The migration of technical workers

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PRELIMINARY DRAFT

Abstract

Using panel data on the Danish population, we explore the revealed preferences of scientists and engineers for the places in which they choose to work. Our results indicate that these technical workers exhibit substantial sensitivity to differences in wages but that they have even stronger preferences for living close to family and friends. The magnitude of these preferences, moreover, suggests that the greater geographic mobility of scientists and engineers, relative to the population as a whole, stems from more pronounced variation across regions in the wages that they can expect. These results remain robust to estimation on a sample of individuals who must select new places of work for reasons unrelated to their preferences—those who had been employed at establishments that discontinued operations.

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1 Introduction

Bureaucrats, politicians and social scientists believe that engineers and scientists play a particularly important role in the economic vitality of the regions in which they work. By stimulating the regional rate of innovation, these individuals not only create a great deal of value for local economies themselves, but also their innovations often increase the productivity of others around them (Romer, 1986). As a result, much attention has been given to the movement of these technical workers from one place to another. Some have spun this movement in a positive light, focusing on the contributions of these individuals to the places that receive them. Foreign-born scientists, for example, account for a large share of the academics in the United States, and an even larger share of the prominent ones (Levin and Stephan, 1999; Stephan and Levin, 2001). Others have pointed to its potential downside for the regions losing this valuable human capital, the so-called "brain drain" (Bhagwati and Hamada, 1974; Galor and Tsiddon, 1997).

Despite this interest and the importance of these individuals to the economy, social scientists nevertheless have a relatively limited understanding of why these individuals move. Most of the research to date has focused on the flows of professionals, scientists and engineers across countries. Though these individuals appear more mobile than the general population (Dumont and Lemaitre, 2005), several factors might account for this pattern. On the one hand, these highly educated individuals may have more to gain economically from moving than their compatriots with less human capital. On the other hand, scientists and engineers may place less value than others on remaining proximate to family and friends. Alternatively, these patterns may simply reflect immigration policy. Countries, particularly in the latter half of the twentieth century, have been more welcoming of highly educated immigrants. Even if technical and non-technical workers have similar interests in moving, one might

therefore expect these policies to produce higher observed rates of international migration among the well educated.

To learn more about the individual-level factors underlying the geographic mobility of technical workers, we focus on the within-country migration of these individuals. Though less pronounced than when moving across national borders, within-country moves also undoubtedly reflect the preferences that people place on the possibility of earning higher income versus the value of remaining close to family and friends. They have the advantage, however, of not being distorted by immigration policies. The intra-country mobility of scientists and engineers also deserves attention in its own right. To the extent that the spillovers generated by these individuals occur at a more local level than the nation as a whole, understanding their decisions about where to work within a country can improve our understanding of why some regions grow while others stagnate.

To examine this within-country migration of technical workers, we analyze data from Denmark. Though a small country, the Danish labor market exhibits similar levels of both organizational and geographic mobility to the United States (Sørensen and Sorenson, 2007; Dahl and Sorenson, 2008).[1] We therefore have no reason to believe that the results might not extrapolate to other populations. The Danish data, moreover, have two central advantages over comparable data from the United States, the most commonly studied country. First, they include detailed education data on every employee in Denmark, allowing us to construct counterfactual incomes for the amount that technical workers could expect to earn if they moved elsewhere. Second, they contain links from individuals to their families and to their specific educational institutions, allowing us to calculate the distances from various locations to family and friends (classmates).

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[1]Because of its size, one can only compare geographic mobility in Denmark to within-state movements in the United States. A move of the distance of Los Angeles to New York would land a Dane in Dubai.

We estimate choice models of where those trained in science and engineering choose to work in 2006. Our analysis focuses on these decisions among two samples of those educated in science and engineering: (i) a random sample of those working anywhere in 2005, and (ii) all those employed in 2004 at workplaces that closed in 2004 or employed in 2005 at workplaces that close in 2005. The latter sample addresses the fact that individuals may vary (endogenously) in their propensities to consider changes in employment. We find that technical workers value (in order of importance from most to least): (i) proximity to places they have lived in the past 25 years, (ii) proximity to college classmates, (iii) proximity to their current homes, (iv) urban areas, (v) proximity to high school classmates, (vi) proximity to parents, and (vii) income. The magnitudes of these preferences for proximity to friends and family, moreover, are large. For example, the average Danish scientist or engineer appears willing to tradeoff $41,572 in annual income for a one standard deviation increase in the number of high school classmates in the region.

