Statistisk sentralbyrå
Statistics Norway

Empirical modelling of internal migration and commuting flows for economic regions in Norway

Tom Kornstad, Terje Skjerpen and Lasse S. Stambøl

TALL SOM FORTELLER

DISCUSSION PAPERS

966

Discussion Papers No. 966, October 2021
Statistics Norway, Research Department

Tom Kornstad, Terje Skjerpen and Lasse S. Stambøl

Empirical modelling of internal migration and commuting flows for economic regions in Norway

Abstract:
This paper provides empirical results for internal migration and commuting flows using panel data for 89 economic regions in Norway for the years 2001-2014. The emphasis is on the potential effects of different incentive variables. We consider both in- and out-migration as well as in- and out-commuting with a common set of explanatory variables. We perform panel data analysis for four educational groups using seemingly unrelated regression (SUR) models, acknowledging that the effects of the incentive variables may vary across educational groups. Generally, we find weak responses to the incentive variables for the eight response variables, but they differ somewhat across the educational groups. The group comprised of those with a low education appears to be most responsive.

Keywords: Internal migration; commuting; panel data; educational groups; sets of regressions

JEL classification: C33; C51; J11; J61

Acknowledgements: We should like to thank Astri Syse and Michael Thomas for valuable comments. The authors are solely responsible for any remaining errors and weaknesses. We acknowledge financial support from the Norwegian Research Council, grant no. 283398. Address: Postboks 2633 St. Hanshaugen, 0131 Oslo, Statistics Norway, Research Department. E-mail: tes@ssb.no

Address: Tom Kornstad, Statistics Norway, Research Department. E-mail: Tom.Kornstad@ssb.no

Terje Skjerpen, Statistics Norway, Research Department. E-mail: Terje.Skjerpen@ssb.no

Discussion Papers comprise research papers intended for international journals or books. A preprint of a Discussion Paper may be longer and more elaborate than a standard journal article, as it may include intermediate calculations and background material etc.

The Discussion Papers series presents results from ongoing research projects and other research and analysis by SSB staff. The views and conclusions in this document are those of the authors

Abstracts with downloadable Discussion Papers
in PDF are available on the Internet:
http://www.ssb.no/en/forskning/discussion-papers
http://ideas.repec.org/s/ssb/dispap.html

ISSN 1892-753X (electronic)

Sammendrag

Vi modellerer flyttestrømmer og pendling mellom 89 økonomiske regioner i Norge (NUTS 4) for individer i alderen 15-74 år og utnytter 'makro' paneldata for årene 2001-2014. Både migrasjon inn til en økonomisk region fra en av de øvrige regionene og migrasjon ut fra en økonomisk region til en annen økonomisk region modelleres. Det samme gjelder i forbindelse med pendling. Hovedsaken er å se på om ulike insentivvariabler, som arbeidsledighetsrater og realtimelønninger kan forklare utviklingen i de ulike strømningsvariablene. En insentivvariabel er beregnet som den relative forskjellen mellom insentivvariabelen for observasjonsenheten og et veid gjennomsnitt av intensivvariabelen for de øvrige økonomiske regionene, der antall personer i årene 15-74 utnyttes som vekter.

Det skilles mellom individer i 4 utdanningsgrupper, dvs. (i) individer med lav utdanning, (ii) individer med fagutdanning, (iii) individer med studieorientert videregående utdanning og (iv) individer med høy utdanning, dvs. universitets- og høyskoleutdanning. På denne måten tillater vi at de ulike utdanningsgruppene kan ha ulike responser til insentivvariabler. Vi bruker et modellrammeverk basert på sett av regresjonsligninger der det også inngår dummyvariabler for de ulike økonomiske regionene for å fange opp tidsuavhengig uobserverbar variasjon knyttet til de ulike regionene. Intern migrasjon og pendling modelleres uavhengig av hverandre, men de samme forklaringsvariablene brukes i begge sammenhenger. Til sammen er det 8 ligninger i hver av de to tilfellene siden vi modellerer bruttostrømmene. Estimeringen skjer ved hjelp av iterativ multivariat regresjon.

For å analysere robusthet reestimeres modellene også på innskrenkede datamaterialer. Vi betrakter 2 varianter. I den ene fjerner vi en og en av observasjonsenhetene og reestimerer modellen for å se hvilken virkning dette har på parameterestimatene. I den andre fjerner vi enten et år i starten eller slutten av observasjonsperioden. Resultatene er forholdsvis robuste overfor slike datainnskrenkinger. De empiriske resultater viser generelt sett små effekter av insentivvariablene på bruttostrømmene. Mange av parameterestimatene knyttet til insentivvariablene er ikke signifikante, selv om de oftest har de forventede fortegn. De meste signifikante estimeringsresultatene forekommer for gruppen med lav utdanning.

1. Introduction

Internal migration and commuting are important from several perspectives. Low internal mobility may hamper economic growth at the national level, as human resources are not optimally allocated. Norway has pursued a policy aimed at reducing out-migration from the districts, which is believed to have contributed to limiting the mobility. Another factor is a possible mismatch in the balance between in- and out-migration. In many parts of the country there is negative population growth in both the short and the long run due to high out-migration and a low number of births (Leknes and Løkken, 2020).[1] This makes it difficult to maintain public services and raises concerns over the sustainability of certain communities in the long run. Several municipalities run campaigns to motivate young persons to move back after finishing their education, but the effects of such efforts are often considered to be limited (NOU 2020: 15).

Commuting and internal migration are closely intertwined. Opportunities for commuting allow one to settle in less central areas without this being at the expense of opportunities to obtain satisfactory work. Reasons for choosing to settle in less central areas may, for example, be high housing prices in central areas or a preference for living in less densely populated areas. In general, more dynamic locations are expected to have higher in-commuting and in-migration rates. In addition, larger cities tend to yield higher rewards to human capital than rural areas (Anlin *et al.*, 2014). For out-migration/commuting the relationship is the reverse.

Internal migration and commuting constitute an old and well-established research area that has been been approached from many angles. Sjaastad (1962) considers migration from the perspective of resource allocation. Over time, some industries expand while others experience downturns, and this gives rise to increased wage differentials across industries/occupations. Due to differences in business composition in different parts of the country, this change generates incentives for domestic migration. By collecting information on the costs and returns of migration, it is in principle possible to assess whether the reallocations are sufficient to yield efficient allocation of labor.

We follow another common line of research which points to the relationship between economic incentives and geographic mobility; see for instance Greenwood (1975, 1985) and Mitze and Reinkowski (2011). However, the results from previous studies of economic driving forces have been somewhat inconsistent. For instance, Cebula (2005) considered gross state-level in-migration in the

[1] In Norway birth rates are not particularly low in many districts, but the number of births might be low because the number of women of childbearing age is small.

United States and found that per capita income had an effect, but unemployment rate differentials did not. Mitze and Dall Schmidt (2015), using Danish data, found mixed evidence of traditional incentive variables. Meanwhile, Piras (2012), using a cointegration framework on Italian data, found results with the expected signs for regional per capita GDP and unemployment rates, although the results varied somewhat with the different empirical specifications applied.

An issue that we have not considered in this paper is the distinction between international immigrants and individuals born in Norway when it comes to internal migration in Norway. Individuals born abroad (immigrants) are believed to follow a pattern that differs from that of individuals born in Norway. This issue has also been raised by other researchers with respect to other countries, see for instance Schündeln (2014). Another issue that has been addressed is whether there is any response by natives to internal migration of international immigrants, see for instance Kritz and Gurak (2001) and Ali *et al*. (2012).

The empirical analysis in this paper builds only loosely on economic theory. From a theoretical point of view, one should take into account that decisions to migrate and commute are taken simultaneously in order to maximize some target function, i.e. a utility function. The groundbreaking contribution by Monte *et al.* (2018), who consider the US, provides a guideline to how this can be done within a general equilibrium context.

Our analysis employs data for 89 Norwegian economic regions and the observation period is 2001-2014. Our main attention is on two incentive variables: the unemployment rate and the real hourly wage. In Norway a relatively high fraction of workers are members of trade unions and economic policy is aimed at reducing geographic wage differences. Compared to other countries, the wage distribution has traditionally been relatively narrow, but over time the wage gap has widened.

This paper makes two contributions. First, we allow gross migration and commuting flows to vary across four different educational groups. Thus, we allow the responses to changes in relative real hourly wages and relative unemployment rates to differ across educational groups from the outset.[2] Many papers on internal migration illuminate the relationship between human capital and internal migration, even though human capital is not always the main issue addressed. However, many of them

[2] In contrast, Carlsen *et al*. (2013) modelled net domestic migration rates and they also used another education classification than what we employ. Their interest was also directed to heterogeneous response to incentive variables by different education groups.

operate with a less detailed classification than that employed here. Examples include Devillanova (2004), Piras (2012), Clemente *et al*. (2013), Korpi and Clark (2017) and Epplesheimer and Möller (2019).

Second, we employ seemingly unrelated regression (SUR) models for panel data. The main reason for estimating a set of equations simultaneously is related to estimation efficiency. Faced with estimates that have the expected sign but low significance, valid parametric constraints applied across the equations produce more efficient estimates.

Our model specification differs from those of, for instance, Liu (2018) and Poghosyan (2018), in that we model not bilateral flows, but aggregate flows. That is, we consider the total inflows and outflows from the economic regions. An advantage of doing this is that we can use far more disaggregated data. In a setting with 89 observational units, a substantial number of observation pairs are characterized by zeros, for either one or both the observational units. This constitutes an issue when the models are specified in terms of log-transformed variables. Consistent with our choice, for each economic region we operate with 'outside' variables which are weighted averages of the values of the variables outside the economic region at hand. We use working age population shares as weights.

We study the robustness of the results to changes in the sample applied for estimation. First, we consider parameter estimates obtained when the observational units are removed sequentially. Second, we retain all observational units but consider shorter time periods. Our conclusion is that the results are reasonably robust.

