tag{2}$$

where the index a=1,…,A denotes the individual age groups. To sum up, in line with the predictions of the neoclassical migration model, we expect that the power of labor market stimuli declines with migrant age whilst the relative importance of regional amenities and housing effects increases for older age groups (Millington, 2000, Chen and Rosenthal, 2008).

2.3. Econometric Specification

For the empirical operationalization of the augmented neoclassical migration model we draw on previous studies, such as Jauer et al. (2014) and Mitze (2018) among others, and use a standard log-linear specification to model the aggregate net in-migration rate of age group a in region i at time t as

$$\begin{aligned} nmr_{a,i,t} = {} & \underbrace{(\alpha_1 u_{a,i,t-1} - \alpha_2 u_{a,j,t-1})}_{\substack{\text{age-specific difference} \\ \text{in unemployment rate}}} + \underbrace{(\alpha_3 y_{a,i,t-1} - \alpha_4 y_{a,j,t-1})}_{\substack{\text{age-specific} \\ \text{income difference}}} \\ & + \underbrace{(\alpha_5 hk_{a,i,t-1} - \alpha_6 hk_{a,j,t-1})}_{\substack{\text{age-specific difference} \\ \text{in human capital}}} + \underbrace{(\gamma' \mathbf{z}_{i,t-1} - \delta' \mathbf{z}_{j,t-1})}_{\substack{\text{overall differences in} \\ \text{regional amenities}}} + \mu_i + \pi_a + \varepsilon_{a,i,t}. \end{aligned} \tag{3}$$

In eq.(3), $nmr_{a,i,t} = \ln\left(\frac{NM_{a,i,t} - Pop_{a,i,t-1}}{Pop_{a,i,t-1}}\right)$ is the log-transformed net migration-induced annual population growth of age group a in region i, where annual net migration flows for municipality *i* ($NM_{a,i,t}$) are defined as the difference between the age-group specific gross in-migration and gross out-migration for municipality *i* at time *t* and $Pop_{a,i,t-1}$ is the age-group specific population level in region *i* at time *t-1*. Small letters denote logarithmic transformations of the unemployment rate (u), the income level (*y*), human capital endowment (*hk*) and the set of further socio-economic regressors ($\boldsymbol{z}$), respectively. Accordingly, the terms in brackets denote (age-group) specific regional differences between region *i* and *j*, where we proxy *j* by the average of all other Danish municipalities (excluding region *i*); μ_i and π_g are region- and age group-fixed effects and $\varepsilon_{i,t}$ is a stochastic error term.

As shown in eq.(3), we impose a one-period lag structure to account for the delays in the course of dissemination of labor market signals to migration (Puhani, 2001). Moreover, the use of lagged regressors shall minimize the risk of a simultaneous feedback effect running from the endogenous variable to the set of regressors (since we are working with a single-equation model). The regression coefficients α_1 and α_2, are the associated elasticities for the net in-migration with respect to changes in the unemployment rate in region *i* and the rest of the country (region *j*), respectively. Accordingly, α_3 and α_4 are the elasticities with respect to regional income changes and α_5 and α_6 are the elasticities for changes in the human capital endowment in region *i* and the rest of the country; γ and δ are coefficient vectors for the included set of regional amenities in region *i* and *j*.

In applied migration research, typically a restricted version of eq.(3) is estimated to reduce the number of coefficients to be estimated and enhance the interpretability of the model coefficients (Puhani, 2001). In this case, for each log-transformed variable, such as the unemployment rate, the following interregional difference is computed as $\breve{u}_{a,i,t} = \left(u_{a,i,t-1} - u_{a,j,t-1}\right)$. By doing so, $\breve{u}_{a,i,t}$ is expressed as the difference between the age group-specific unemployment rate in municipality *i* and the average unemployment rate in all other Danish municipalities (excluding municipality *i*). To give an example, if the relative regional unemployment rate for persons aged 30-34 amounts to 6% in Copenhagen but is only 4% in the rest of the country, then the associated value of $\breve{u}_{a,i,t}$ for Copenhagen (in year *t*) is log(6%/4%)=log(1.5). The value can be interpreted as follows: A value of $\breve{u}_{a,i,t}$ larger than 1 (or 0 for the log-transformed version) indicates that the age-group specific unemployment rate in region *i* (i.e. Copenhagen) exceeds the corresponding unemployment rate in region *j* (i.e. the rest of Denmark); a value smaller than 1 (or 0) points to a relatively better labor market performance in region *i* compared to region *j*. Hence, we can assume that larger values for $\breve{u}_{a,i,t}$ are negatively correlated with the region's net in-migration rate. A similar interpretation can be given to the other variables of the migration equation. In its restricted form, eq.(3) can be rewritten more compactly as

$$nmr_{a,i,t} = \beta_1 \breve{u}_{a,i,t-1} + \beta_2 \breve{y}_{a,i,t-1} + \beta_3 \widetilde{hk}_{a,i,t-1} + \theta' \breve{\mathbf{z}}_{i,t-1} + \mu_i + \pi_a + \varepsilon_{a,i,t}. \tag{4}$$

The empirical validity of the coefficient restrictions imposed on eq.(4) can be tested by means of a set of Wald-tests for coefficient equality in eq.(3) as $\alpha_1 = \alpha_2$, $\alpha_3 = \alpha_4$ and $\gamma = \delta$.

Another potentially too restrictive assumption underlying eq.(3) and eq.(4) is that the migration response to changes in the set of regressors is equal across age groups, i.e. the data are pooled over age groups once age group-fixed effects are incorporated in the regression specification through the inclusion of π_a. In order to test whether the strength of age-specific peer signals differs along the work-life cycle, we can relax this assumption by estimating separated variable coefficients for each age group a as

$$nmr_{a,i,t} = \sum_{a=1}^{A} \beta_{1,a}\, \breve{u}_{a,i,t-1} + \sum_{a=1}^{A} \beta_{2,a}\, \breve{y}_{a,i,t-1} + \sum_{a=1}^{A} \beta_{3,a}\, \breve{hk}_{a,i,t-1} + \sum_{a=1}^{A} \theta'_a\, \breve{\mathbf{z}}_{i,t-1}$$

$$+\mu_i + \pi_a + \varepsilon_{a,i,t}. \tag{5}$$

As a second type of decomposition of the estimation results, we are interested to investigate whether the results vary between rural and urban areas, for instance, in order to see whether the (age-specific) migration response to changes in local labor market differences and further amenities is stronger for urban vis-à-vis rural areas. As Buch et al. (2013) have recently pointed out, rural-urban differences in the migration response may be related to a shift in the importance of certain amenities such as cultural infrastructure and matching externalities in urban labor markets, which are both linked to city size. To test for rural-urban heterogeneities (along the work-life cycle), we build an interaction term between the individuals regressors in the migration equation and a binary dummy (*urban*) indicating whether region *i* is an urban municipality or not. The interaction term-augmented migration equation can be written as

$$nmr_{a,i,t} = \sum_{a=1}^{A} \beta_{1,a}\, \breve{u}_{a,i,t-1} + \sum_{a=1}^{A} \varphi_{1,a}\left(urban \times \breve{u}_{a,i,t-1}\right) + \sum_{a=1}^{A} \beta_{2,a}\, \breve{y}_{a,i,t-1}$$

$$+ \sum_{a=1}^{A} \varphi_{2,a}\left(urban \times \breve{y}_{a,i,t-1}\right) + \sum_{a=1}^{A} \beta_{3,a}\, \breve{hk}_{i,t-1} + \sum_{a=1}^{A} \varphi_{3,a}\left(urban \times \breve{hk}_{a,i,t-1}\right)$$

$$+ \sum_{a=1}^{A} \theta'_a\, \breve{\mathbf{z}}_{i,t-1} + \sum_{a=1}^{A} \tau_a\left(urban \times \breve{\mathbf{z}}_{,i,t-1}\right) + \mu_i + \pi_a + \varepsilon_{a,i,t}. \tag{6}$$

Since eq.(3) to eq.(6) shows variations in the cross-sectional as well as over time, the use of panel data estimators is a natural choice here. As a benchmark estimator we apply fixed-effects (FE) estimation; we report two-way clustered standard errors over regions and age groups when estimating the migration equations in eq.(3) and eq.(4). In addition, a common factor extension of the standard FE estimator will be presented below.

2.4. Common Factor Structure

Since our sample period covers the global economic crisis of 2007/08, we add a common factor structure to the migration equations outlined above. This allows us to account for the likely presence of cross-sectional dependence through latent common shocks. A major difference between the alternative common factor specifications applied here is whether the cross-sectional response to unobserved common shocks is assumed to be homogeneous or heterogeneous across regions. While, for instance, Coakley et al. (2002) adopt a panel model with a common unobserved components structure for all cross-sectional units (i.e. homogeneous factor loadings), Pesaran (2006) has developed a common correlated effects pooled (CCEP) estimator, which allows controlling for region-specific factor loadings. Specifically, Pesaran splits the error term into a vector of unobserved common factors $(\mathbf{f}_t)$ and a remainder *i.i.d.* error term $\left(\epsilon_{i,t}\right)$, where the unobserved set of factor-loadings (λ_i) for $\mathbf{f}_t$ are assumed to be independently and identically distributed across regions.