We believe that the paper offers several contributions. First, it offers an approach for estimating the revealed preferences of individuals for trading off income versus other factors in their choices of where to work. Prior research has typically focused on either economic or social factors in location choice, but not both (Dahl and Sorenson, 2008). Second, it provides a rare look at the within-country geography and migration of scientists and engineers. Even within Denmark, we observe substantial net migrations of technical workers from some regions to others. But the pattern is far from simple. Neither differences in income nor in population can adequately explain these flows. Third, it documents the fact that these individuals place a high value of locating close to family, and especially, friends. That fact has important implications for the geographic distribution of skilled labor, return migration, and the persistence of economic inequality across regions.

2 Inter-regional migration

Although the more general research on migration has examined both the international and the within-country flows of individuals, the research specific to the geographic mobility of scientists and engineers has been almost exclusive in its focus on the movements of these technical workers across countries—perhaps most frequently investigating the possibility of a brain drain from less developed to more developed economies (e.g., Dumont and Lemaitre, 2005). These international flows of scientists and engineers remain an important issue, but we see the intra-country movements of technical workers as an almost equally significant topic for two reasons. First and foremost, just as a brain drain may handicap the economic growth of developing nations, the movement of scientists and engineers from some regions to others within a country could exacerbate, rather than dampen, within-country inequalities. Second, the examination of these within-country moves may lead to a better understanding of migration in general by studying it in a setting free from the influence of immigration policies and linguistic differences.

Our analysis here focuses on the within-country movement of scientists and engineers in Denmark using the Integrated Database for Labor Market Research (referred to by its Danish acronym, IDA) maintained by Statistics Denmark. Although ideally one might want to explore the location choices of technical workers in a larger country, such as the United States, the Danish data offer several advantages that counterbalance the potential limited generalizability of focusing on such a small country: The IDA database, for example, allows researchers to distinguish between earned and unearned income, to track all residents of Denmark for 26 years, to identify the educational degrees that they earned, and to link individuals to their parents, siblings and high school and college classmates.

We identify (potential) technical workers through their educational backgrounds. In

particular, we consider someone a technical worker if they received a master's or doctorate degree in a biological or physical science, engineering or medicine (regardless of whether they needed such an educational credential for their current job). Alternatively, one could use occupational codes as a means of identifying those employed in technical positions. Such an approach would nevertheless have two critical disadvantages.[2] First, individuals with similar backgrounds and engaged in similar activities can hold a wide variety of job titles. An engineer, for example, might have the job of professor, supervisor or consultant. Second, and probably more important, an individual's occupation may depend on the availability of jobs in a region. Such an approach, therefore, could lead to the unpalatable consequence that a person's status as a technical worker might depend on his or her choice of location.

2.1 The geography of technical employment

We begin our analysis with some descriptive information on the geography of technical employment in Denmark. Figure 1 depicts the concentration of those educated as scientists and engineers per thousand employees in 2006. Each delineated boundary outlines a township (*kommune* in Danish). Note that the regions with the highest concentrations have at least five times the density of technical workers as those regions with the lowest concentrations. In terms of situating these concentrations relative to specific places, the densest concentrations on this map appear in and around Copenhagen and Århus – the two largest cities in Denmark, both home to large universities – but many smaller towns, such as Kalundborg, Nordborg and Viborg, show similarly high concentrations of these workers.

What might explain these differences? The literature on the international flows on sci-