We disregard the impact of variation in housing prices across the observational units.[3] The regional housing price data do not fit well with our regional classification since they focus on areas where the turnover is of some size. For papers emphasizing the explanatory power of housing prices for internal mobility, see Cannari *et al.* (2000) and Hämäläinen and Böckerman (2004). Another issue related to housing is that home ownership is widespread in Norway. The rental market is quite limited and is primarily restricted to the largest cities. Palomares and van Ham (2020) noted that home ownership was an important factor for limiting internal mobility in Spain, and it is possible that high levels of home ownership in Norway may also work to lower migration propensities in Norway.

---

[3] The regional fixed effects will reflect the effects of differences in price levels between the regional units, but not changes in relative housing prices over time. Carlsen *et al*. (2013), which is an earlier study on Norwegian data at mainly the same regional classification as used in the current paper, utilized gouse transaction data to account for time-varying regional differences in costs of living.

We did not take differences in age and gender into account when modelling internal migration and commuting flows.[4] Such variables seem more relevant in a microeconometric setting. Since the time span is somewhat limited, the age and gender distribution will remain stable through the period.

The rest of the paper is organized as follows: In Section 2 we specify our econometric models and make various assumptions. Section 3 provides information on the data. In Section 4 we present and discuss our empirical results, before we conclude in Section 5. Some technical documentation may be found in the appendices.

2. Model specification

A typical equation for internal migration may be written as

$$\begin{aligned} \text{(1)} \qquad & \log(MIG_{it}^{de}) = \mu_i^{Mde} + \lambda_t^{Mde} + \beta^{Mde}\log(POP_{it}^{e}) + \gamma^{Mde} \times [\log(UR_{t-1}^{e}) - \log(UROTH_{i,t-1}^{e})] + \\ & \theta^{Mde} \times [\log(RHWAGE_{i,t-1}^{e}) - \log(UROTHOTH_{i,t-1}^{e})] + \\ & \eta^{Mde} \times [\log(EMPSHARE_{i,t-1}^{e}) - \log(EMPSHAREOTH_{i,t-1}^{e})] + \varepsilon_{it}^{Mde}, \end{aligned}$$

where the superscript $d=\{IN, OUT\}$ indicates inflow or outflow and the superscript $e=\{LOW, VOC, SUS, HIGH\}$ indicates educational category. The superscript *M* stands for migration. The left-hand variable is the log of a domestic migration flow for region *i* in period *t* for a particular educational group. When *d=IN* it is an inflow variable and when *d=OUT* it is an outflow variable. The observed variables on the right-hand side of (1) are (i) the log of the population with education type *e* at the beginning of year *t,* $\log(POP_{it}^{e})$, the relative difference in the unemployment rate between region *i* and other regions among those belonging to education category *e* in period *t*, $\log(UR_{t-1}^{e}) - \log(UROTH_{i,t-1}^{e})$, the relative difference in the average real hourly wage in region *i* and other regions among those belonging to education category *e* in period *t*, $\log(RHWAGE_{i,t-1}^{e}) - \log(UROTHOTH_{i,t-1}^{e})$ and the relative difference in the employment share in region *i* and in other regions among those belonging to education category *e* in period *t*, $\log(EMPSHARE_{i,t-1}^{e}) - \log(EMPSHAREOTH_{i,t-1}^{e})$. Altogether, (1) contains 8 different equations, combining domestic inflows and outflows of migrants with four different types of education. The four equations in (1) are estimated as a set of regression equations.

[4] Carlsen *et al.* (2013) found that the response in domestic migration rates to local unemployment shocks was larger in absolute value among the population aged 25-40 years than the population aged 41-66 years, and especially for those with tertiary education.

The contemporaneous error terms are assumed to be correlated, but free from autocorrelation and heteroskedasticity. The parameters in this model are estimated by iterative SUR estimation until convergence, which under normal conditions yields maximum likelihood estimates.
When analyzing commuting patterns, we apply the same explanatory variables as for internal migration rates. We now have the following equations:

$$
\begin{aligned}
&\log(COM_{it}^{de}) = \mu_i^{Cde} + \lambda_t^{Cde} + \beta^{Cde}\log(POP_{it}^{e}) + \gamma^{Cde} \times [\log(UR_{t-1}^{e}) - \log(UROTH_{i,t-1}^{e})] + \\
(2)\quad &\theta^{Cde} \times [\log(RHWAGE_{i,t-1}^{e}) - \log(UROTHOTH_{i,t-1}^{e})] + \\
&\eta^{Cde} \times [\log(EMPSHARE_{i,t-1}^{e}) - \log(EMPSHAREOTH_{i,t-1}^{e})] + \varepsilon_{it}^{Cde}.
\end{aligned}
$$

The superscript *C* stands for commuting. The left-hand variable is the log of a commuting flow related to region *i* in period *t* for a particular educational group.

3. Data[5]

We combine data from different sources for the years 2001-2014. The stock and flow population data are taken from the Population Statistics of Statistics Norway. Data have been aggregated from municipal to regional level; see Appendix Table B1 for an overview of the regions.[6] The population stocks relate to where individuals reside at the beginning of the year and cover persons in the age interval 15-74 years. From the employment statistics we have information on the labor market status of each person and where workers have their main job. We utilize this information to calculate time series for the unemployment rates for the economic regions. Utilizing data for those individuals who are employed, we can calculate time series of mean hourly wage rates for the economic regions. Thus, only the fraction represented by the workers is considered, i.e., the mean hourly wages used are those of individuals who are full-time workers. To calculate real hourly wages, we deflate by the consumer price index. A third data source is Statistics Norway's education statistics (NUDB). These statistics provide data on the highest education achieved by the individuals in terms of duration and type. Appendix Table C1 provides an exact definition of the educational groupings we employ according to the Norwegian Standard Classification of Education; see Barrabés and Østli (2016). Combining information from the population and employment statistics, we also calculate time series for

[5] See Appendix A for an overview of definition of variables.
[6] The classification of economic regions corresponds to what is referred to by Statistics Norway as the NUTS 4 level.

employment shares at regional level. This share is defined as the ratio between the number of employed individuals and the total number of individuals in the age interval 15-74 years.

We calculate the variables mentioned above for each educational group. In our empirical analysis we consider relative real wages, relative unemployment rates and relative employment shares. By relative wage we mean wage compared to a mean real wage level in economic regions other than the one being considered. We define the mean real hourly wage outside economic region *i* for a specific educational group as

(3) $$RHWAGEOTH_{it}^{e} = \frac{\sum_{j \in R_i} POP_{jt}^{e} \times RHWAGE_{jt}^{e}}{\sum_{k \in R_i} POP_{kt}^{e}}, \; i \in R; e = \{LOW, VOC, SUS, HIGH\}.$$

As defined earlier, *R* is the set containing all the observational units, while R_i is a subset of *R* consisting of all the regions except region *i*.

This means that the 'outside' real hourly wage of a specific educational group is a weighted (time-varying) mean of the real hourly wage outside the economic region, where weights are based on the size of the (target) population with the selected type of education. We have similar formulae for the unemployment and employment rates. They are given by

(4) $$UROTH_{it}^{e} = \frac{\sum_{j \in R_i} POP_{jt}^{e} \times UR_{jt}^{e}}{\sum_{k \in R_i} POP_{kt}^{e}}, i \in R; \; e = \{LOW, VOC, SUS, HIGH\}$$

and

(5) $$EMPSHAREOTH_{it}^{e} = \frac{\sum_{j \in R_i} POP_{jt}^{e} \times EMPSHAREOTH_{jt}^{e}}{\sum_{k \in R_i} POP_{jt}^{e}}, i \in R; \; e = \{LOW, VOC, SUS, HIGH\}.$$

In Appendix D we report measures related to the variables real hourly wage and unemployment rate. First, we calculate annual coefficients of variation to see whether the cross-sectional dispersion has changed over time. These are reported in Tables D1 and D2. The main impression is that spread changes moderately over time. With respect to the real hourly wage variable for the group with high education, there was a slight increase in dispersion in the first half of the observation period, but then it flattened out. There is a weak downward trend in the dispersion of employment rates. This is seen for all educational groups, but the pattern is most pronounced in the three groups vocational, study-oriented upper secondary and high education. We sort the cross-sectional data for each of the years and give each economic region a ranking number. We can then calculate the empirical correlation between the rank variables for different years. This yields information on the stablility of an economic region's place in the distribution. Tables D3 and D4 portray estimates for those with low education, Tables D5 and D6 for those with vocational education, Tables D7 and D8 for those with study-oriented upper secondary education, whereas Tables D9 and D10 show estimates for those with high education. When Tables D3-D6 are compared with Tables D7-D10, we see that the ranking correlations are higher for the real hourly wage variable than for the unemployment rates. The correlations tend to decrease with the distance in years. Thus, there is some convergence between the economic regions over time.

How do Norwegian domestic migration rates compare to the ones for other countries? It is hard to find data at the NUTS 4 level, which is the most relevant one given the current study. In Appendix E we have included a table which compares domestic mobility at the more aggregated NUTS 2 level. For Norway this classification yields 7 regions. With exception for Norway all figures are taken from Table A9 in Bonin *et al.* (2008). Except for the Netherlands, the table displays figures for the year 2006. The table shows that the intensity of domestic mobility in Norway is slightly lower than the domestic mobility intensity in the Netherlands (with a figure from 1999) and the UK, and at the same level as France and Sweden. Among the countries occurring in the table, Germany, Austria and Poland have the lowest domestic migration rates. However, there is reason to emphasize that even if the classification is at the NUTS 2 level for all the included countries, the size of the regions differs across the countries. This problem resembles a feature often encountered when comparing domestic mobility between Western-Europe and the US.[7]

4. Empirical results

When it comes to the unknown parameters in Eqs. (1) and (2), we expect the population parameters to enter with a positive sign. A larger observational unit population should generate higher inflows as well as higher outflows. We expect the relative unemployment rate and the employment rate to enter with a negative sign for in-migration and in-commuting. For reasons of symmetry, we expect the

[7] See for instance Molloy *et al.* (2011).

relative unemployment rate and the relative employment rate to enter with a positive sign in connection with out-migration and out-commuting. Finally, we expect the relative real wage to enter positively for in-migration and in-commuting and negatively for out-migration and out-commuting. Note that all observed variables in the models except the regional and annual dummies are log-transformed.