For empirical estimation, there are different ways how the unobserved common factors can be proxied by observable measures. While Bai (2009) and Greenaway-McGrevy et al. (2012) compute $\mathbf{f}_t$ based on a principle component analysis of the FE model residuals or the regressand and set of regressors, respectively, Pesaran's (2006) CCEP estimator includes cross-sectional averages of the regressand and set of regressors in the estimation equation. In order to detect cross-sectional dependence (CD) in the model's error term we follow a test setup proposed by Pesaran (2015).

The null hypothesis of the CD-test is that the error term is weakly cross-sectional dependent. Weak cross-sectional dependence means that the correlation between two units i and j at each point in time converges to zero as the number of cross-sections goes to infinity. A rejection of the null hypothesis points to strong cross-sectional dependence and inconsistent estimation results. The test statistic is distributed as $CD \sim N(0,1)$. If the test rejects the normality of residuals for the benchmark FE model, we first refer to Coakley et al. (2002) and assume that factor loadings are equal across regions ($\lambda_i = \lambda \ \forall i$). If these homogenous factor loadings are still not sufficient to account for the underlying cross-sectional dependence structure, we turn to region-specific factor loadings (λ_i). Proxies for the unobserved common factors are computed as suggested in Pesaran (2006) using cross-sectional averages of variables as $\mathbf{f}_t = [\bar{y}_t, \bar{u}_t, \overline{hc}_t, \bar{\boldsymbol{z}}_t]$, where bars denote cross-sectional averages calculated as $\bar{y}_t = \frac{1}{A \times N}\left(\sum_{a=1}^{A}\sum_{i=1}^{N} y_{i,t}\right)$.

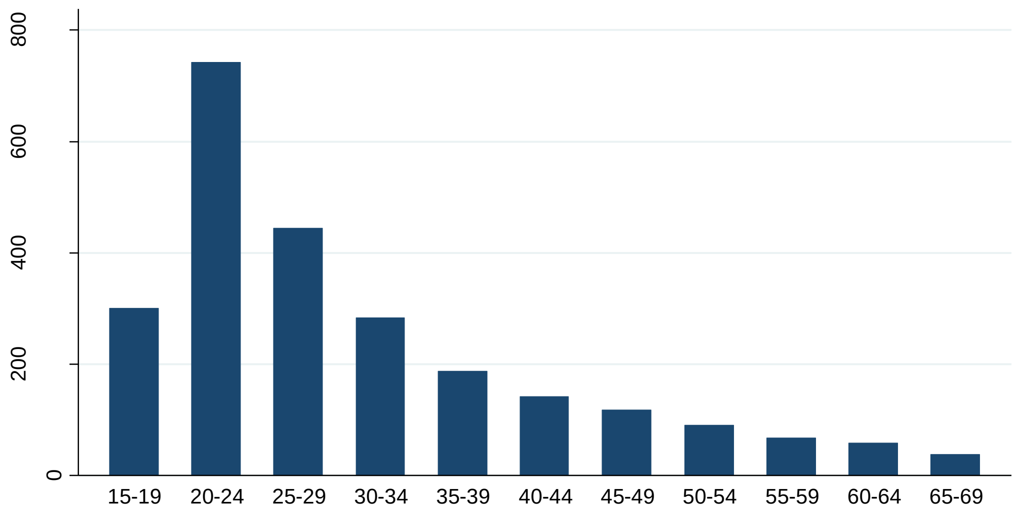
3. Data and Stylized Facts

We build a panel data set for 98 Danish municipalities (*Local Administrative Units, LAU Level 2*) over the period 2007–2015.[2] Data on internal migration flows between Danish municipalities, local labor market signals and further socio-economic indicators at the municipality level are obtained from Denmark Statistics (freely available at: www.statbank.dk). We stratify net in-migration rates and local labor market indicators into a total of 9 age groups with an explicit labor market context (20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64 years). Danish municipalities are further classified into rural and urban regions. For this purpose we use an urban-rural categorization of the 98 Danish

[2] Due to an administrative reform in Denmark unfortunately no data are available prior to 2007. The terms “municipality” and “region” are used interchangeably throughout the remainder part of this analysis.

municipalities based on 14 socio-economic indicators describing the municipalities' socio-economic functionality and connectedness (Iwasa Weiss Hansen et al., 2012).

Figure 1: Distribution of gross internal migration across age groups (sum for 2007-2015)



Source: Data from Statistics Denmark (2018) obtained from www.statbank.dk.

As Figure 1 highlights, the age profile for interregional migration in Denmark shows the typical 'spike' for migrants in the early work-life cycle (Wilson, 2010). Over the life-cycle, migration intensities gradually decline with increasing age. This observation can be brought in line with Becker's (1964) assumption that age is negatively correlated with migration due to a decrease in expected lifestyle gains from moving to a new location. In addition to this stylized age profile of internal migration in Denmark, Table 1 reports key summary statistics for age group-specific net in-migration rates (in addition, Figure A.1 in the Appendix provides detailed Kernel density plots for the age-group specific distribution of net in-migration rates across Danish municipalities).

Table 1: Descriptions and summary statistics for age-specific net in-migration rates

Variable	Description	Mean	S.D.	Min.	Max.
Gross in-migration	Total number of gross in-migrants in region *i* (per age group)	226.72	661.26	0	17617
Gross out-migration	Total number of gross out-migrants in region *i* (per age group)	226.72	506.45	0	9694
Net in-migration	Gross in- minus gross out-migrants in region *i* (per age group)	0	313.75	-3210	8776
Net in-migration rate	See main text for exact definition	1	0.05	0.4	3
	> age group 20-24	0.91	0.09	0.49	2
	> age group 25-29	1.02	0.05	0.85	2
	> age group 30-34	1.02	0.08	0.8	3
	> age group 35-39	1	0.03	0.75	1.5
	> age group 40-44	1	0.03	0.4	1.5
	> age group 45-49	1	0.01	0.97	1.25
	> age group 50-54	1	0.01	0.77	1.13
	> age group 55-59	1	0.01	0.91	1.17
	> age group 60-64	1	0.01	0.83	1.1
Unemployment rate	Unemployment rate in region *i* defined as share of unemployed persons in the age-group specific workforce (in %)	4.08	1.89	0.44	12.9
Disposable income	Disposable income per capita (per age group) in region *i* (in 1,000 DKK)	193.93	74.75	23.7	562.58
Human capital	Share of persons with bachelor, master and higher university degrees in age-group specific population in *i* (in %)	6.4	6.79	0	50
House prices	Market value for households real estate in region *i* (in 1,000 DKK)	1901.06	602.32	790.68	4798.94
Crime rate	Total number of crime offenses per population in region *i*	1.32	0.65	0	14.84
Population density	Number of residents per area of region *i* (persons per square kilometer)	36.88	101.29	0	1329.88
Gini index	Gini coefficient for income inequality (in %)	25.39	3.43	20.4	44.38
S80/S20 income ratio	Ratio of the average income of the 20% richest to the 20% poorest percentile of persons residing in region *i*	3.93	1.36	2.85	21.02
Urban	Binary indicator classifying Danish municipalities into urban and rural regions (values of 1 indicate urban municipalities)	0.52	0.49	0	1

Source: Data from Statistics Denmark (2018) obtained from www.statbank.dk.

As Table 1 shows, the coefficient of variation in migration rates is the highest for younger age cohorts along with a wider range between minimum and maximum values, i.e. regions which either face a significant population loss or gain through internal migration. This underlines the fact that the regional significance of migration varies over the work-life cycle and that particularly internal migration of younger age cohorts is associated with specific regional ‘winner’ and ‘loser’ regions in terms of migration-induced population growth (see also Figure A.1).

With regard to peer signals on local labor market, we use per-capita disposable income (per age group) as most relevant indicator for individual earnings since it not only includes the wages but also accounts for taxes and social benefits (Mitze and Reinkowski, 2011, Jauer et al., 2014). The regional unemployment rate is defined as the percentage share of unemployed persons in the age-specific workforce. The regional human capital endowment is calculated as the percentage share of graduates with bachelor, master and higher university degrees in the age-specific population. We also control for further regional amenities such as regional differences in house prices, crime rates and population density together with two indicators for income inequality (Gini index and S80/S20 income quintile share ratio). Differences in the sectoral structure of the regional economy are accounted for by including sectoral employment shares for a total of 36 sectors. Due to the imposed (one-period) lag structure for the set of regressors, the effective estimation period is 2008-2014 (7 years). The reader should finally note that due to some missing observations, the total number of region-age group-year observations used for estimation is 6,111 (out of 6,174 = 98 municipalities × 9 age groups × 7 years).