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[2]In our data, a practical issue also arises. Statistics Denmark maintains far less detailed information on occupation than on education, so classification by occupation would require us to aggregate scientists and engineers much more coarsely than we currently do.
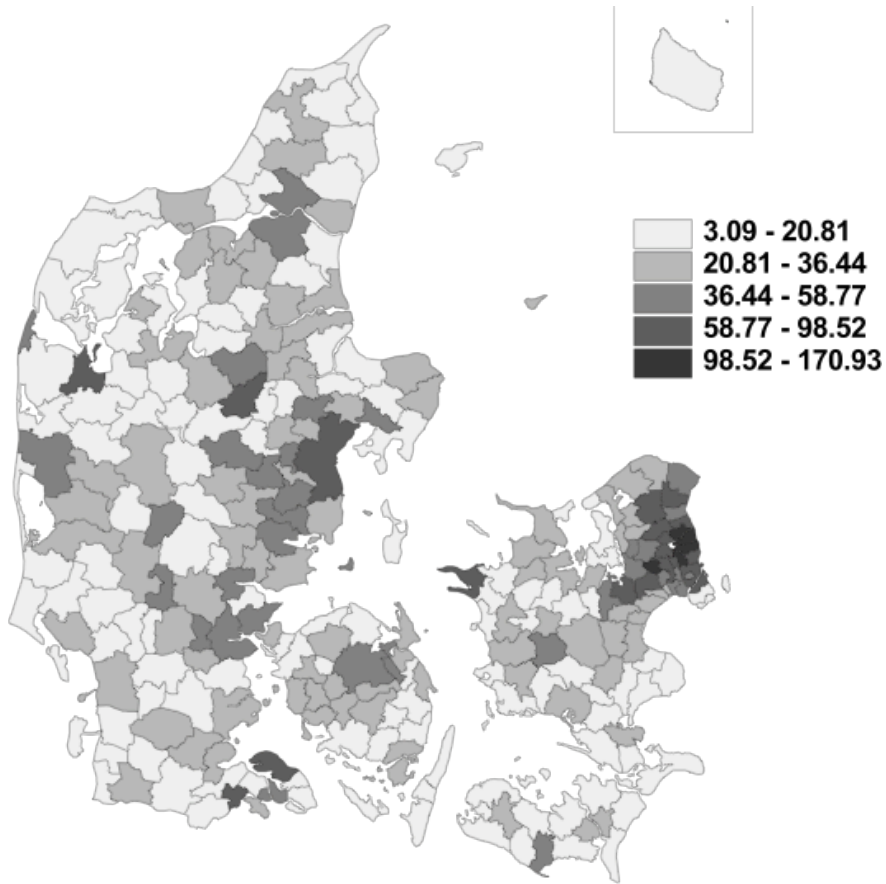
Figure 1: Danish townships (kommuner) shaded by technical workers per 1000

entists and engineers has primarily focused on two mechanisms. The first is migration to escape persecution or repression. In the 1930s, for example, the Nazis dismissed thousands of academics from their posts in Germany, most of whom then moved to institutions in England or the United States (Medawar and Pyke, 2001). This explanation, however, has little to say about the within-country movements of technical workers. The second mechanism is the lure of more attractive economic opportunities. Concerns about brain drains have primarily been in terms of scientists, engineers and professionals leaving less developed countries for places like Canada and the United States where they can earn far more than they could in their home countries, but even within countries technical workers may have much to gain by
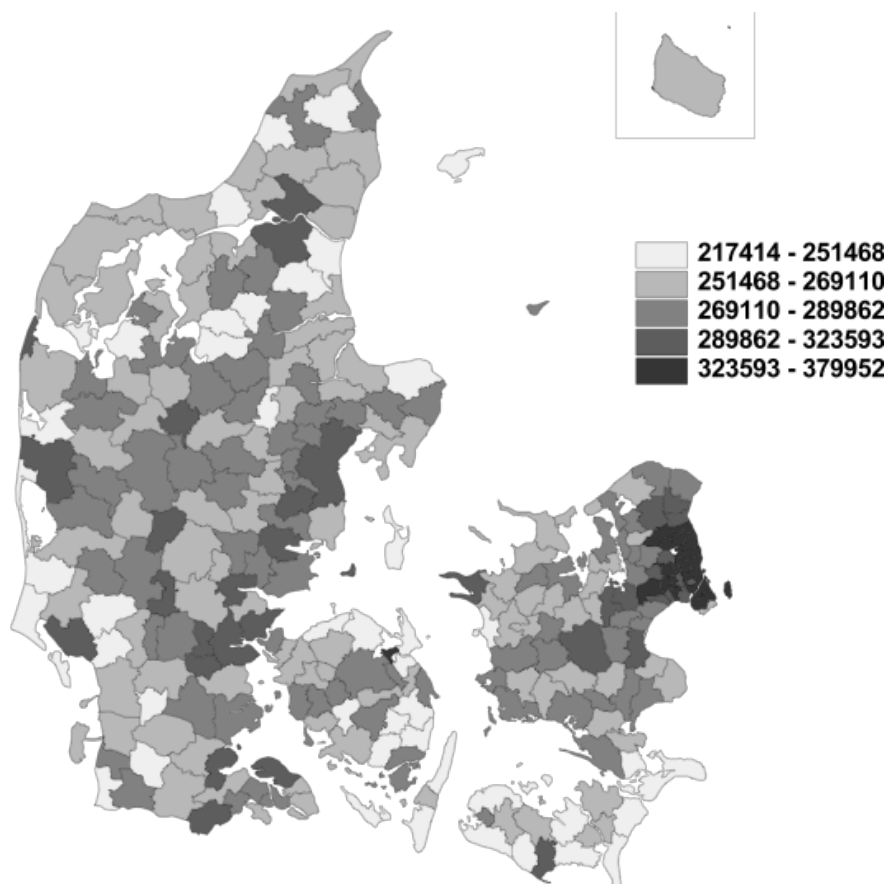
moving from one region to another.