Results for internal migration

For (internal) migration we consider a set of regressions consisting of the eight response variables

$\log(MIG_{it}^{IN,LOW})$, $\log(MIG_{it}^{IN,VOC})$, $\log(MIG_{it}^{IN,SUS})$, $\log(MIG_{it}^{IN,HIGH})$, $\log(MIG_{it}^{OUT,LOW})$, $\log(MIG_{it}^{OUT,VOC})$, $\log(MIG_{it}^{OUT,SUS})$ and $\log(MIG_{it}^{OUT,HIGH})$.

The equation for each of these variables is given by (1). The assumptions with respect to the error terms have been stated above in a qualitative way but are given a formal treatment here. Let

$$\varepsilon_{it}^{M} = \{\varepsilon_{it}^{M,IN,LOW}, \varepsilon_{it}^{M,IN,VOC}, \varepsilon_{it}^{M,IN,SUS}, \varepsilon_{it}^{M,IN,HIGH}, \varepsilon_{it}^{M,OUT,LOW}, \varepsilon_{it}^{M,OUT,VOC}, \varepsilon_{it}^{M,OUT,SUS}, \varepsilon_{it}^{M,OUT,HIGH}\}'. \qquad (6)$$

We assume $\varepsilon_{it}^{M} \sim NIID(0, \Omega^{M})$, where Ω^{M} is an unrestricted covariance matrix containing 36 second-order moments of the errors.

The estimation results for a restricted case, in which significant estimates and right signs are emphasized, are reported in Table 1. Table 2 reports the standard error of regression (SER) for each of the estimated equations and Table 3 reports the estimation results in qualitative form. Table 1 is ordered such that the results for the four inflow equations are reported first followed by the results for the four outflow equations. We comment on the estimation results for the inflow equations first. The relative unemployment rate variable is only significant at the 5 per cent significance level for the group with low education. There is also a weak relative unemployment effect for the group with vocational education. For the two remaining groups, the unemployment effect has been constrained to zero because of the low significance of the estimates. When it comes to relative real wage, there is a significant and positive effect on those with study-oriented upper secondary education. There is also a weak positive, but insignificant, effect on the group with low education. For the two remaining groups the effect has been set to zero a priori. For those with high education we report that the effect of the employment share variable on inflow is significant but at a low positive level.

Table 1. Internal migration. Iterative SUR estimates

Left-hand variable	Parameter	Type of variable	Estimate	*t*-value
$\log(MIG_{it}^{IN,\,LOW})$				
	$\beta^{M,IN,\,LOW}$	Population	0.838	9.299
	$\gamma^{M,IN,\,LOW}$	Unemployment	-0.055	-2.667
	$\theta^{M,IN,\,LOW}$	Real wage	0.168	1.287
	$\eta^{M,IN,\,LOW}$	Employment share	0[a]	
$\log(MIG_{it}^{IN,\,VOC})$				
	$\beta^{M,IN,\,VOC}$	Population	1.013	11.473
	$\gamma^{M,IN,\,VOC}$	Unemployment	-0.020	-1.031
	$\theta^{M,IN,\,VOC}$	Real wage	0[a]	
	$\eta^{M,IN,\,VOC}$	Employment share	0[a]	
$\log(MIG_{it}^{IN,\,SUS})$				
	$\beta^{M,IN,\,SUS}$	Population	0.924	7.533
	$\gamma^{M,IN,\,SUS}$	Unemployment	0[a]	
	$\theta^{M,IN,\,SUS}$	Real wage	0.491	2.201
	$\eta^{M,IN,\,SUS}$	Employment share	0[a]	
$\log(MIG_{it}^{IN,\,HIGH})$				
	$\beta^{M,IN,\,SUS}$	Population	1.069	12.073
	$\gamma^{M,IN,\,SUS}$	Unemployment	0[a]	
	$\theta^{M,IN,\,SUS}$	Real wage	0[a]	
	$\eta^{M,IN,\,SUS}$	Employment share	0.526	1.023

Table 1. (Cont.)

Left-hand variable	Parameter	Type of variable	Estimate	*t*-value
$\log(MIG_{it}^{OUT,\,LOW})$				
	$\beta^{M,OUT,\,LOW}$	Population	0.951	22.362
	$\gamma^{M,OUT,\,LOW}$	Unemployment	0.095	3.544
	$\theta^{M,OUT,\,LOW}$	Real wage	-0.135	-2.107
	$\eta^{M,OUT,\,LOW}$	Employment share	0.370	2.331
$\log(MIG_{it}^{OUT,\,VOC})$				
	$\beta^{M,OUT,\,VOC}$	Population	1.196	20.073
	$\gamma^{M,OUT,\,VOC}$	Unemployment	0[a]	
	$\theta^{M,OUT,\,VOC}$	Real wage	-0.135[b]	
	$\eta^{M,OUT,\,VOC}$	Employment share	0[a]	
$\log(MIG_{it}^{OUT,\,SUS})$				
	$\beta^{M,OUT,\,SUS}$	Population	1.468	9.842
	$\gamma^{M,OUT,\,SUS}$	Unemployment	0.036	1.920
	$\theta^{M,OUT,\,SUS}$	Real wage	0[a]	
	$\eta^{M,OUT,\,SUS}$	Employment share	0[a]	
$\log(MIG_{it}^{OUT,\,HIGH})$				
	$\beta^{M,OUT,\,HIGH}$	Population	1.290	23.235
	$\gamma^{M,OUT,\,HIGH}$	Unemployment	0[a]	
	$\theta^{M,OUT,\,HIGH}$	Real wage	-0.135[b]	
	$\eta^{M,OUT,\,HIGH}$	Employment share	0[a]	

[a]A priori restriction, [b]A priori restrictions: $\theta^{M,OUT,\,LOW} = \theta^{M,OUT,\,VOC} = \theta^{M,OUT,\,HIGH}$.

Note: Region-specific fixed effects and annual fixed effects are included in all equations. *t*-values are based on

Let us next turn to the outflow equations. Here, a positive effect of the relative unemployment rate is found for those with low and study-oriented upper secondary education. For the latter group, the estimated coefficient of the unemployment variable is borderline significant at the 5 per cent test level, while the estimated coefficient for those with low education is clearly significant at this test level. The coefficients of the relative real wage variables are constrained to be the same for all groups except those with study-oriented upper secondary education, where it is constrained to be zero. The common parameter estimate is negative and significant at the 5 per cent test level. The relative employment share enters significantly for those with low education. The population size variable enters significantly in all eight equations with a value close unity. As seen from Table 2, most of the standard errors of regression are somewhat above 10 per cent.

Table 2. Standard error of regression in the case with multiple equations. Internal migration

$\log(MIG_{it}^{IN,LOW})$	0.113
$\log(MIG_{it}^{IN,VOC})$	0.132
$\log(MIG_{it}^{IN,SUS})$	0.171
$\log(MIG_{it}^{IN,HIGH})$	0.136
$\log(MIG_{it}^{OUT,LOW})$	0.095
$\log(MIG_{it}^{OUT,VOC})$	0.112
$\log(MIG_{it}^{OUT,SUS})$	0.127
$\log(MIG_{it}^{OUT,HIGH})$	0.096

Table 3. Qualitative summary of results. Internal migration [a]

Educational group	Type of flow variable	Rel. wage	Rel. unemp. rate	Rel. empl. share
LOW				
	Inflow		–	
	Outflow	–	+	+
VOC				
	Inflow			
	Outflow	–		
SUS				
	Inflow	+		
	Outflow		(+)	
HIGH				
	Migration: Inflow			
	Migration: Outflow	–		

[a]A cell with '–' denotes a negative estimate with a *t*-value higher than 2 in absolute value. A cell with '(–)' denotes a negative estimate with a *t*-value higher than 1.5 but lower than 2 in absolute value. A cell with '+' denotes a positive estimate with a *t*-value higher than 2. A cell with '(+)' denotes a positive estimate with a *t*-value higher than 1.5 but lower than 2.

Sensitivity analysis for internal migration

As a sensitivity analysis, we investigated the robustness of the estimation results reported in Table 1 with respect to slight changes in the sample. We look at two different ways of reducing the sample. In the first, we sequentially omit one of the observational units (economic regions) and reestimate the model. This procedure therefore involves 89 estimations, i.e., we obtain 89 different sets of estimates. We calculated summary statistics using this material, and they are reported in Table F1 in Appendix F.

The mean and median values are fairly close to the estimates obtained using the complete sample. The spread is also modest, as seen from the last column of the table, which reports the inter-quartile range of the parameter estimates. Our second sensitivity analysis retains all the observational units but omits the data for either the first or the last year. The results are reported in Table F2 in Appendix F. The results are somewhat less robust in the time series dimension than in the observational-units dimension. However, the sign of the parameter estimates does not change if the sample period is limited (cf. Table F2).

Results for commuting

As for internal migration, we estimated a SUR specification for commuting workers. Again, there are eight equations. The first four equations are for inflow of commuting workers with different educational backgrounds, while the last four are for outflow of commuting workers with different educational backgrounds. The empirical results are reported in Table 4. Table 5 also reports the SER for each equation and Table 6 provides qualitative estimation results. In view of the preliminary estimation results, we constrained some parameters to zero. The relative real wage only plays a role for inflow commuting for those with low education. The relative unemployment rate variable is allowed to have an effect on inflow of commuting workers for all educational groups, except those with study-oriented upper secondary education. It enters with the expected negative sign, but the estimates differ in size and in significance. The estimate is largest in (absolute) value for those with low education. It is -0.06 and the associated *t*-value is about 2.5 in absolute value. The estimate for vocational workers is only half the estimate for workers with low education, and the *t*-value is about 1.7 in absolute value. For those with high education the estimate is even lower, and the *t*-value is just above 1 in absolute value. The relative employment share variable enters for those with low and vocational education. The estimates are positive and significant at the 5 per cent level, but the estimated effect is significantly higher for those with vocational education. Lastly, we turn to the results for outflow of commuting workers. Here, we find that the relative real wage only plays a role for workers with study-oriented upper secondary and high education. The estimates are negative and significant in both instances, but somewhat larger for those with study-oriented upper secondary education than for those with high education. The relative unemployment rate does not enter for those with either low or vocational education. For the two other groups we estimated a positive effect, but the estimates are not significant at the 5 per cent level. The relative employment share variable enters with a negative sign for those with low and study-oriented upper secondary education. Both estimates are significant, but the estimate is largest in absolute value for those with study-oriented upper secondary education.