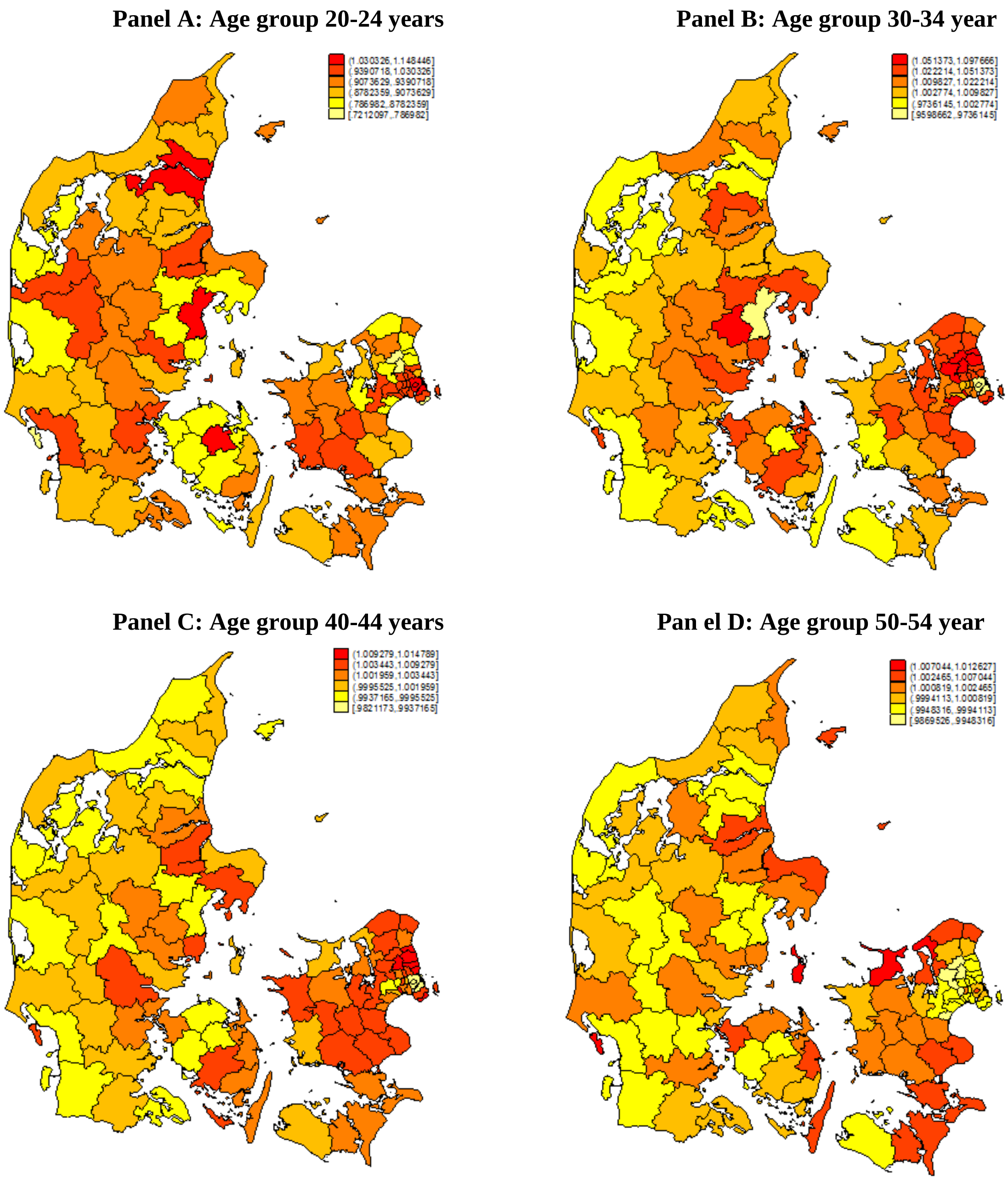
In order to gain some further insights on the spatial dynamics of migration rates and local labor market indicators, Figure 2 to Figure 4 plot choropleth maps for selected age group-specific net in-migration rates, the (log) unemployment rate difference and (log) income difference. When we take a first look at the spatial variation in age-specific migration rates, Figure 2 points to significant differences across age groups: While for younger age cohorts (Panel A and Panel B) a general pattern of positive net in-migration into large urban areas such as Copenhagen and Aarhus can be observed, older age groups are observed to move out of these regions. Moreover, when we further zoom in into the spatial dynamics taking place within these areas (see also Figure A.2 in the Appendix for a close-up presentation of the Copenhagen capitol region), we can see that young migrations (20-24 years) show a clear tendency to migrate into urban centers, whereas the spatial distribution of net in-migration rates in Panel B and Panel C points to a sub-urbanization trend with highest net in-migration rates being observed for the municipalities surrounding Copenhagen, Aarhus and Odense. Beyond these age group-specific particularities, also some common trends across age groups can be observed – such as a general depopulation trend of rural areas along the Danish west coast.

Similar spatial trends can also be observed when plotting the distribution of regional unemployment rates (Figure 3) and disposable income levels (Figure 4) for two exemplary age groups. While the age group-specific heterogeneity is moderate for regional differences in the unemployment rate, very particular regimes can be observed for regional income differences. With regard to the latter, Panel B in Figure 4 highlights that for older age groups the relatively highest income levels are in the Copenhagen capital region.[3] The lowest income municipalities are predominately located in the region Zealand (Lolland, Guldborgsund) and in southern Denmark (Langeland, Ærø, Tønder). For younger age groups, this pattern is less pronounced. Similarly, when we look at particularities in the spatial distribution of age-specific unemployment rates, low to moderate rates can be observed across age groups in the Dan-

[3] Gentofte, Lygby-Taarbeak, Rudersdal, Fursø, Allerød and Hørsholm are municipalities with particular high income levels.

ish mainland part. However, for urban areas, in particular Copenhagen, we observe that regional employment possibilities decrease with increasing age.

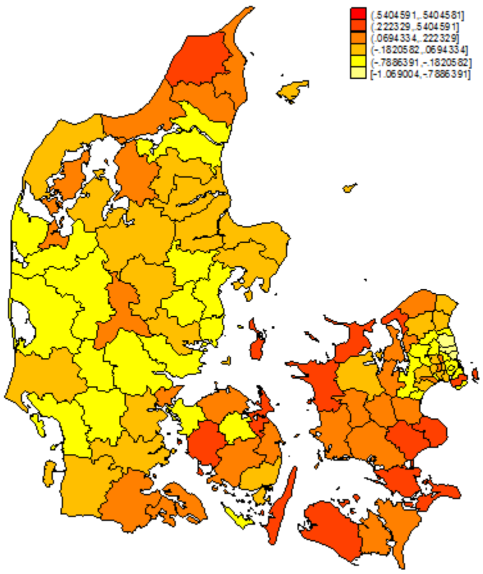
Figure 2: Age-group specific net in-migration rates of Danish municipalities (average 2007-2015)



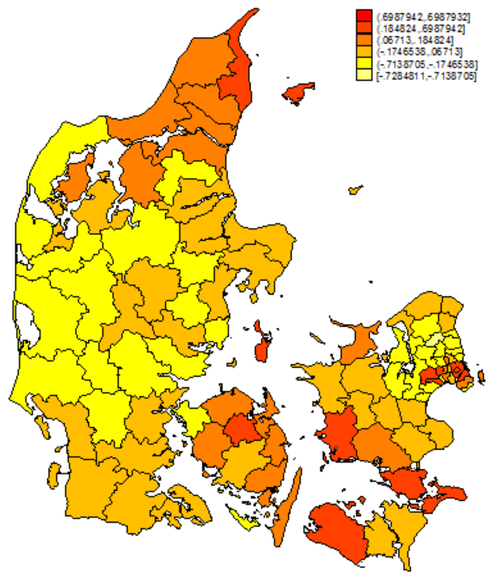
Source: Own figure based on data from Statistics Denmark (2018).

Figure 3: Spatial variation in regional unemployment rate differences (average 2007-2014)

Panel A: Age group 20-24



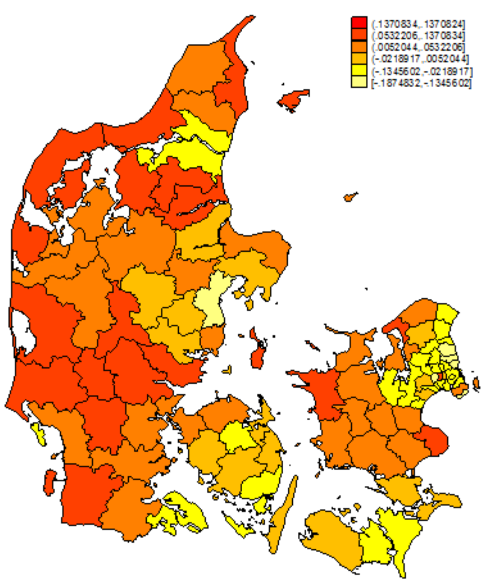
Panel B: Age group 40-44



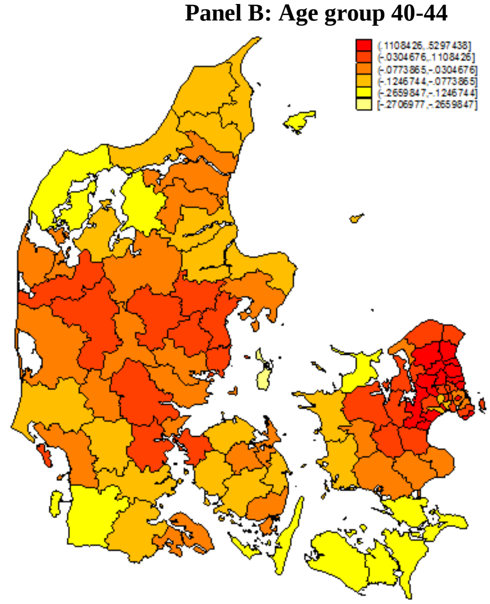
Source: Own figure based on data from Statistics Denmark (2018).