Figure 2: Danish townships (kommuner) shaded by average income

To consider how income differences might influence within-country migration patterns, let us first examine how income varies across Denmark. In figure 2, the shading of each region (*kommune*) on the map represents its average income per employed person, in 2006, in kroner per year. Using the average exchange rate for 2006 of 5.94 kroner per dollar, these income categories would convert to the following in dollar amounts: $36,572 to $42,300; $42,301 to $45,269; $45,270 to $48,759; $48,760 to $54,434; and $54,435 to $63,914. The residents of some regions enjoy average incomes 30% higher than others. Perhaps not surprisingly, the same regions with the densest concentrations of technical workers also have the highest
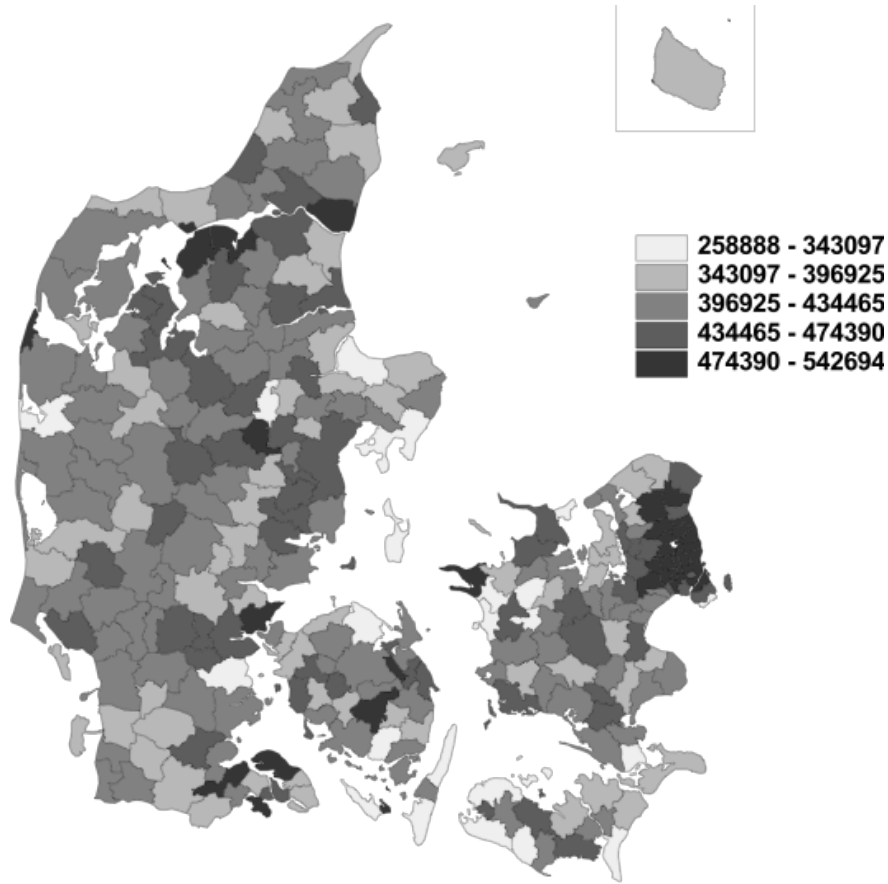
average incomes.

Figure 3: Danish townships (kommuner) shaded by average technical worker income

But this variation in average income does not necessarily mean that scientists and engineers earn more in these regions. It could instead reflect compositional differences in the people employed there or in the kinds of work they do. Most obviously, these averages include the incomes of technical workers themselves, who tend to earn more than the median employee in the population. To address these issues, we isolate technical employees and examine their average incomes by location in figure 3. Again, converting these income categories to 2006 dollars yields: $43,584 to $57,760; $57,761 to $66,822; $66,823 to $73,142; $73,143 to $79,864; and $79,865 to $91,363. A comparison of these two graphs suggests relatively few

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differences; in general, technical workers earn more in the regions in which all employees have higher average incomes. Interestingly, after focusing on this more homogenous subsample of individuals the differences across regions actually widen.