Table 4. Iterative SUR estimates in a set of regression models for commuting

Left-hand variable	Parameter	Type of variable	Estimate	*t*-value
$\log(COM_{it}^{IN,\,LOW})$				
	$\beta^{C,\,IN,\,LOW}$	Population	0.786	12.076
	$\gamma^{C,\,IN,\,LOW}$	Unemployment	-0.060	-2.430
	$\theta^{C,\,IN,\,LOW}$	Real wage	0.193	1.789
	$\eta^{C,\,IN,\,LOW}$	Employment share	0.353	2.630
$\log(COM_{it}^{IN,\,VOC})$				
	$\beta^{C,\,IN,\,VOC}$	Population	0.768	12.400
	$\gamma^{C,\,IN,\,VOC}$	Unemployment	-0.032	-1.705
	$\theta^{C,\,IN,\,VOC}$	Real wage	0[a]	
	$\eta^{C,\,IN,\,VOC}$	Employment share	0.934	2.778
$\log(COM_{it}^{IN,\,SUS})$				
	$\beta^{C,\,IN,\,SUS}$	Population	0.649	11.703
	$\gamma^{C,\,IN,\,SUS}$	Unemployment	0[a]	
	$\theta^{C,\,IN,\,SUS}$	Real wage	0[a]	
	$\eta^{C,\,IN,\,SUS}$	Employment share	0[a]	
$\log(COM_{it}^{IN,\,HIGH})$				
	$\beta^{C,\,IN,\,HIGH}$	Population	0.337	7.331
	$\gamma^{C,\,IN,\,HIGH}$	Unemployment	-0.015	-1.170
	$\theta^{C,\,IN,\,HIGH}$	Real wage	0[a]	
	$\eta^{C,\,IN,\,HIGH}$	Employment share	0[a]	
$\log(COM_{it}^{OUT,\,LOW})$				
	$\beta^{C,\,OUT,\,LOW}$	Population	0.350	3.188
	$\gamma^{C,\,OUT,\,LOW}$	Unemployment	0[a]	
	$\theta^{C,\,OUT,\,LOW}$	Real wage	0[a]	
	$\eta^{C,\,OUT,\,LOW}$	Employment share	-0.266	-3.432
$\log(COM_{it}^{OUT,\,VOC})$				
	$\beta^{C,\,OUT,\,VOC}$	Population	0.391	4.718
	$\gamma^{C,\,OUT,\,VOC}$	Unemployment	0[a]	
	$\theta^{C,\,OUT,\,VOC}$	Real wage	0[a]	
	$\eta^{C,\,OUT,\,VOC}$	Employment share	0[a]	

Table 4. (Cont.)

Left-hand variable	Parameter	Type of variable	Estimate	*t*-value
$\log(COM_{it}^{OUT,SUS})$				
	$\beta^{C,OUT,SUS}$	Population	0.604	4.753
	$\gamma^{C,OUT,SUS}$	Unemployment	0.019	1.371
	$\theta^{C,OUT,SUS}$	Real wage	-0.208	-2.575
	$\eta^{C,OUT,SUS}$	Employment share	-0.413	-2.522
$\log(COM_{it}^{OUT,HIGH})$				
	$\beta^{C,OUT,HIGH}$	Population	0.442	7.010
	$\gamma^{C,OUT,HIGH}$	Unemployment	0.014	1.896
	$\theta^{C,OUT,HIGH}$	Real wage	-0.150	-3.388
	$\eta^{C,OUT,HIGH}$	Employment share	0[a]	

[a]A priori restriction.
Note: Region-specific fixed effects and annual fixed effects are included in all equations. *t*-values are based on heteroskedasticity-consistent estimates of standard errors.

Table 5. Standard error of regression. Commuting

$\log(COM_{it}^{IN,LOW})$	0.119
$\log(COM_{it}^{IN,VOC})$	0.127
$\log(COM_{it}^{IN,SUS})$	0.127
$\log(COM_{it}^{IN,HIGH})$	0.098
$\log(COM_{it}^{OUT,LOW})$	0.066
$\log(COM_{it}^{OUT,VOC})$	0.064
$\log(COM_{it}^{OUT,SUS})$	0.078
$\log(COM_{it}^{OUT,HIGH})$	0.065

Table 6. Summary of results, qualitative. Commuting[a]

Educational group	Type of flow variable	Rel. wage	Rel. unploy. rate	Rel. empl. share
LOW				
	Inflow	(+)	–	+
	Outflow			–
VOC				
	Inflow		(–)	+
	Outflow			
SUS				
	Inflow			
	Outflow	–		–
HIGH				
	Inflow			
	Outflow	–	(+)	

[a]A cell with '–' denotes a negative estimate with a *t*-value higher than 2 in absolute value. A cell with '(–)' denotes a negative estimate with a *t*-value higher than 1.5 but lower than 2 in absolute value. A cell with '+' denotes a positive estimate with a *t*-value higher than 2. A cell with '(+)' denotes a positive estimate with a *t*-value higher than 1.5 but lower than 2.

Sensitivity analysis for commuting

As in the case of internal migration, we also performed some robustness analyses for commuting. The results are reported in Appendix F, Tables F3 and F4. In our first robustness analysis, we sequentially omitted a single observational unit from the estimation sample and re-estimated the model. This was done for all 89 observational units and thus left us with 89 estimates of the parameters of interest. We calculated summary statistics on these estimates, and the results are reported in Table F3. First, note that mean and median values are very similar. Second, the interquartile range is fairly small. The minimum and maximum values have the same sign as the mean value, but for some parameters there is some difference between the mean value of the estimates and the maximum or minimum values. The deviations seem to be somewhat larger than was the case for internal migration. In the other type of sensitivity analysis, we retained all the observational units, but used shorter times series, i.e., data for the two periods 2003-2014 or 2002-2013. Table F4 reports results for these two subperiods, but also, for reasons of comparison, repeats the results reported earlier for the full sample. The results seem fairly robust and the estimated signs are the same for the subsamples as for the full data. As an example, let us look at the estimate of the parameter $\beta^{C,\,OUT,\,SUS}$, i.e., the parameter associated with the population variable in the equation for out-commuting workers among persons with study-oriented upper secondary education. Using the full sample, the estimate is 0.604. For the sample limited to 2003-2014 the estimate is 0.570 and for the sample limited to 2002-2013 the estimate is 0.700.

5. Conclusions

Employing data for economic regions in Norway, we used panel data SUR models to analyze the extent to which internal migration and commuting activity are influenced by incentive variables. Our model is disaggregated in the educational dimension in that we consider four different educational groups. Sixteen flow variables played the part of response variables. For both internal migration and commuting we looked at both inflow and outflow. For a given educational group, the explanatory variables are common to both response variables. In many cases we do not find significant effects of the explanatory variables. Generally, the group with the lowest education appears to be the most sensitive with respect to the incentive variables. When we consider migration inflow, we only find an effect of the relative wage variable for the group with study-oriented upper secondary education, and it is not estimated very precisely in this case either. In the case of migration outflow the groups with low and vocational education are influenced by relative wages, but the estimate is most precise for the former group. For in-commuting, we only find a relative wage variable effect on the group with low education. When out-commuting is considered, effects are found for more groups. We fail to find an effect only for those with study-oriented upper secondary education. In all cases where we found at least some effect, the signs are in accordance with a priori expectations.

For the group with low education an increase in a region's relative unemployment rate leads to significantly higher out-migration and significantly lower in-migration. For the group with study-oriented secondary education we find a weak positive effect on out-migration, but no effect on in-migration. We have found no significant effects on an increase in the relative employment rate on internal migration for the two remaining groups, comprising those with vocational and high education, respectively.

We find that an increase in the relative unemployment rate leads to significantly lower in-commuting for the group with low education. There is also a weak effect on in-commuting for the group with vocational education. For both these groups we fail to find a significant effect on out-commuting. For the group with high education we find that an increase in the relative unemployment rate for an economic region has a weak positive effect on out-commuting, but no effect on in-commuting. For the last group, comprising those with study-oriented upper education, we find no significant effect on commuting.

In addition to the incentive variables and the population size of the region, we included regional fixed effects as well as annual fixed effects. Thus, our econometric framework is simpler than the approach based on pair-wise observations used by other researchers in this area. This more sophisticated approach, in the tradition of gravity models, is characterized by including population variables and fixed effects for both the 'sending' and the 'receiving' economic region. One challenge associated with this approach, when there are many observational units, is the predominance of zeros. Dropping observation pairs with zeros may have an undesirable effect on the inference. Researchers have recently started to employ a model that uses maximum likelihood estimation based on the Poisson distribution which also accounts for the zero observations (see Santos Silva and Tenreyro, 2006). However, in this approach the response variables cannot be log-transformed, as we have done in our analysis.[8] It is an interesting topic for further analysis, nevertheless.

[8] Abstracting from the problem with zeros, the log-transformation is believed to generate a more well-behaved model specification than models based on untransformed variables.

In summary, we find overall weak responses to the incentive variables employed in this study. There is, however, some interesting variation across educational levels. The lowest educated appears to be most responsive. Because of increased educational attainment in the population, there will be still fewer individuals in this group, which is dominated by immigrants. According to our model and empirical results this will impair the government's possibility to influence domestic migration by measures impacting the two incentive variables. Said in another way, the stimuli will need to be stronger to maintain the same effect as when there are more individuals in this group.