Figure 4: Spatial variation in regional income differences (average 2007-2015)

Panel A: Age group 20-24



Panel B: Age group 40-44

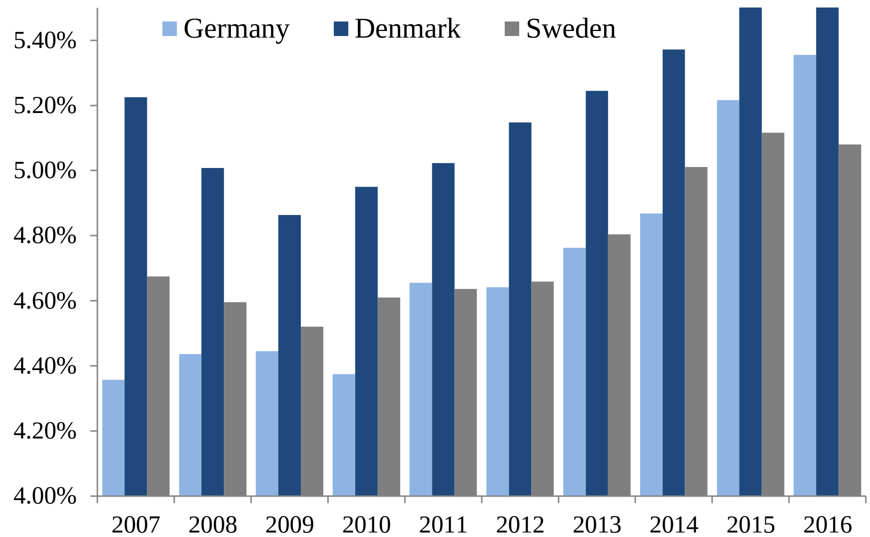


Source: Own figure based on data from Statistics Denmark (2018).

The Danish labor market is typically regarded as very flexible when it comes to its wage and employment dynamics. Regional differences in labor market and further socio-economic conditions are thereby accounted for as the main sources of interregional migration in the country. Among other determinants, educational attainment (Nordstrand and Andersen, 2002) and matching employment opportunities (Deding and Filges, 2004) have been identified as two main reasons for interregional migration in Denmark. Moreover, age and gender, the family, (un)employment and housing situations are also considered to be relevant socio-economic factors, which directly or indirectly affect interregional migration patterns in Denmark (see, for instance, Andersen, 2011). The relative significance of internal migration processes in Denmark can also be gathered from Figure 5, which compares internal gross migration rates in Germany, Sweden and Denmark during the period 2007-2016 (using comparable administrative areas of similar size; *local administrative units*). This graphical inspection supports the above stated view that the Danish labor market is highly flexible in a European perspective, especially in the time period following the global economic crisis of 2007/08.

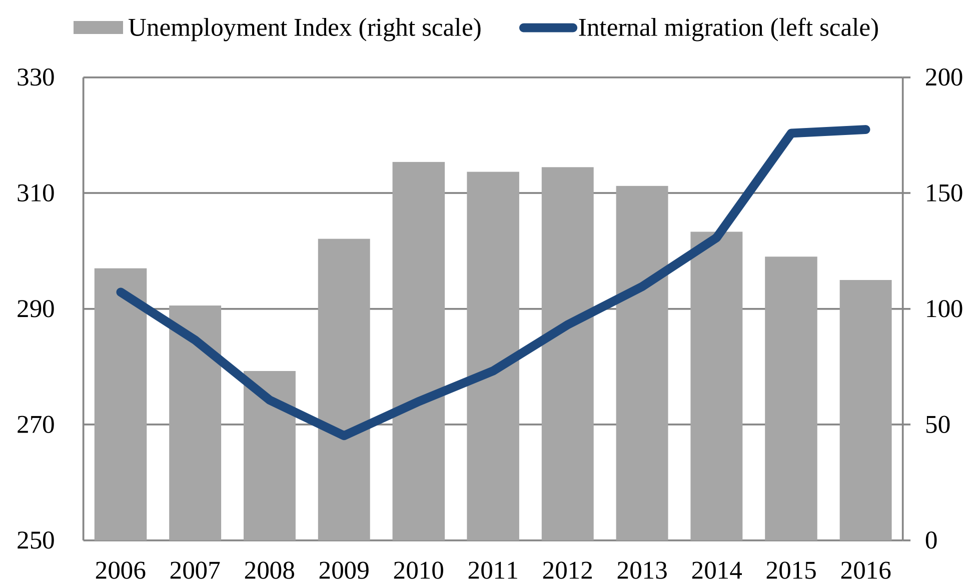
If we finally take a look at the labor market context of the global economic crisis, Figure 6 points to a clear trend reversal in the number of unemployed persons coinciding with the start of the crisis in 2008. During the global economic crisis the number of unemployed persons is observed to rise sharply between 2009 and 2012 and thereafter starts to fall again. As the figure further shows, internal gross migration flows react with a lag of approximately one year to this labor market weakening. Moreover, the rise in gross migration flows after 2008 is less pronounced than the one for the number of unemployed persons but shows a constant upwards trend between 2010 and 2015. Nonetheless, the co-movement of both variables before and after the global economic crisis points to the labor market context of migration decisions and the role played by migration in processing the crisis shock on the labor market.

Figure 5: Country comparison of internal gross migration rates (2007-2016, in % of population)



Source: Own figure based on data from Denmark Statistics (2018); Statistics Sweden (2018) and German Statistical Office (2018). *Notes:* In order to compare administrative regions of comparable size (local administrative units), we have counted all internal migration flows over the boundaries of 11313 *Gemeinden* in Germany and 290 *municipalities* in Sweden.

Figure 6: Danish internal gross migration and unemployed persons (2006-2016, in 1000)



Source: Own figure based on data from Denmark Statistics (2018).

4. Empirical Results

4.1. Pooled Specification

This section presents the estimation results for alternative migration equations that estimate a common migration response across age groups to variations in local labor market disparities (i.e. we pool the data over age groups and only account for age group-specific fixed effects). We start with a fairly simple benchmark specification according to eq.(3) which only includes core labor market variables (unemployment rate, income level and human capital endowment). The results in Column I of Table 2 underline the working of the key mechanisms as identified by the neoclassical migration theory. That is, a *ceteris paribus* 1% increase in region *i*'s unemployment rate decrease the region's net in-migration rate by 0.026%, while an increase in the unemployment rate outside region *i* is associated with an increase in the region's net in-migration rate. These results are in line with previous studies, which show that unemployed persons are more willing to out-migrate from regions with high unemployment rates (e.g. Carlsen et al., 2013, Fischer and Malmberg, 2001, Jackman and Savouri, 1992). Moreover, increases in region *i*'s income level and human capital endowment are positively related to the region's net in-migration rate, while associated increases in income and human capital outside region *i* have the expected negative coefficient (albeit being statistically insignificant).

Next, we also estimate a restricted specification (according to eq.(4)) using regional differences in the labor market signals and test for the validity of these particular restrictions by means of a set of Wald tests. As the results in Column II of Table 2 shows, we cannot reject the validity of these variable restrictions for reasonable significance levels. As before, the coefficients of the core labor market variables in the restricted regression specification turn out to be highly statistically significant and have the a-priori expected coefficient signs for regional differences in the unemployment rate, income levels and human capital endowments. However, the reported test statistics for cross-sectional dependence (CD) in the residuals of the benchmark specifications point to ill-behaved residuals as a source for an estimation bias. We account for this source of model misspecification in the following by adding further control variables and proxies for unobserved common shocks to the system of Danish municipalities.

Table 3 reports the results for the augmented net in-migration equation adding further controls as inter-regional differences in house prices, population density, crime rates, the Gini index, the S80/S20 income distribution and regional industry structures. As before, we estimate the model by means of FE estimation as well as augmented FE+CCE specifications building on a common factor structure as suggest by Pesaran (2006), which allows controlling for unobserved common macroeconomic shocks to Danish municipalities. As the result of the CD-test shows, even after the inclusion of additional control variables in Column I of Table 3 the FE estimates suffer from a statistically significant cross-sectional correlation in the residuals of the model equation. If we compare the CD-test statistics for the standard FE and the two augmented FE+CCE specification, we see that the degree of cross-sectional dependence is strongly reduced through the inclusion of unobserved common factors (indicated by a drop in the test statistic). While the FE+CCE specification with homogeneous facto -loadings still reports a statistically significant CD-test statistics at the 5% level (Column II), the augmented FE+CCE specification using municipality-specific factor loadings does not show any remaining signs of model misspecification through error cross-sectoral dependence (Column III).