2.2   The mobility of technical workers

Although scientists and engineers appear highly concentrated in some regions, this concentration does not necessarily imply geographic mobility. As noted above, some of the places with the densest concentrations also have large universities. Those receiving degrees from these institutions might simply tend to stay in the surrounding area. We therefore must consider not just the stocks of individuals by region but also their flows.

We begin our examination of the migration of scientists and engineers by mapping the source and sink regions for those educated in science and engineering. Figure 4 colors townships (*kommune*) according to the net migration of technical workers per 1000 employees into and out of the regions in which they received their high school educations. Those shaded in green received more scientists and engineers than they lost. Those regions colored in red, meanwhile, experienced a net exodus of technical workers. Regions with no coloring may have experienced migration, but the inflows and outflows balanced. Most of the regions gaining scientists and engineers appear to border either the east coast of Jutland, the west or east coast of Funen, or the north or south coast of Zealand. Interestingly, a comparison of this map to figures 1 and 3 reveals that many of the regions with the greatest gains in technical workers neither have the highest current concentrations of those employees nor do they offer them the highest average incomes.

One can also examine migration at the level of the individual. Here, we find it instructive to compare the geographic mobility of scientists and engineers to non-technical workers.
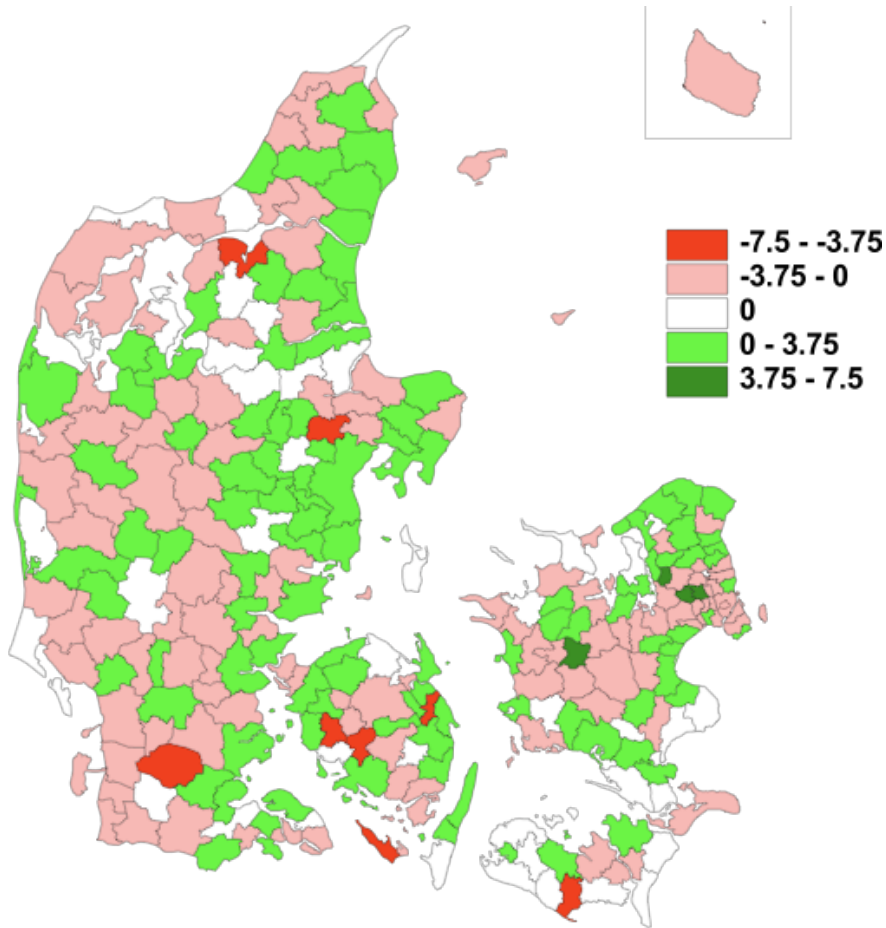
Figure 4: Danish townships (kommuner) colored by net technical worker migration per 1000

Figure 5 graphs the kernel density estimates of the distribution of the distance between where individuals worked in 2005 and where they worked in 2006. Among both technical and non-technical workers, we see that the largest number of individuals stays employed in the same place – often with the same employer – and that the mass of the probability distribution drops rapidly from a distance of zero to roughly 10 km. Beyond that point, the distribution flattens out. If one must move residences, it appears that the distance of that move may not matter much.