References

Ahlin, L., Andersson, M. and P. Thulin (2014): Market Thickness and the Early Labour Market Career of University Graduates: An Urban Advantage? *Spatial Economic Analysis*, 9(4), 396–419

Ali, K., Partridge, M.D. and D.S. Rickman (2012): International Immigration and Domestic Out-Migrants: Are Domestic Migrants Moving to new Jobs or away from Immigrants? *Annals of Regional Science,* 49, 397–415.

Barrabés, N. and G. K. Østli (2016): Norwegian Standard Classification of Education 2016. Revised 2000 Documentation (Updated 2016). Documents 2017/02. Statistics Norway.

Bonin, H., Eichhorst, W., Florman, C., Hansen, M.O., Skiöld, Stuhler, J., Tatsiramos, K., Thomasen, H. and K.F. Zimmermann (2008): Geographic Mobility in the European Union: Optimising its Economic and Social Benefits. IZA Research Report No. 19.

Cannari, L., Nucci, F. and P. Sestito (2000): Geographic labour mobility and the cost of housing: evidence from Italy. *Applied Economics*, 32(14), 1899–1906.

Carlsen, F., Johansen, K. and L.S. Stambøl (2013): Effects of Regional Labour Markets on Migration flows, by Education Level, *Labour*, 27(1), 80–92.

Cebula, R.J. (2005): Internal migration determinants: recent evidence. *International Advances in Economic Research*, 11, 267–274.

Clemente, J., Larramona, G. and V. Montuenga (2013): Scale and Composition Effects of Human Capital on Spanish Regional Migration. *Applied Economics Letters*, 20(18), 1644–1647.

Devillanova, C. (2004): Interregional Migration and Labor Market Imbalances. *Journal of Population Economics*, 17, 229–247.

Epplesheimer, J. and J. Möller (2019): Human Capital Spillovers and the Churning Phenomenon: Analyzing Wage Effects from Gross In- and Outflows of High-Skilled Workers. *Regional Science and Urban Economics*, 78, 103461.

Geist, C. and P.A. McManus (2012): Different reasons, different results: implications of migration by gender and family status. *Demography*, 49(1), 197–217.

Greenwood, M.J. (1975): Research on internal migration in the United States: a survey. *Journal of Economic Literature*, 13, 397–433.

Greenwood, M.J. (1985): Human migration: theory, models and empirical studies. *Journal of Regional Science* 25, 521–544.

Hämäläinen, K. and P. Böckerman (2004): Regional Labor Market Dynamics, Housing, and Migration, *Journal of Regional Science*, 44(3), 543–568.

Korpi, M. and W.A.W. Clark (2017): Human Capital Theory and Internal Migration: Do Average Outcomes Distort Our Wiew of Migrant Motives? *Migration Letters*, 14(2), 237–250.

Kritz, M. M. and D.T. Gurak (2001): The Impact of Immigration on the Internal Migration of Natives and Immmigrants. *Demography*, 38(1), 133–145.

Leknes, S. and Løkken, S. (2020): *Befolkningsframskrivinger for kommunene, 2020–2050 (Population projections for the municipalities, 2020–2050).* Rapporter 2020/27, Statistics Norway.

Liu, L. Q. (2018): Regional Labor Mobility in Spain. IMF Working Paper no. 18/282.

Mitze, T. and T. Dall Schmidt (2015): Internal migration, regional labor markets and the role of agglomeration economies. *Annals of Regional Science*, 55, 61–101.

Mitze, T. and J. Reinkowski (2011): Testing the neoclassical migration model: overall and age-group specific results for German regions. *Journal for Labour Market Research*, 43(4), 277–297.

Molloy, R., Smith, C. L. and A. Wozniak (2011): Internal Migration in the United States. *Journal of Economic Perspectives,* 25(3), 173–196.

Monte, F., Redding, S. J. and E. Rossi-Hansberg (2018): Commuting, Migration, and Local Employment Elasticities. *American Economic Review*, 108(12), 3855–3890.

NOU 2020: 15 (2020): Det handler om Norge. Bærekraft i hele landet. Utredning om konsekvenser av demografiutfordringer i distriktene (It's about Norway. Sustainability throughout the country. Study on the consequences of demographic challenges in the districts.). Kommunal- og moderniseringsdepartementet.

Poghosyan, T. (2018): Regional Labor Mobility in Finland. IMF Working Paper no. 18/252.
Palomares-Linares, I. and M. van Ham (2020): Understanding the effects of homeownership and regional unemployment levels on internal migration during the economic crisis in Spain. *Regional Studies*, 54(4), 515–526.

Piras, R. (2012): Disantangling the role migrants' educational level in the long-run Italian internal migration trends. *Studies in Regional Science*, 42(2), 377–396.

Piyapromdee, S. (2021): The Impact of Immigration on wages, internal migration, and welfare. *Review of Economic Studies*, 88(1), 406–453.

Santos Silva, J. M. C. and S. Tenreyro (2006): The Log of Gravity, *Review of Economics and Statistics*, 88 (4), 641–658

Schündeln, M. (2014): Are Immigrants more Mobile than Natives? Evidence from Germany. *Journal of Regional Science*, 54(1), 70–95.

Sjaastad, L. A. (1962): The Costs and Returns of Human Migration. *Journal of Political Economy*, 70(5), Part 2: Investment in Human Beings, 80–93.

Appendix A. Definition of symbols

Table A1. List of variables

Variable	Description
$MIG_{it}^{IN,LOW}$	Inflow (migration) of persons with low education to region *i* from other internal regions in year *t*
$MIG_{it}^{IN,VOC}$	Inflow (migration) of persons with vocational education to region *i* from other internal regions in year *t*
$MIG_{it}^{IN,SUS}$	Inflow (migration) of persons with study-oriented upper secondary education to region *i* from other internal regions in year *t*
$MIG_{it}^{IN,HIGH}$	Inflow (migration) of persons with high education to region *i* from other internal regions in year *t*
$MIG_{it}^{OUT,LOW}$	Outflow (migration) of persons with low education from region *i* to other internal regions in year *t*
$MIG_{it}^{OUT,VOC}$	Outflow of persons (migration) with vocational education from region *i* to other internal regions in year *t*
$MIG_{it}^{OUT,SUS}$	Outflow of persons (migration) with study-oriented upper secondary education from region *i* to other internal regions in year *t*
$MIG_{it}^{OUT,HIGH}$	Outflow of persons (migration) with high education from region *i* to other internal regions in year *t*
$COM_{it}^{IN,LOW}$	Inflow of commuting workers with low education to region *i* from other internal regions in year *t*
$COM_{it}^{IN,VOC}$	Inflow of commuting workers with vocational education to region *i* from other internal regions in year *t*
$COM_{it}^{IN,SUS}$	Inflow of commuting workers with study-oriented upper secondary education to region *i* from other internal regions in year *t*
$COM_{it}^{IN,HIGH}$	Inflow of commuting workers with high education to region *i* from other internal regions in year *t*
$COM_{it}^{OUT,LOW}$	Outflow of commuting workers with low education to region *i* from other internal regions in year *t*
$COM_{it}^{OUT,VOC}$	Outflow of commuting workers with vocational education to region *i* from other internal regions in year *t*
$COM_{it}^{OUT,SUS}$	Outflow of commuting workers with study-oriented upper secondary education to region *i* from other internal regions in year *t*
$COM_{it}^{OUT,HIGH}$	Outflow of commuting workers with low education to region *i* from other internal regions in year *t*
POP_{it}^{LOW}	Size of the population of age 15-74 years in region *i* and year *t* with low education
POP_{it}^{VOC}	Size of the population of age 15-74 years in region *i* and year *t* with vocational education
POP_{it}^{SUS}	Size of the population of age 15-74 years in region *i* and year *t* with study-oriented upper secondary education
POP_{it}^{HIGH}	Size of the population of age 15-74 years in region *i* and year *t* with high education
$RHWAGE_{it}^{LOW}$	Real mean average hourly wage in region *i* in year *t* among those with low education
$RHWAGEOTH_{it}^{LOW}$	Weighted real mean average hourly wage outside region *i* in year *t* among those with low education

Table A1. (Cont.)

Variable	Description
$RHWAGE_{it}^{VOC}$	Real mean average hourly wage in region *i* in year *t* among those with vocational education
$RHWAGEOTH_{it}^{VOC}$	Weighted real mean average hourly wage outside region *i* in year *t* among those with vocational education
$RHWAGE_{it}^{SUS}$	Real mean average hourly wage in region *i* in year *t* among those with study-oriented upper secondary education
$RHWAGEOTH_{it}^{SUS}$	Weighted real mean average hourly wage outside region *i* in year *t* among those with study-oriented upper secondary education
$RHWAGE_{it}^{HIGH}$	Real mean average hourly wage in region *i* in year *t* among those with study-oriented upper secondary education
$RHWAGEOTH_{it}^{HIGH}$	Weighted real mean average hourly wage outside region *i* in year *t* among those with study-oriented upper secondary education
UR_{it}^{LOW}	Unemployment rate in region *i* in year t among those with low education
$UROTH_{it}^{LOW}$	Weighted unemployment rate across other regions than *i* in year *t* among those with low education
UR_{it}^{VOC}	Unemployment rate in region *i* in year *t* among those with vocational education
$UROTH_{it}^{VOC}$	Weighted unemployment rate across other regions than *i* in year *t* among those with vocational education
UR_{it}^{SUS}	Unemployment rate in region *i* in year *t* among those with study-oriented upper secondary education
$UROTH_{it}^{SUS}$	Weighted unemployment rate across other regions than *i* in year *t* among those with study-oriented upper secondary education
UR_{it}^{HIGH}	Unemployment rate in region *i* in year *t* among those with high education
$UROTH_{it}^{HIGH}$	Weighted unemployment rate across other regions than *i* in year *t* among those with high education
$EMPSHARE_{it}^{LOW}$	Employment share of those with low education in region *i* in year *t*
$EMPSHAREOTH_{it}^{LOW}$	Weighted employment share of those with low education outside region *i* in year *t*
$EMPSHARE_{it}^{VOC}$	Employment share of those with vocational education in region *i* in year *t*
$EMPSHAREOTH_{it}^{VOC}$	Weighted employment share of those with vocational education outside region *i* in year *t*
$EMPSHARE_{it}^{SUS}$	Employment share of those with study-oriented upper secondary education in region *i* in year *t*
$EMPSHAREOTH_{it}^{SUS}$	Weighted employment share of those with study-oriented upper secondary education outside region *i* in year *t*
$EMPSHARE_{it}^{HIGH}$	Employment share of those with high education in region *i* in year *t*
$EMPSHAREOTH_{it}^{HIGH}$	Weighted employment share of those with high education outside region *i* in year *t*