Table 2: Estimation results and coefficient restriction tests for benchmark migration model

Dependent Variable: $nmr_{a,i,t}$ Age Groups	FE model Pooled	FE model Pooled	Coef. restrictions (*P*-Value)
Unemployment rate in *i*	-0.026		
	(0.005)***		
Unemployment rate in *j*	0.022		
	(0.006)***		
Unemployment rate diff		-0.025	$\chi^2(1)= 1.78$
		(0.005)***	(0.18)
Disposable income in *i*	0.040		
	(0.011)***		
Disposable income in *j*	-0.024		
	(0.019)		
Disposable income diff		0.040	$\chi^2(1)=1.27$
		(0.011)***	(0.26)
Human capital in *i*	0.020		
	(0.003)***		
Human capital in *j*	-0.168		
	(0.103)		
Human capital diff		0.020	$\chi^2(1)=2.13$
		(0.003)***	(0.14)
Region fixed effects	YES	YES	
Age group fixed effects	YES	YES	
Obs	6,111	6,111	
R^2	0.54	0.54	
CD-Test	11.39***	10.03***	

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% significance level. Two-way clustered standard errors are given in brackets. As default we use a one-year lag structure for the right-hand side variables. The CD-test is Pesaran's (2015) test for weak cross-sectional dependence in the residuals of the model equation. Under the null hypothesis of cross-sectional independence the test statistic is distributed as CD ~ *N*(0,1).

Focusing on the latter specification, the regression results in Column III of Table 3 indicate that the coefficients for the included core labor market variables continue to be statistically significant and of theoretically expected signs. This finding underlines the role played by local labor markets differences in driving internal migration when pooling over all age groups. Opposed to the strong importance of labor market indicators, the role played by further regional amenities is limited. Here we only observe that a relative increase in region *i*'s crime rate is associated with a lower net in-migration rate. However, insignificant effects stemming from differences in the population density and regional inequality may be an artefact of pooling over heterogeneous age groups. We will thus turn to a discussion of age group-specific estimation results in the next sub-section.

To better interpretation of the estimation results in Table 3, two further questions need to be addressed: First, although age group-specific peer signals on local labor markets appear to be statistically significant and the associated effects turn out to be in line with the theoretical predictions of the neoclassical migration model, their relative importance compared to a measure of aggregate local labor market signals is unclear. In other words: Do migrants base their migration decision specifically on age-group related peer signals or do they simply follow aggregate local labor market signals? In order to answer this question, we re-estimate the migration equation specifications reported in Table 3 but replace the age group-specific regional unemployment rate, income levels and human capital endowment by their aggregate indicator values observed on local labor markets (i.e. the overall regional unemployment, over disposable income and human capital endowment). We calculate aggregate values by averaging labor market signals across age groups as it is typically done in the related literature – even when endogenous migration variable is still stratified by age groups (e.g. Millington, 2000, Mitze and Reinkowski, 2011).

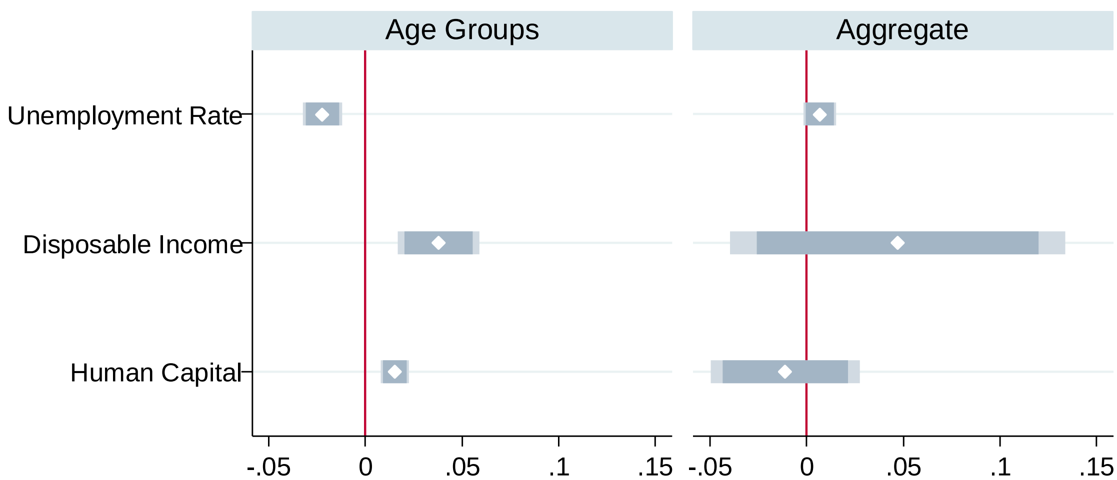
Table 3: Estimation results for augmented migration specification with common factor structure

Dependent Variable: $nmr_{a,i,t}$	FE model	FE+CCE model (homogeneous factor loadings λ)	FE+CCE model (heterogeneous factor loadings λ_i)
Age Groups	Pooled	Pooled	Pooled
Unemployment rate diff	-0.022	-0.022	-0.032
	(0.005)***	(0.005)***	(0.007)***
Disposable income diff	0.038	0.037	0.043
	(0.011)***	(0.011)***	(0.011)***
Human capital diff	0.015	0.015	0.016
	(0.004)***	(0.004)***	(0.004)***
House prices diff	-0.006	-0.003	0.010
	(0.010)	(0.010)	(0.054)
Population density diff	0.009	0.012	-0.002
	(0.008)	(0.009)	(0.011)
Crime rate diff	-0.017	-0.014	-0.028
	(0.008)**	(0.008)*	(0.013)**
Gini index diff	-0.047	-0.038	0.087
	(0.024)**	(0.024)	(0.111)
S80/S20 income ratio diff	0.020	0.015	-0.040
	(0.008)**	(0.008)*	(0.047)
Region fixed effects	YES	YES	YES
Age group fixed effects	YES	YES	YES
Sectoral employment shares	YES	YES	YES
Obs	6,111	6,111	6,111
R^2	0.56	0.56	0.58
CD-Test	4.93***	3.28**	1.41

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% significance level. Two-way clustered standard errors are given in brackets. As default we use a one-year lag structure for the right-hand side variables. For details on the FE+CCE model specification, see text. The CD-test is Pesaran's (2015) test for weak cross-sectional dependence in the residuals of the model equation. Under the null hypothesis of cross-sectional independence the test statistic is distributed as CD ~ $N(0,1)$.

Figure 7 compares the estimation results for the three core labor market variables for these two settings: Whereas the age group-specific results from Table 3 reflect the basic predictions of the neoclassical migration model (i.e. an increase in the relative regional unemployment rate decreases the net in-migration rate while an increase in relative income levels and the regional human capital endowment are positively related to the net in-migration rate), aggregate local labor market signals turn out to be statistically insignificant. Hence, this comparison underlines the role played by peer signals in driving internal migration in Denmark.

Figure 7: Comparison of alternative estimates for age group-specific and total labor market signals



Notes: Estimates for age group-specific labor market signals are taken from column I in Table 3. The equivalent regression results for overall differences in the unemployment rate, disposable income and human capital endowment are given in Table A.1 in the Appendix.

A second question relates to the economic significance of the estimation results from Table 3. In order to assess this question, we follow the approach outlined in Jauer et al. (2014) and conduct a simple back-of-the-envelope calculation to quantify the strength of the estimated migration-induced population change in adjusting regional unemployment levels. The calculation involves the following steps: First, as outlined in Jauer et al. (2014), we can draw a direct link between a 1% increase in the unemployment rate and a 1% increase in the total number of unemployed persons, which follows from

$$1.01 \times \left(\frac{u_{a,i,t}}{u_{a,j,t}}\right) = \frac{1.01 \times \left(\frac{unemp_{a,i,t}}{pop_{a,i,t}}\right)}{\left(\frac{unemp_{a,j,t}}{pop_{a,j,t}}\right)}$$

with $unemp_{a,i,t}$ being the total number of unemployed persons per age group a in region i in time period t. Second, having established this relationship, we can calculate the associated absolute value of a 1% increase in the number of unemployed persons by using overall the sample average per municipality and year (1,350 persons). Hence, a 1% increase in the latter corresponds to roughly 14 persons. Third, we apply the estimated elasticity from column III in Table 3 (0.032) to calculate the migration response in year *t* that follows from a 1% increase in the number of unemployed in *t*-1. As the average number of gross internal migration across Danish municipalities per year is 2,494 persons, 0.032% of this average is roughly 8 persons. In other words, on average, 14 additional unemployed persons decrease regional population due to net out-migration by 8 persons in the following year. This means that roughly 59% of the initial unemployment increase is offset by internal migration.

For EU-27 (Eurozone) NUTS2 regions in the period 2009-11, Jauer et al. (2014) report corresponding adjustment rates of 37% (32%), which underlines the fact that the Danish labor market has been very flexible in its response to demand shocks during the period of the global economic crisis. One should note, though, that the size of a Danish municipality (*LAU Level 2*) is smaller than those of NUTS2 regions used by Jauer et al. Accordingly, it should be taken into account that parts of this higher adjustment rate are due to these size differences in the underlying regional units of observation. Moreover, as Puhani (2001) points out, such simple back-of-the-envelope should be interpreted carefully since they build on the strong assumption that every internal migrant counts as an unemployed person who immediately finds a job outside his or her home region. In all, however, the results support the initially stated hypothesis that the Danish labor market can be considered as relatively flexible in a European comparison when assessed from the perspective of the geographical mobility of the labor force.