Although the graphs look quite similar, note that the peak of the density distribution

Figure 5: Geographic mobility of technical and non-technical workers

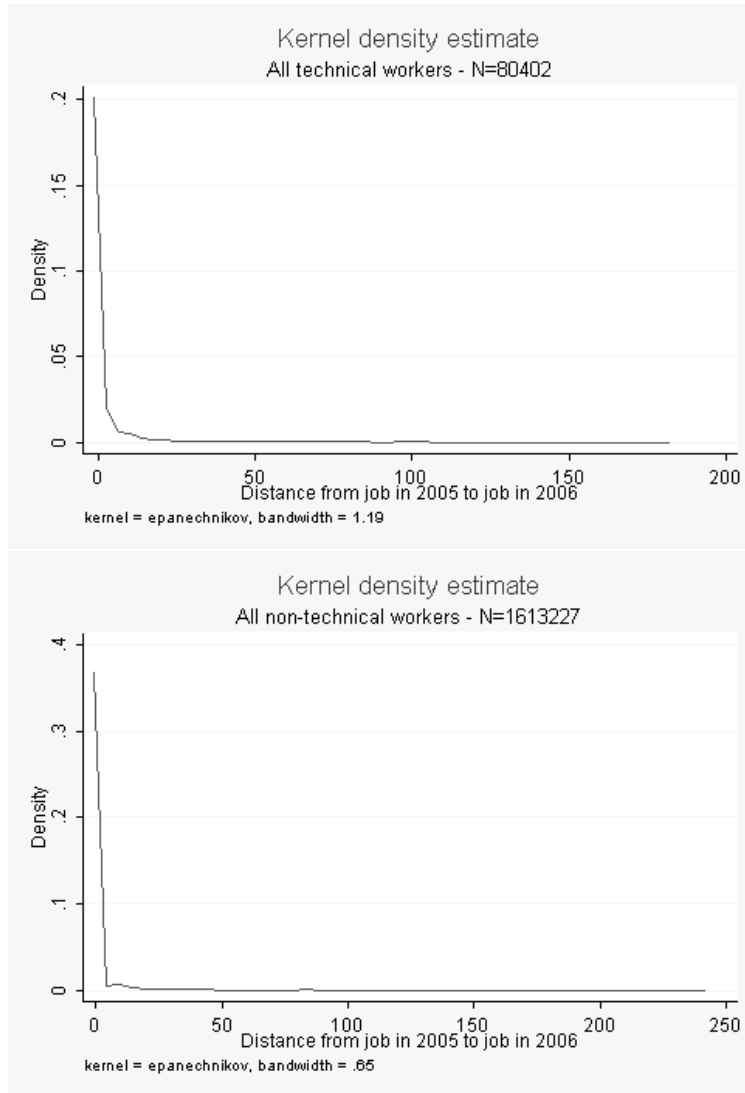for technical workers represents roughly 20% of individuals while the peak for non-technical workers captures more than 35% of the distribution. Technical workers are nearly twice as likely to move to employment in another township. By comparison, the United States Census Bureau reports that 14.4% of Americans between the ages of 18 and 64 moved residences