Appendix B. Economic regions

Table B1. An overview of the economic regions

Economic region	County	Region number	Current region
Halden	Østfold	0191	1
Moss	Østfold	0192	2
Fredrikstad/Sarpsborg	Østfold	0193	3
Askim/Mysen	Østfold	0194	4
Follo	Akershus	0291	5
Bærum/Asker	Akershus	0292	6
Lillestrøm	Akershus	0293	7
Ullensaker/Eidsvoll	Akershus	0294	8
Oslo	Oslo	0391	9
Kongsvinger	Hedmark	0491	10
Hamar	Hedmark	0492	11
Elverum	Hedmark	0493	12
Tynset	Hedmark	0494	13
Lillehammer	Oppland	0591	14
Gjøvik	Oppland	0592	15
Midt-Gudbrandsdalen	Oppland	0593	16
Nord-Gudbrandsdalen	Oppland	0594	17
Hadeland	Oppland	0595	18
Valdres	Oppland	0596	19
Drammen	Buskerud	0691	20
Kongsberg	Buskerud	0692	21
Hønefoss	Buskerud	0693	22
Hallingdal	Buskerud	0694	23
Tønsberg/Horten	Vestfold	0791	24
Holmestrand	Vestfold	0792	25
Sandefjord/Larvik	Vestfold	0793	26
Sande/Svelvik	Vestfold	0794	27
Skien/Porsgrunn	Telemark	0891	28
Notodden/Bø	Telemark	0892	29
Kragerø	Telemark	0893	30
Rjukan	Telemark	0894	31
Vest-Telemark	Telemark	0895	32
Risør	Aust-Agder	0991	33
Arendal	Aust-Agder	0992	34
Lillesand	Aust-Agder	0993	35
Setesdal	Aust-Agder	0994	36
Kristiansand	Vest-Agder	1091	37
Mandal	Vest-Agder	1092	38
Lyngdal/Farsund	Vest-Agder	1093	39
Flekkefjord	Vest-Agder	1094	40
Egersund	Rogaland	1191	41
Stavanger/Sandnes	Rogaland	1192	42
Haugesund	Rogaland	1193	43
Jæren	Rogaland	1194	44
Bergen	Hordaland	1291	45
Odda	Hordaland	1294	46
Voss	Hordaland	1295	47

Sunnhordland	Hordaland	1296	48

Table B1 (Cont.)

Economic region	County	Region number	Current number
Florø	Sogn og Fjordane	1491	49
Høyanger	Sogn og Fjordane	1492	50
Sogndal/Årdal	Sogn og Fjordane	1493	51
Førde	Sogn og Fjordane	1494	52
Nordfjord	Sogn og Fjordane	1495	53
Molde	Møre og Romsdal	1591	54
Kristiansund	Møre og Romsdal	1592	55
Ålesund	Møre og Romsdal	1593	56
Ullsteinvik	Møre og Romsdal	1594	57
Ørsta/Volda	Møre og Romsdal	1595	58
Sunndalsøra	Møre og Romsdal	1596	59
Surnadal	Møre og Romsdal	1597	60
Trondheim	Sør-Trøndelag	1691	61
Frøya/Hitra	Sør-Trøndelag	1692	62
Brekstad	Sør-Trøndelag	1693	63
Oppdal	Sør-Trøndelag	1694	64
Orkanger	Sør-Trøndelag	1695	65
Røros	Sør-Trøndelag	1696	66
Steinkjer	Nord-Trøndelag	1791	67
Namsos	Nord-Trøndelag	1792	68
Stjørdalshalsen	Nord-Trøndelag	1793	69
Leveanger/Verdalsrør	Nord-Trøndelag	1794	70
Grong	Nord-Trøndelag	1795	71
Rørvik	Nord-Trøndelag	1796	72
Bodø	Nordland	1891	73
Narvik	Nordland	1892	74
Brønnøysund	Nordland	1893	75
Sandnessjøen	Nordland	1894	76
Mosjøen	Nordland	1895	77
Mo i Rana	Nordland	1896	78
Lofoten	Nordland	1897	79
Vesterålen	Nordland	1898	80
Harstad	Troms	1991	81
Tromsø	Troms	1992	82
Andselv	Troms	1993	83
Finnsnes	Troms	1994	84
Nord-Troms	Troms	1995	85
Vadsø	Finnmark	2091	86
Hammerfest	Finnmark	2092	87
Alta	Finnmark	2093	88
Kirkenes	Finnmark	2094	89

Appendix C. Classification of education

Table C1. Educational groups

Own Codes	Description	Classification numbers of education	English abbreviations used in the current paper
1	Compulsory education	0,1,2	*LOW*
2	Study-oriented upper secondary education	30, 315, 368, 40, 415, 468, 34, 44, 50, 54	*SUS*
3	Vocational education	3, 4, 5 (except for codes mentioned above)	*VOC*
4	First stage of higher education, undergraduate level	6	*HIGH*
4	Second stage of higher education (post- graduate education)	7, 8	*HIGH*
5	Unspecified/Unknown	9	

Appendix D. Measures of dispersion across observational units

Table D1. Annual coefficients of variation for the real hourly wage variable

	Type of education			
Year	LOW	VOC	SUS	HIGH
2001	0.071	0.076	0.082	0.084
2002	0.065	0.079	0.080	0.082
2003	0.064	0.081	0.081	0.097
2004	0.077	0.089	0.094	0.123
2005	0.061	0.070	0.081	0.104
2006	0.068	0.075	0.086	0.106
2007	0.065	0.078	0.088	0.115
2008	0.063	0.079	0.085	0.117
2009	0.065	0.086	0.089	0.123
2010	0.073	0.084	0.087	0.121
2011	0.059	0.076	0.084	0.112
2012	0.057	0.075	0.086	0.110
2013	0.060	0.076	0.086	0.110
2014	0.063	0.080	0.082	0.107

Table D2. Annual coefficient of variation for the unemployment rate variable

	Type of education			
Year	LOW	VOC	SUS	HIGH
2001	0.358	0.457	0.382	0.361
2002	0.326	0.404	0.356	0.337
2003	0.300	0.348	0.312	0.306
2004	0.293	0.356	0.286	0.324
2005	0.281	0.330	0.283	0.301
2006	0.284	0.354	0.302	0.295
2007	0.318	0.372	0.333	0.327
2008	0.321	0.395	0.327	0.331
2009	0.294	0.354	0.343	0.315
2010	0.283	0.288	0.279	0.261
2011	0.300	0.311	0.286	0.272
2012	0.311	0.304	0.268	0.266
2013	0.319	0.333	0.299	0.279
2014	0.322	0.337	0.289	0.269

Table D3. Spearman correlation coefficients of mean real hourly wage. Individuals with low education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.88	1.00												
‘03	0.85	0.89	1.00											
‘04	0.85	0.87	0.91	1.00										
‘05	0.84	0.87	0.86	0.93	1.00									
‘06	0.82	0.84	0.86	0.90	0.92	1.00								
‘07	0.81	0.80	0.82	0.89	0.87	0.89	1.00							
‘08	0.76	0.73	0.76	0.80	0.80	0.83	0.89	1.00						
‘09	0.74	0.77	0.75	0.78	0.79	0.80	0.84	0.93	1.00					
‘10	0.76	0.77	0.78	0.80	0.79	0.79	0.89	0.89	0.93	1.00				
‘11	0.75	0.73	0.77	0.76	0.72	0.74	0.85	0.85	0.84	0.89	1.00			
‘12	0.73	0.71	0.76	0.76	0.73	0.72	0.80	0.81	0.84	0.87	0.92	1.00		
‘13	0.71	0.66	0.72	0.75	0.72	0.71	0.82	0.84	0.84	0.84	0.89	0.93	1.00	
‘14	0.71	0.68	0.73	0.74	0.71	0.74	0.82	0.81	0.83	0.87	0.88	0.93	0.92	1.00

Table D4. Spearman correlation coefficient of unemployment rates. Individuals with low education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.94	1.00												
‘03	0.88	0.90	1.00											
‘04	0.81	0.84	0.87	1.00										
‘05	0.73	0.77	0.77	0.90	1.00									
‘06	0.75	0.78	0.77	0.80	0.88	1.00								
‘07	0.64	0.70	0.70	0.76	0.82	0.87	1.00							
‘08	0.69	0.71	0.73	0.73	0.77	0.84	0.88	1.00						
‘09	0.73	0.74	0.75	0.74	0.77	0.82	0.83	0.91	1.00					
‘10	0.51	0.52	0.58	0.63	0.60	0.63	0.66	0.76	0.79	1.00				
‘11	0.50	0.54	0.59	0.66	0.65	0.69	0.77	0.81	0.82	0.87	1.00			
‘12	0.52	0.52	0.57	0.60	0.61	0.70	0.75	0.82	0.81	0.79	0.93	1.00		
‘13	0.52	0.51	0.54	0.61	0.61	0.70	0.76	0.81	0.80	0.78	0.89	0.95	1.00	
‘14	0.52	0.51	0.59	0.64	0.67	0.74	0.76	0.83	0.82	0.79	0.86	0.90	0.92	1.00