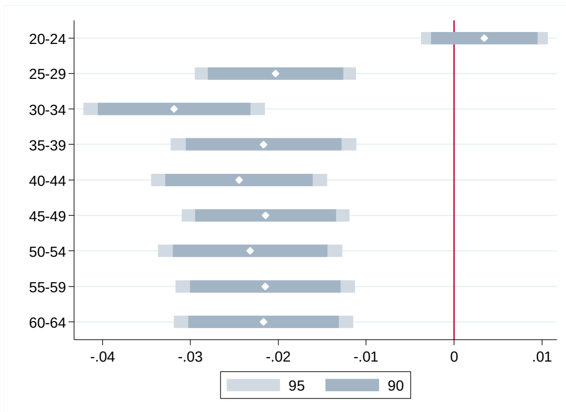
4.2. Age Group-Specific Results

Figure 8 highlights the range of estimated coefficients over age groups for each regressor included in the full migration according to Column III of Table 3.[4] The underlying migration equation corresponds to eq.(6) from above. The reported 95% and 90% confidence intervals additionally allow for an interpretation of the statistical significance of the estimated effects. As the figure shows, in line with the predictions of the neoclassical migration model, a relative rise in the age group-specific regional unemployment rate is associated with lower net in-migration rate for most age groups. The response to this peer signal is thereby the strongest for the age group 30-34 years indicating that migrants in this stage of the work-life cycle are extremely sensitive to changes the probability of finding an employment. In comparison, the degree of risk aversion with regard to local labor market signals is the lowest for the age group 20-24 years indicating that at this stage of the work-life cycle income maximization is the dominant factor in the migrant's decision making process. This can also be seen from Panel B in Figure 8, which points to a very strong correlation between interregional differences in income levels and internal migration. While the migration response to income difference is thus vital during the early stages of the work-life cycle, for older age groups this peer signal is of no significant importance.

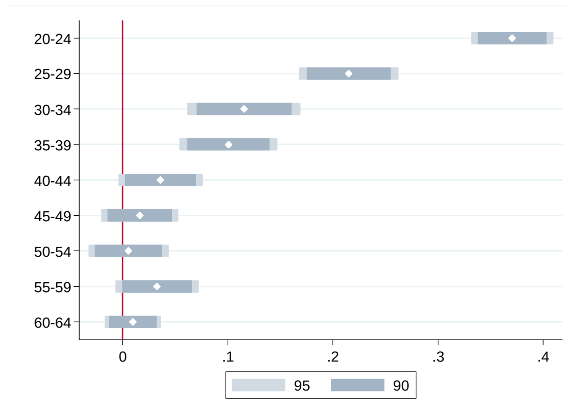
[4] Summary graphs for the Gini index and the S80/S20 ratio have been skipped here as we do not find any significant results across age groups; detailed estimation results can be obtained from the authors upon request.

Figure 8: Estimated coefficients for migration response to labor market signals by age cohorts

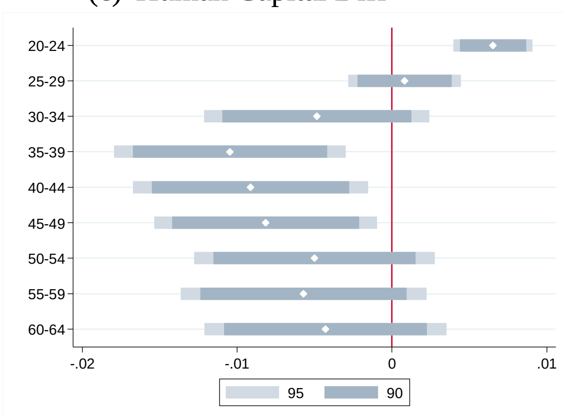
(a) Unemployment Rate Diff



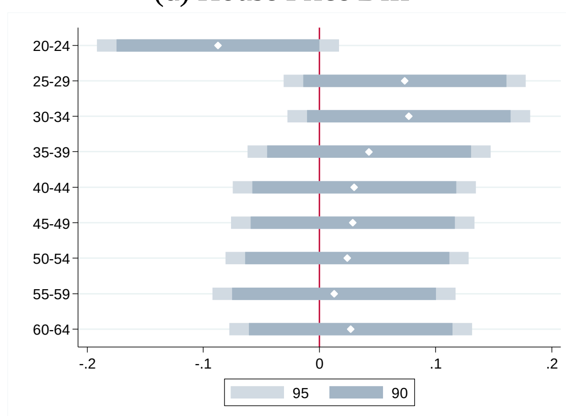
(b) Disposable Income Diff



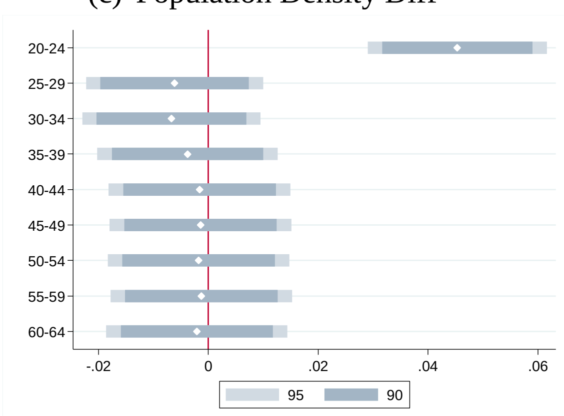
(c) Human Capital Diff



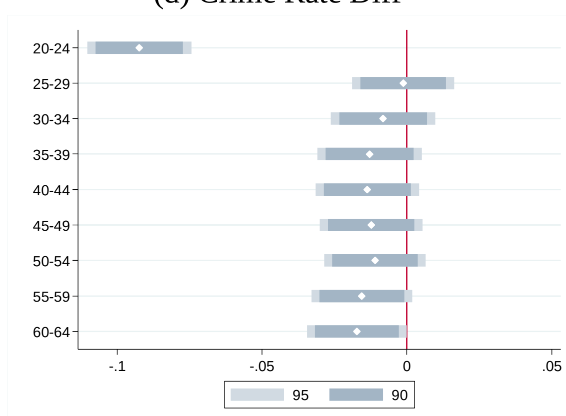
(d) House Price Diff



(c) Population Density Diff



(d) Crime Rate Diff



Notes: Solid squares mark the point estimates for the coefficients of the interaction terms as described in eq.(7) together with a ± one standard errors (hollow circles). Point estimates and standard deviation are computed on the basis of the FE+CCE estimator with region-specific factor-loadings (λ_i).

Looking at the further panels in Figure 8, we can see that age group-specific differences are also in order for most other variables. That is, while the regional endowment with (age-specific) human capital is an important peer signal in the early stage of the work-life cycle, we observe adverse effects for medium aged migrants (i.e. age groups 35-39, 40-44 and 45-49). With regard to the relative regional human capital endowment, we find a positive migration-induced population growth effect for the age cohort 20-24 years, most likely reflecting migration flows linked to education decisions (e.g. the move to university towns and metropolitan regions with a large relative human capital endowment) and labor market entry decisions linked to peer behaviour.