between 2006 and 2007.[3] Of these, 64% moved within the same county (i.e. moved less than 34 km on average). Only 5.1% of Americans moved to another county in that year, a rate quite comparable to the proportion of moves over 35 km in the Danish population.
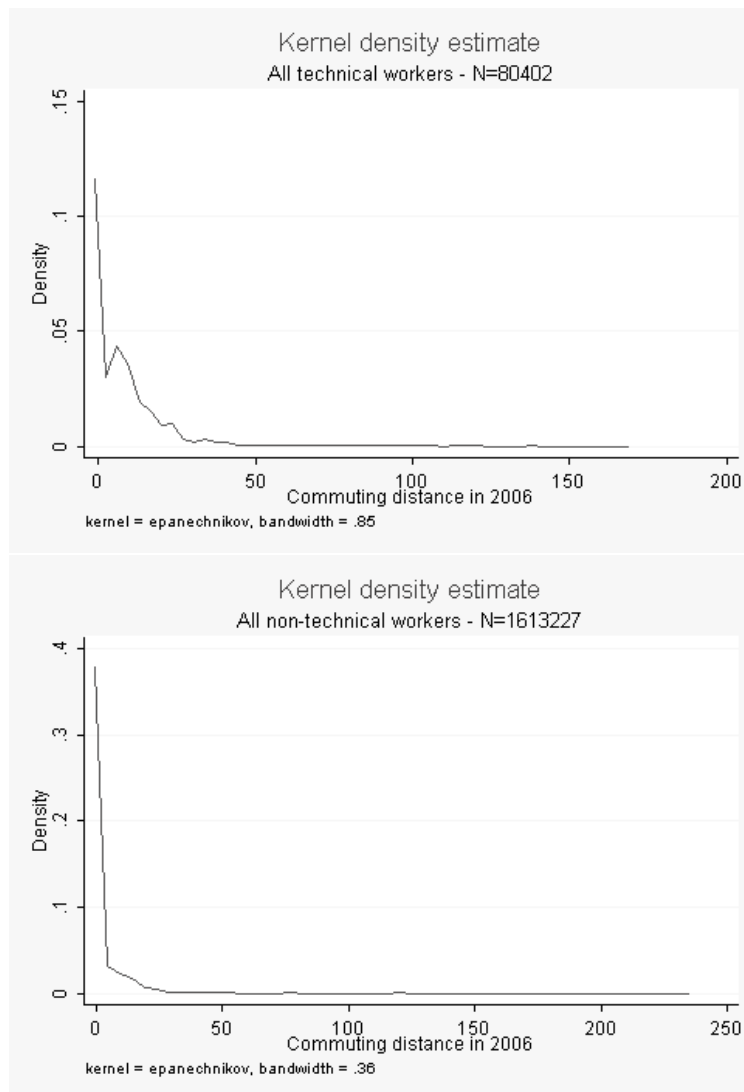

Figure 6: Commuting distances of technical and non-technical workers

[3]Although one could perhaps calculate it, given access to the Integrated Public Use Microdata, the Census Bureau does not currently disaggregate the geographic mobility of residents into an occupational category that corresponds to technical workers.

Individuals also have a choice in terms of whether they decide to reside close to their jobs or not. In figure 6, we graph the commuting distances for technical and non-technical workers. These figures suggest a much higher willingness to commute among technical workers. Although most individuals have commutes of no more than 10 km to 15 km, more than a few scientists and engineers commute up to 40km. By comparison, among non-technical workers, commuting more than 20 km is rare. On this dimension, Danes do appear to differ from Americans, where the median commute is 11 miles (~ 17 km).

3 Determinants of migration

Though interesting, these aggregate patterns allow us to say little about why workers move from one place to another (and even less about who moves). We therefore turn to an individual-level estimation of the determinants of work location choice.

3.1 Samples

Although we have panel data, our analysis focuses on where individuals with degrees in science and engineering chose to work in 2006 on the basis of the attributes of those individuals and regions in 2005 (or in some cases, in 2004). We estimated our models on three separate samples. In all three cases, we excluded all individuals under 18 and over 42. Those under 18 often move with their parents, and we could not track those over 42 to their hometowns because they left secondary school before the beginning of the IDA data. We also eliminated all employees of the public sector, as their expected incomes do not vary meaningfully across regions in Denmark.

From the 40,231 individuals that met these criteria in 2005, we extracted two samples

(of identical size to ease comparisons across the samples): (1) a simple random sample of 7,500 individuals; (2) a random sample of 7,500 individuals that changed employers from 2005 to 2006 (99.6% of the 7,533 eligible). Although the simple random sample may appear the obvious one for understanding the importance of various factors in the population of technical workers, we explored this second sample for a variety of reasons. Most importantly, our estimation essentially assumes that individuals consider the available alternatives each year and decide whether or not to continue in their current jobs and regions. Once a job has been found, however, many individuals may not consider alternatives unless they become dissatisfied with their employers (Vroom, 1964). As a result, the simple random sample may provide biased estimates of the relative weightings that individuals place on various factors when actively choosing a job.