Table D5. Spearman correlation coefficient of mean real hourly wage. Individuals with vocational education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.87	1.00												
‘03	0.87	0.96	1.00											
‘04	0.84	0.87	0.89	1.00										
‘05	0.85	0.88	0.93	0.92	1.00									
‘06	0.84	0.87	0.91	0.92	0.97	1.00								
‘07	0.83	0.87	0.92	0.91	0.96	0.97	1.00							
‘08	0.87	0.83	0.87	0.87	0.92	0.91	0.95	1.00						
‘09	0.81	0.87	0.89	0.87	0.92	0.92	0.95	0.94	1.00					
‘10	0.78	0.83	0.88	0.85	0.91	0.90	0.94	0.92	0.96	1.00				
‘11	0.78	0.83	0.87	0.81	0.87	0.85	0.90	0.89	0.94	0.96	1.00			
‘12	0.75	0.81	0.84	0.79	0.86	0.85	0.87	0.87	0.93	0.93	0.96	1.00		
‘13	0.73	0.77	0.82	0.77	0.84	0.83	0.87	0.86	0.92	0.93	0.95	0.97	1.00	
‘14	0.75	0.78	0.82	0.81	0.85	0.85	0.89	0.89	0.94	0.94	0.96	0.96	0.97	1.00

Table D6. Spearman correlation coefficient of unemployment rates. Individudals with vocational education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.93	1.00												
‘03	0.83	0.85	1.00											
‘04	0.80	0.80	0.82	1.00										
‘05	0.62	0.68	0.69	0.80	1.00									
‘06	0.61	0.69	0.66	0.70	0.89	1.00								
‘07	0.57	0.66	0.62	0.65	0.76	0.90	1.00							
‘08	0.52	0.62	0.59	0.59	0.71	0.81	0.90	1.00						
‘09	0.47	0.57	0.55	0.51	0.64	0.75	0.82	0.84	1.00					
‘10	0.34	0.38	0.38	0.38	0.48	0.60	0.65	0.64	0.80	1.00				
‘11	0.38	0.42	0.41	0.50	0.58	0.61	0.62	0.57	0.66	0.80	1.00			
‘12	0.33	0.41	0.38	0.49	0.59	0.66	0.64	0.58	0.67	0.69	0.83	1.00		
‘13	0.27	0.36	0.34	0.43	0.54	0.67	0.70	0.65	0.72	0.74	0.77	0.90	1.00	
‘14	0.23	0.34	0.30	0.41	0.52	0.63	0.67	0.62	0.70	0.70	0.68	0.83	0.85	1.00

Table D7. Spearman correlation coefficient of mean real hourly wage. Individuals with study-oriented upper secondary education

	Year													
Year	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	'13	'14
'01	1.00													
'02	0.87	1.00												
'03	0.86	0.95	1.00											
'04	0.84	0.86	0.91	1.00										
'05	0.87	0.89	0.93	0.92	1.00									
'06	0.85	0.86	0.91	0.89	0.94	1.00								
'07	0.83	0.86	0.91	0.87	0.93	0.95	1.00							
'08	0.87	0.89	0.92	0.89	0.91	0.92	0.95	1.00						
'09	0.83	0.86	0.87	0.87	0.89	0.91	0.94	0.95	1.00					
'10	0.87	0.84	0.87	0.86	0.87	0.88	0.90	0.91	0.91	1.00				
'11	0.82	0.84	0.89	0.85	0.89	0.90	0.93	0.93	0.95	0.92	1.00			
'12	0.80	0.84	0.90	0.85	0.87	0.88	0.91	0.91	0.92	0.90	0.95	1.00		
'13	0.81	0.87	0.90	0.84	0.87	0.88	0.90	0.93	0.93	0.90	0.95	0.96	1.00	
'14	0.81	0.87	0.89	0.85	0.86	0.87	0.88	0.92	0.91	0.89	0.93	0.94	0.97	1.00

Table D8. Spearman correlation coefficient of unemployment rates. Individuals with study-oriented upper secondary education

	Year													
Year	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	'13	'14
'01	1.00													
'02	0.89	1.00												
'03	0.82	0.87	1.00											
'04	0.73	0.74	0.82	1.00										
'05	0.63	0.62	0.63	0.79	1.00									
'06	0.73	0.66	0.67	0.76	0.83	1.00								
'07	0.68	0.59	0.58	0.68	0.78	0.83	1.00							
'08	0.69	0.60	0.61	0.60	0.60	0.71	0.79	1.00						
'09	0.62	0.62	0.59	0.55	0.59	0.64	0.69	0.73	1.00					
'10	0.48	0.50	0.46	0.51	0.50	0.54	0.56	0.65	0.71	1.00				
'11	0.42	0.45	0.43	0.48	0.53	0.58	0.63	0.61	0.62	0.78	1.00			
'12	0.41	0.40	0.43	0.48	0.55	0.56	0.65	0.61	0.62	0.65	0.78	1.00		
'13	0.33	0.36	0.37	0.41	0.44	0.55	0.55	0.53	0.59	0.65	0.74	0.75	1.00	
'14	0.30	0.28	0.34	0.52	0.53	0.55	0.60	0.54	0.57	0.66	0.65	0.69	0.75	1.00

Table D9. Spearman correlation coefficient of mean real hourly wage. Individuals with high education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.74	1.00												
‘03	0.80	0.76	1.00											
‘04	0.70	0.44	0.80	1.00										
‘05	0.78	0.54	0.81	0.84	1.00									
‘06	0.78	0.59	0.81	0.82	0.92	1.00								
‘07	0.78	0.66	0.87	0.80	0.87	0.92	1.00							
‘08	0.84	0.69	0.86	0.80	0.89	0.89	0.92	1.00						
‘09	0.82	0.70	0.88	0.81	0.88	0.87	0.91	0.96	1.00					
‘10	0.80	0.69	0.85	0.78	0.83	0.86	0.89	0.93	0.95	1.00				
‘11	0.83	0.76	0.87	0.75	0.84	0.86	0.91	0.94	0.95	0.93	1.00			
‘12	0.82	0.75	0.89	0.75	0.85	0.84	0.92	0.95	0.95	0.92	0.96	1.00		
‘13	0.81	0.72	0.85	0.74	0.82	0.83	0.89	0.92	0.94	0.92	0.95	0.96	1.00	
‘14	0.80	0.73	0.87	0.79	0.83	0.83	0.89	0.93	0.94	0.92	0.93	0.95	0.96	1.00

Table D10. Spearman correlation coefficient of unemployment rates. Individuals with high education

	Year													
Year	‘01	‘02	‘03	‘04	‘05	‘06	‘07	‘08	‘09	‘10	‘11	‘12	‘13	‘14
‘01	1.00													
‘02	0.68	1.00												
‘03	0.62	0.73	1.00											
‘04	0.73	0.64	0.81	1.00										
‘05	0.58	0.55	0.76	0.85	1.00									
‘06	0.61	0.58	0.66	0.74	0.72	1.00								
‘07	0.54	0.54	0.62	0.66	0.64	0.73	1.00							
‘08	0.50	0.54	0.52	0.60	0.58	0.70	0.76	1.00						
‘09	0.37	0.56	0.53	0.45	0.56	0.56	0.57	0.72	1.00					
‘10	0.43	0.47	0.61	0.66	0.67	0.61	0.60	0.69	0.65	1.00				
‘11	0.36	0.37	0.53	0.54	0.55	0.48	0.54	0.54	0.41	0.77	1.00			
‘12	0.31	0.39	0.46	0.49	0.46	0.37	0.38	0.45	0.48	0.65	0.74	1.00		
‘13	0.20	0.30	0.44	0.40	0.44	0.36	0.39	0.43	0.40	0.67	0.73	0.72	1.00	
‘14	0.26	0.23	0.43	0.43	0.49	0.42	0.40	0.42	0.40	0.62	0.63	0.61	0.80	1.00

Appendix E. Comparison of migration rates in an international context

Table E1. Regional mobility rates at the NUTS 2 level in selected European countries in 2006

Country	Regional mobility rate[a]
Norway	1.6
Austria	0.7
Germany	1.3
Spain	1.0
France	1.7
Netherlands	1.9[b]
Sweden	1.6
UK	1.9
Poland	0.2

[a] Percent of population which has moved residence within the country from one NUTS-2 region to another since 2005.
[b]The figure is for the year 1999.
Source for all countries expect Norway: Table A9 in Bonin *et al.* (2008).

Appendix F. Additional estimation results

Table F1. Robustness of the estimates in Table 1 with respect to sample for estimation[a]

Parameter	Mean	Std. dev	Mini-mum	Maxi-mum	Median	1st Quar-tile	3rd Quar-tile	IQ range
$\beta^{M,IN,LOW}$	0.836	0.022	0.639	0.861	0.838	0.836	0.840	0.003
$\gamma^{M,IN,LOW}$	-0.055	0.003	-0.070	-0.046	-0.054	-0.056	-0.053	0.003
$\theta^{M,IN,LOW}$	0.168	0.018	0.109	0.224	0.170	0.162	0.176	0.014
$\beta^{M,IN,VOC}$	1.010	0.033	0.706	1.029	1.013	1.012	1.015	0.003
$\gamma^{M,IN,VOC}$	-0.020	0.002	-0.029	-0.014	-0.020	-0.021	-0.019	0.002
$\beta^{M,IN,SUS}$	0.925	0.013	0.906	1.039	0.925	0.922	0.926	0.004
$\theta^{M,IN,SUS}$	0.491	0.024	0.403	0.569	0.489	0.482	0.503	0.021
$\beta^{M,IN,HIGH}$	1.067	0.029	0.795	1.080	1.070	1.068	1.072	0.003
$\eta^{M,IN,HIGH}$	0.526	0.051	0.365	0.642	0.525	0.502	0.548	0.047
$\beta^{M,OUT,LOW}$	0.950	0.017	0.799	0.965	0.951	0.949	0.953	0.004
$\gamma^{M,OUT,LOW}$	0.094	0.004	0.077	0.104	0.095	0.093	0.096	0.003
$\theta^{M,OUT,LOW}$	-0.135	0.008	-0.174	-0.118	-0.134	-0.138	-0.131	0.008
$\eta^{M,OUT,LOW}$	0.368	0.032	0.197	0.449	0.369	0.362	0.380	0.018
$\beta^{M,OUT,VOC}$	1.200	0.042	1.176	1.589	1.195	1.194	1.197	0.003
$\beta^{M,OUT,SUS}$	1.481	0.145	1.452	2.831	1.467	1.464	1.468	0.004
$\gamma^{M,OUT,SUS}$	0.036	0.003	0.026	0.043	0.036	0.035	0.038	0.002
$\beta^{M,OUT,HIGH}$	1.293	0.041	1.274	1.677	1.289	1.288	1.290	0.002

[a]We sequentially omitted one of the observational units and re-estimated the model. This procedure yields 89 different estimates, since there are 89 observational units. The table shows summary statistics based on these estimates for the 17 parameters in the systematic part of the model.