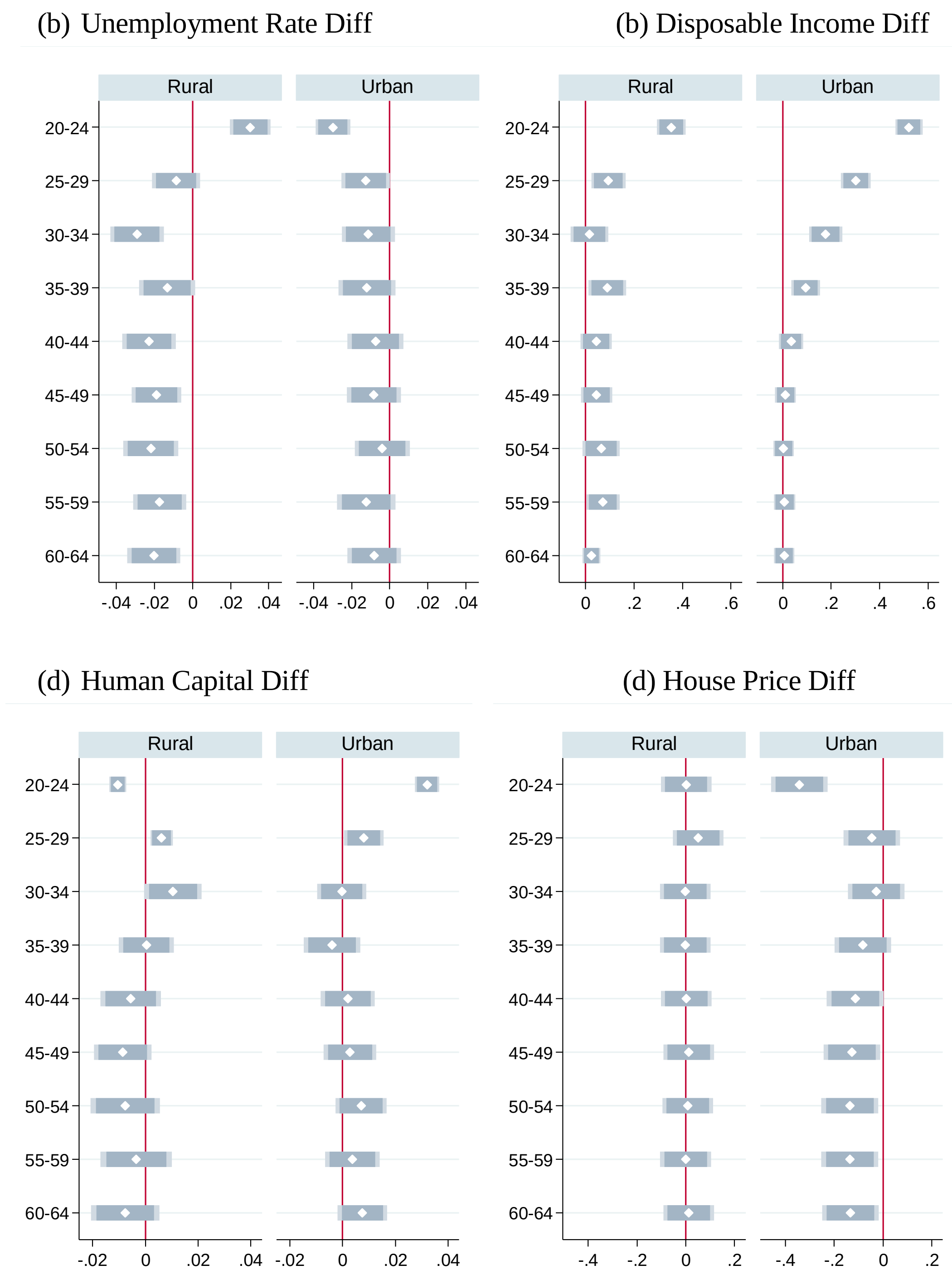
In comparison, middle-aged migrants are observed to show a positive (albeit marginally significant) migration response to increasing house price difference, while this factor is a strong impediment to migration for the youngest age group (20-24 years) in the sample. Similarly, this age group is also most responsive to regional differences in crime rates and most positively affected by rising levels of population density. This latter fact may point to differences in rural-urban migration patterns across age groups, which will be explored in greater depth next.

4.3. Rural-Urban Differences

As a final sensitivity analysis, we interact the included regressors in the migration equation with a binary dummy for urban areas in order to split the estimated age group-specific migration responses into rural and urban regions (see eq.(7)). As Figure 8 shows, local labor market signal work ‘better’, i.e. conform to the theoretical predictions from the neoclassical migration model, in an urban context compared to a rural context. As Panel B in Figure 8 shows, the migration response to changes in interregional income differences is stronger in urban regions, particularly for younger age cohorts (20-24. 25-29 and 30-34 years). Similarly, for urban regions young migrants (20-24 years) show the expected negative in-migration response when the relative regional unemployment rate increases vis-à-vis the rest of the country. In comparison, we find an adverse effect for young migration patterns in rural regions, i.e. higher unemployment is associated with a positive net in-migration rate. Only for middle-aged migrants (between 30 and 45 years), the estimation results for rural regions show the expected negative correlation between the net in-migration rate and the relative regional unemployment rate.

Similar observations can also be made for the regional endowment with human capital. While the latter is a strong attractor for net in-migration into urban areas, reverse effects can be observed for rural areas. Most likely, these different trends reflect the spatial location of higher education institutions in Denmark, which are mostly concentrated in urban areas (Mitze and Javakhishvili-Larsen, 2018). Indeed, Panel C in Figure 8 shows that regional human capital becomes gradually important over the work-life cycle for the net in-migration rate of rural areas. With regard to regional house price signals, interregional price differences do not appear to significantly affect the net in-migration rate in rural regions over the entire work-life cycle. However, in urban areas both young (20-24 years) and older age groups (particularly from 45 years onwards) show a significant negative migration response to house price differences – stressing the heterogeneous effects of (pecuniary) migration costs along the work-life cycle.

Figure 7: Add-on effects for net in-migration rates in urban vis-à-vis rural areas



Notes: Solid squares mark the point estimates for the coefficients of the interaction terms as described in eq.(7) together with a ± one standard errors (hollow circles). Point estimates and standard deviation are computed on the basis of the FE+CCE estimator with region-specific factor loadings (λ_i)

5. Conclusion

This work has assessed the role played by peer signals on local labor markets in driving internal migration. Using age group-specific data on internal migration and local labor market indicators for Danish municipalities during the period 2007-2015, our empirical results have shown that age group-specific peer signals have a much stronger impact on the internal migration response over the work-life cycle than aggregate local labor market disparities. This finding thus adds a novel aspect to our understanding of the labor market context of internal migration. The empirical results thereby support the basic predictions of the (augmented) neoclassical migration theory that regional differences in the unemployment rate and the region's average disposable income level are particular drivers of migration-induced changes in the regional population levels.

Moreover, the estimation results also reveal significant differences in the weight given to different peer labor market signals across age groups. While middle-aged migrants are, for instance, most sensitive to changes in relative regional differences of the unemployment rate, the degree of risk aversion on local labor markets is the lowest for the young migrants in the age group 20-24 years indicating that at this stage of the life cycle income maximization is the dominant factor in the migrant's decision making process. Similar differences can also be observed when assessing the role played by the regional endowment in age-specific human capital and further regional covariates, such as house price differences.

Next, we have also identified differences in the role played by peer signals on local labor markets when controlling for rural-urban differences. Our general observation here is that local labor market signals work 'better', i.e. conform to the theoretical predictions from the neoclassical migration model, in an urban context compared to a rural context. The migration response to changes in interregional income differences is stronger in urban regions. Similarly, young migrants in urban regions show the expected negative in-migration response to changes in the regional unemployment rate, while we find an adverse effect in the rural context. Only for the group of middle-aged migrants, the estimation results show the expected negative correlation between the net in-migration rate and the relative regional unemployment rate in rural regions. Taken together, these heterogeneous findings add to the revealed complex nature of migration patterns across the work-life cylce.

With regard to the economic significance of the estimated link between local labor market signals and internal migration, simple back-of-the-envelope calculations show that the regional unemployment adjustment due to internal migration amounts to roughly 59% and thus higher than analogous adjustment rates calculated for NUTS2 regions in the EU and the Eurozone (Jauer et al., 2014). The results thus support the initially stated hypothesis that the Danish labor market can be considered to be relatively flexible in a European comparison when assessed from the perspective of the geographical mobility of the labor force. From a policy perspective, our results stress several facts: First, (active) labor market policies targeting certain (age) groups of the population also have immediate effects on the regional population structure. Policy makers should bear this in mind – both as a potential restriction to the working of policy instruments but also as a chance to target the regional population structure and attract certain age groups through impact channels identified by the augmented neoclassical migration theory. Second, policy makers should be aware that the working of labor market policies may have adverse effects in a rural and urban context. Thus, no one-size-fits-all policy approach should be taken if it is the goal to support local development through migration and labor market policy. Third, given the high flexibility of the Danish labor market, our results also point to the need to compensate "shocked" regions that significantly lose population after an economic shock such as the global economic crisis. As such, our (partial) results due not allow to shed light on the mid- to long-run regional consequences of regional out-migration in response to a labor market shock. Particularly for rural regions in Denmark, this may further foster the depopulation trend even if out-migration is able to reduce interregional labor market disparities.

Obviously, our results are also not without limitations. Particularly, the link between age-specific migration processes and regional labor market disparities appears to be a fruitful avenue for future research efforts. Here, the identification of distinct life events along a person's life-cycle (e.g. entering the labor market after completing an education, marriage and the birth of children etc.) may act as an even more precise source of exogenous variation for migration decisions than proxying these events by age-specific mobility trends as done in this work. This may also then shift the analysis towards the generation of causal statements as opposed to the revealed correlations here (see, for instance, Fratesi and Percoco, 2014, on causality in the migration-labor market nexus). Similarly, earlier research has shown that differences across education levels are a further channel for model heterogeneity worth exploring (Carlsen et al., 2012). Nevertheless, we hope that our empirical findings can be considered as helpful in this endeavor as well as serve as valuable input for policymaking in need for monitoring and maintaining interregional labor market efficiency in a national labor market context.

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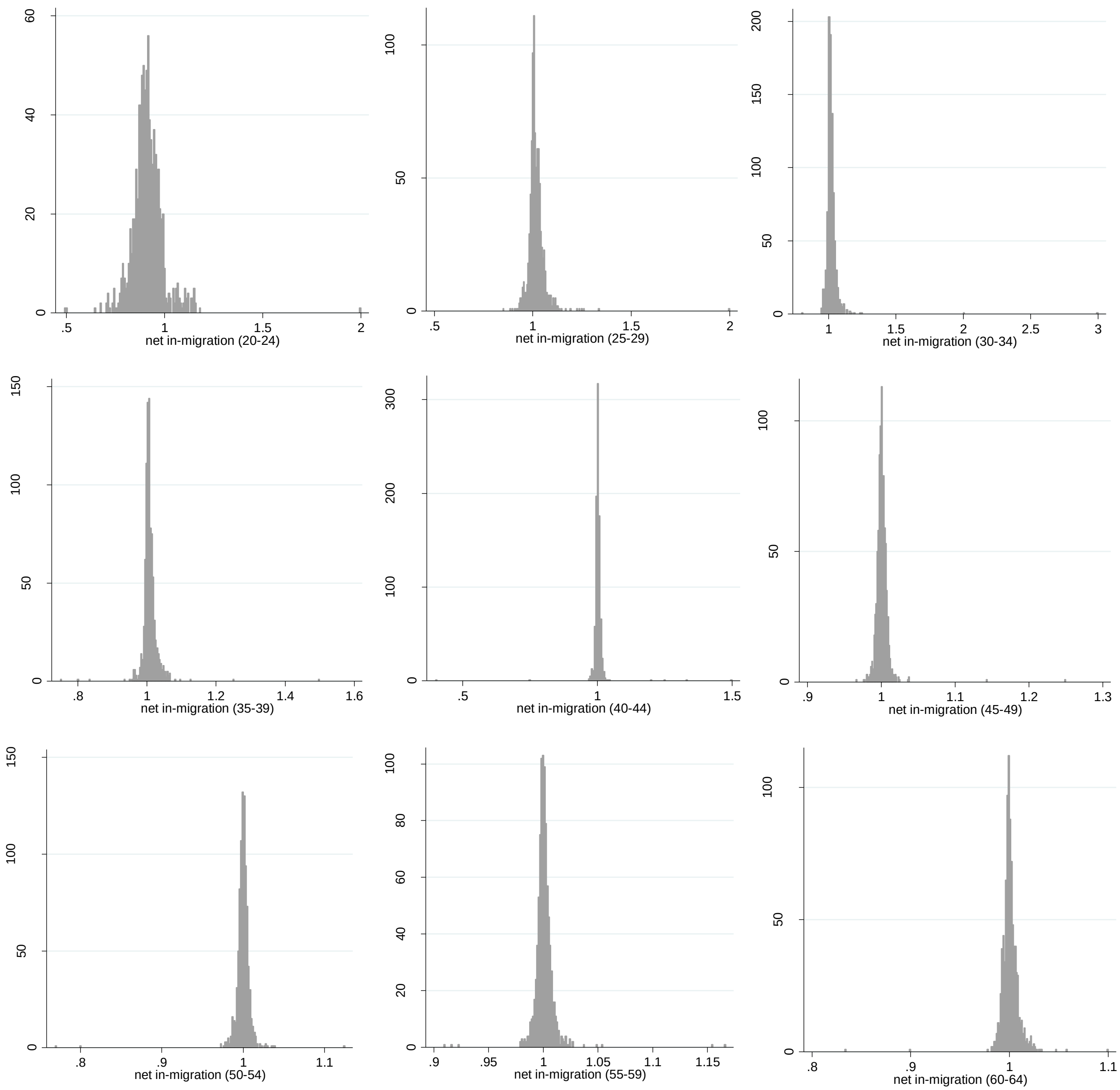
Appendix

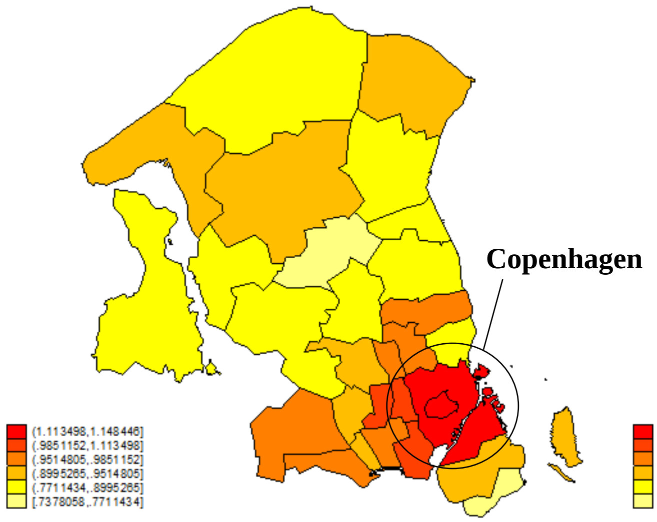
Figure A.1: Kernel density plots for regional distribution of net in-migration rates by age groups



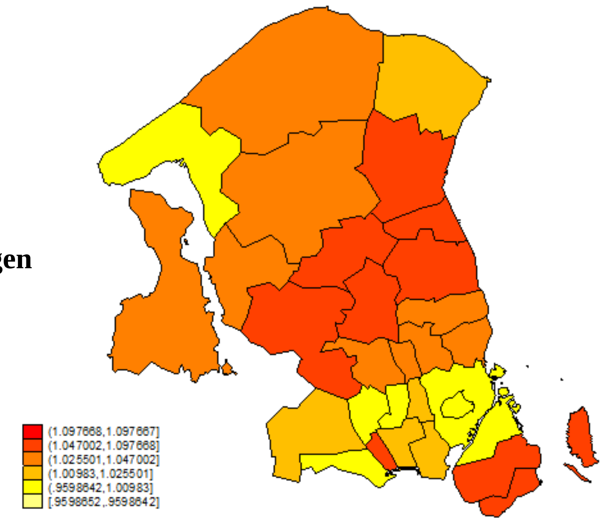
Source: Data from Statistics Denmark (2018) obtained from www.statbank.dk.

Figure A.2: Age-group specific net in-migration rates for capital region of Denmark

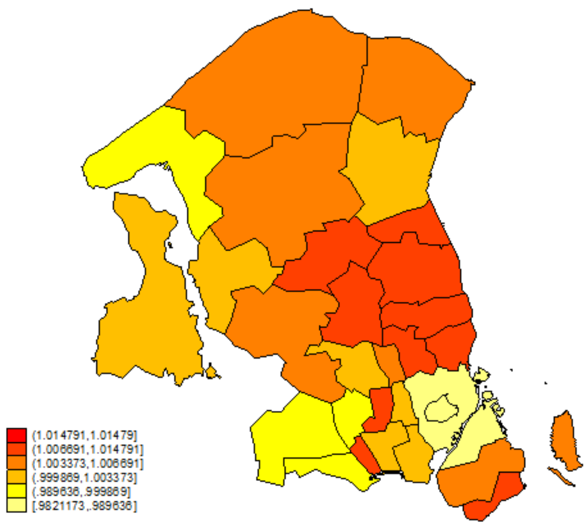
Panel A: Age group 20-24 years



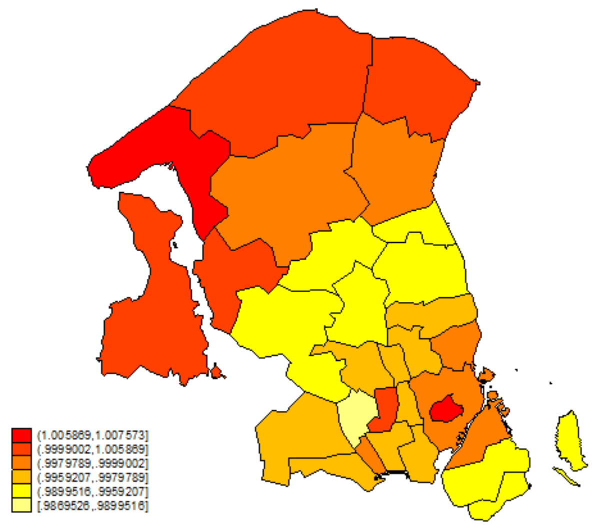
Panel B: Age group 30-34 year



Panel C: Age group 40-44 years



Pan el D: Age group 50-54 year



Source: Own figure based on data from Statistics Denmark (2018).

Table A.1: Estimation results for regional net in-migration rates for aggregate labor market signals

Dependent Variable: $nmr_{a,i,t}$	FE model	FE+CCE model (homogeneous factor loadings λ)	FE+CCE model (heterogeneous factor loadings λ_i)
Age Groups	Pooled	Pooled	Pooled
Aggregate unemployment rate diff	0.007	0.007	-0.002
	(0.004)	(0.005)	(0.029)
Aggregate disposable income diff	0.047	0.019	-0.066
	(0.044)	(0.044)	(0.252)
Aggregate human capital diff	-0.011	-0.017	0.036
	(0.020)	(0.019)	(0.092)
House prices diff	-0.010	-0.002	0.005
	(0.011)	(0.011)	(0.059)
Population density diff	0.026	0.030	0.006
	(0.008)***	(0.009)***	(0.011)
Crime rate diff	-0.019	-0.016	-0.042
	(0.007)***	(0.008)**	(0.012)***
Gini index diff	-0.052	-0.030	0.095
	(0.026)**	(0.026)	(0.147)
S80/S20 income ratio diff	0.019	0.008	-0.048
	(0.010)*	(0.010)	(0.070)
Region fixed effects	YES	YES	YES
Age group fixed effects	YES	YES	YES
Sectoral employment shares	YES	YES	YES
Obs	6,111	6,111	6,111

Notes: ***, **, * denote statistical significance at the 1%, 5% and 10% significance level. Two-way clustered standard errors are given in brackets. As default we use a one-year lag structure for the right-hand side variables. For details on the FE+CCE model specification, see text.