Table F2. Parameter estimates in the set of regression models of internal migration. Different samples

Parameter	Type of variable	2002-2014	2003-2014	2002-2013
$\beta^{M,IN,LOW}$	Population	0.838	0.818	0.847
		(9.299)	(8.163)	(7.327)
$\gamma^{M,IN,LOW}$	Unemployment rate	-0.055	-0.031	-0.070
		(-2.267)	(-1.152)	(-2.763)
$\theta^{M,IN,LOW}$	Real wage	0.168	0.243	0.155
		(1.287)	(1.643)	(1.126)
$\beta^{M,IN,VOC}$	Population	1.013	0.993	0.978
		(11.473)	(9.928)	(8.579)
$\gamma^{M,IN,VOC}$	Unemployment rate	-0.020	-0.010	-0.021
		(-1.030)	(-0.446)	(-1.011)
$\beta^{M,IN,SUS}$	Population	0.924	0.890	0.808
		(7.533)	(6.806)	(9.718)
$\theta^{M,IN,SUS}$	Real wage	0.491	0.292	0.372
		(2.201)	(1.218)	(1.571)
$\beta^{M,IN,SUS}$	Population	1.069	1.063	0.984
		(12.073)	(10.958)	(10.754)
$\eta^{M,IN,SUS}$	Employment share	0.548	0.497	0.668
		(1.244)	(0.883)	(1.260)
$\beta^{M,OUT,LOW}$	Population	0.950	0.961	0.940
		(22.362)	(24.587)	(21.783)
$\gamma^{M,OUT,LOW}$	Unemployment	0.095	0.094	0.089
		(3.544)	(3.320)	(3.191)
$\theta^{M,OUT,LOW}$	Real wage	-0.135	-0.119	-0.105
		(-2.107)	(-1.773)	(-1.573)
$\eta^{M,OUT,LOW}$	Employment share	0.370	0.241	0.377
		(2.331)	(1.474)	(2.320)
$\beta^{M,OUT,VOC}$	Population	1.196	1.168	1.231
		(20.073)	(22.080)	(13.623)
$\theta^{M,OUT,VOC}$	Real wage	-0.135[a]	-0.119[a]	-0.105[a]
$\beta^{M,OUT,SUS}$	Population	1.468	1.429	1.506
		(9.842)	(10.713)	(5.214)
$\gamma^{M,OUT,SUS}$	Unemployment	0.036	0.035	0.039
		(1.920)	(1.755)	(1.911)
$\beta^{M,OUT,HIGH}$	Population	1.290	1.278	1.379
		(23.235)	(23.934)	(15.708)
$\theta^{M,OUT,HIGH}$	Real wage	-0.135[a]	-0.119[a]	-0.105[a]

[a]A priori restrictions: $\theta^{M,OUT,HIGH} = \theta^{M,OUT,VOC} = \theta^{M,OUT,LOW}$.

Note: The number of observations is 1,157 for the estimates in the first column and 1,068 for the estimates in the two last columns. Region-specific fixed effects and annual fixed effects are included in all equations. *t*-values (in parentheses) are based on heteroskedastic-consistent estimates of standard errors.

Table F3. Robustness of the estimates in Table 3 (commuting workers) with respect to sample for estimation[a]

Parameter	Mean	Std. dev	Minimum	Maximum	Median	1st Quartile	3rd Quartile	IQ range
$\beta^{C,IN,LOW}$	0.787	0.015	0.758	0.900	0.786	0.782	0.789	0.007
$\gamma^{C,IN,LOW}$	-0.060	0.004	-0.069	-0.046	-0.060	-0.062	-0.058	0.003
$\theta^{C,IN,LOW}$	0.354	0.026	0.290	0.456	0.353	0.343	0.365	0.022
$\eta^{C,IN,LOW}$	0.192	0.016	0.129	0.237	0.194	0.188	0.201	0.012
$\beta^{C,IN,VOC}$	0.767	0.010	0.724	0.803	0.767	0.763	0.771	0.008
$\gamma^{C,IN,VOC}$	-0.032	0.003	-0.044	-0.021	-0.032	-0.034	-0.031	0.002
$\eta^{C,IN,VOC}$	0.936	0.074	0.662	1.186	0.937	0.909	0.957	0.048
$\beta^{C,IN,SUS}$	0.645	0.043	0.246	0.680	0.649	0.647	0.652	0.005
$\beta^{C,IN,HIGH}$	0.340	0.031	0.303	0.624	0.337	0.335	0.339	0.004
$\gamma^{C,IN,HIGH}$	-0.015	0.002	-0.022	-0.012	-0.015	-0.016	-0.014	0.002
$\beta^{C,OUT,LOW}$	0.353	0.049	0.329	0.805	0.349	0.346	0.351	0.005
$\eta^{C,OUT,LOW}$	-0.265	0.021	-0.301	-0.105	-0.267	-0.274	-0.261	0.014
$\beta^{C,OUT,VOC}$	0.393	0.037	0.376	0.737	0.390	0.387	0.392	0.005
$\beta^{C,OUT,SUS}$	0.612	0.099	0.585	1.531	0.602	0.600	0.604	0.005
$\gamma^{C,OUT,SUS}$	0.019	0.003	0.010	0.032	0.019	0.018	0.019	0.001
$\theta^{C,OUT,SUS}$	-0.409	0.045	-0.491	-0.173	-0.415	-0.428	-0.405	0.022
$\eta^{C,OUT,SUS}$	-0.207	0.012	-0.246	-0.146	-0.208	-0.212	-0.204	0.009
$\beta^{C,OUT,HIGH}$	0.444	0.027	0.430	0.689	0.442	0.439	0.443	0.004
$\gamma^{C,OUT,HIGH}$	0.015	0.001	0.011	0.020	0.014	0.014	0.015	0.001
$\theta^{C,OUT,HIGH}$	-0.150	0.006	-0.162	-0.116	-0.150	-0.153	-0.148	0.005

[a]We sequentially omitted one of the observational units and re-estimated the model. This procedure yields 89 different estimates, since there are 89 observational units. The table shows summary statistics based on these estimates for the 20 parameters in the systematic part of the model.

Table F4. Parameter estimates in the set of regression models for commuting. Different samples

Parameter	Type of variable	2002-2014	2003-2014	2002-2013
$\beta^{C,IN,LOW}$	Population	0.786	0.746	0.810
		(12.076)	(11.230)	(10.942)
$\gamma^{C,IN,LOW}$	Unemployment rate	-0.060	-0.056	-0.054
		(-2.430)	(-2.165)	(-2.108)
$\theta^{C,IN,LOW}$	Real wage	0.193	0.140	0.194
		(1.789)	(1.269)	(1.763)
$\eta^{C,IN,LOW}$	Employment share	0.352	0.281	0.392
		(2.630)	(2.042)	(2.727)
$\beta^{C,IN,VOC}$	Population	0.768	0.764	0.812
		(12.400)	(11.283)	(13.894)
$\gamma^{C,IN,VOC}$	Unemployment rate	-0.032	-0.022	-0.032
		(-1.705)	(-1.140)	(-1.581)
$\eta^{C,IN,VOC}$	Employment share	0.934	0.903	0.764
		(2.778)	(2.673)	(2.057)
$\beta^{C,IN,SYS}$	Population	0.649	0.622	0.644
		(11.703)	(9.914)	(9.920)
$\beta^{C,IN,HIGH}$	Population	0.337	0.322	0.335
		(7.331)	(7.260)	(4.617)
$\gamma^{C,IN,HIGH}$	Unemployment rate	-0.015	-0.017	-0.015
		(-1.170)	(-1.275)	(-1.082)
$\beta^{C,OUT,LOW}$	Population	0.350	0.317	0.435
		(3.188)	(3.030)	(2.391)
$\eta^{C,OUT,LOW}$	Employment share	-0.266	-0.330	-0.188
		(-3.432)	(-4.390)	(-1.855)
$\beta^{C,OUT,VOC}$	Population	0.391	0.364	0.467
		(4.718)	(4.426)	(3.332)
$\beta^{C,OUT,SUS}$	Population	0.604	0.570	0.700
		(4.753)	(4.775)	(3.101)
$\gamma^{C,OUT,SUS}$	Unemployment rate	0.019	0.027	0.011
		(1.371)	(1.884)	(0.854)
$\theta^{C,OUT,SUS}$	Real wage	-0.208	-0.189	-0.207
		(-2.575)	(-2.407)	(-2.575)
$\eta^{C,OUT,SUS}$	Employment share	-0.413	-0.445	-0.361
		(-2.522)	(-2.568)	(-2.072)
$\beta^{C,OUT,HIGH}$	Population	0.442	0.435	0.492
		(7.010)	(6.675)	(5.035)
$\gamma^{C,OUT,HIGH}$	Unemployment rate	0.014	0.011	0.012
		(1.896)	(1.378)	(1.501)
$\theta^{C,OUT,HIGH}$	Real wage	-0.150	-0.148	-0.137
		(-3.388)	(-3.396)	(-3.015)

Note: The number of observations is 1,157 for the estimates in the first column and 1,068 for the estimates in two last columns. Region-specific fixed effects and annual fixed effects are included in all equations. *t*-values (in parentheses) are based on heteroskedasticity-consistent estimates of standard errors.