A logical alternative is to include only those who changed employers, but not necessarily their region of employment (our second sample). Among these individuals, the assumption of an active choice seems more valid. This sample nevertheless has its own weaknesses, most notably, it selects on the dependent variable. A whole host of people may have considered alternatives to their current employers and have decided not to switch. The movers therefore may represent only those cases in which the benefits to moving exceeded the costs, either because they had much to gain by moving or because they placed unusually high or low weights on other features of the region.

To address the potential endogeneity in the decision to change employers, we considered a third sample of individuals that had to find jobs (for reasons unrelated to their preferences or personal performance on the job): those employed at establishments that closed. Because a relatively small number of technical workers find themselves in such a situation (only 745 in 2005), we aggregated two years of data for this sample: those employed at establishments

that closed in either 2004 or 2005. For the 2004 set, we calculate the covariates using data from 2004 and predict the places of employment in 2005. For the 2005 set, the information from 2005 predicts choice in 2006. We pool these groups for estimation in the third sample (N = 1661). Because the closure of these places of business probably had little to do with the turnover of any one individual, we can consider the decision to move in this sample as exogenous to the attributes of the individuals and their preferences across regions. As a result, this third sample should offer the most valid estimates of the weights that individuals place on various factors when actively trading off between locations. On the other hand, the involuntary loss of employment may lead this group to value the social support of family and friends more strongly than the general population.

3.2   Estimation

Our analysis uses a standard choice modeling approach. It assumes that individuals compare the pros and cons of potential places of employment, weight these factors according to their personal preferences and then (stochastically) choose the ones that maximize their expected satisfaction (utility). Under these assumptions, we can write the utility that an individual i would receive from working in a particular region, j, as:

$$u_{ij} = \beta' x_{ij} + \epsilon_{ij}, \tag{1}$$

where x_{ij} denotes a vector of region-specific attributes for individual i (e.g., wage or distance to college classmates), β indicates a vector of weights that the individual places on each of those attributes, and ϵ_{ij} allows for error in individuals' evaluations of the utility that they

would receive from working in the region j.[4]

If individuals choose to work in the regions that maximize their expected utilities and if we assume that the errors (ϵ_{ij}) come from independent and identically distributed draws from an extreme value distribution (Type 1), then the probability that individual i chooses region j is:

$$P(y_i = j) = \frac{e^{\beta' x_{ij}}}{\sum_J e^{\beta' x_{ij}}} \tag{2}$$

We can estimate (2) and the weights for the regional characteristics with the conditional logit (McFadden, 1974). Using this approach, we can estimate the relative importance of the various attributes to technical workers' decisions of where to work.

In choosing an areal unit of analysis, for j, we use the smallest unit available to provide the finest-grain variation possible in our measures of regional attributes. From 2004 to 2006, Denmark comprised 271 mutually exclusive and exhaustive administrative townships (*kommune* in Danish).[5] We nevertheless did not consider all of these townships possible destination states for each of the individuals in our samples. We only consider a region at risk of being chosen if another individual with the same 8-digit educational background as individual i works in the labor market to which region j belongs in 2005 (or 2004). Each individual, on average, faces a choice among 240 townships.

3.3 Covariates

We consider both economic and social factors as predictors of location choice. As noted above, the most prominent factor used to describe why scientists and engineers – and all people more generally – move from one place to another is the search for better employment

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[4]Our initial models assume that all individuals apply the same weights to all factors, but we relax this assumption below by allowing for heterogeneity in the weight coefficients (i.e. a random effects model).

[5]We excluded the island of Christiansø, which has only 55 residents, from our analysis.

opportunities. Although little has been done to examine this thesis among technical workers, studies of the general population have demonstrated that expected wages strongly predict the movement of individuals across regions (e.g., Davies et al., 2001; Scott et al., 2005)

Though not as prevalent in the literature on the geographic mobility of scientists and engineers, the more general literature on migration has considered family and friends important anchors in this process, keeping individuals moored in place. Dahl and Sorenson (2008) estimate the pull of family and friends directly in a sample of blue collar workers and find that people generally exhibit stronger preferences for being near to family than they do for the potential to earn more. A variety of other studies also seem consistent with this notion. Studies, for example, find that people move far less (and shorter distances) than one would expect on purely economic grounds (Sjaastad, 1962). Also, immigrants have a high probability of returning to their home countries, a pattern called return migration, even when their regions of origin remain economically far behind their new homes (for a review, see Gmelch, 1980).

We calculate a variety of variables to capture these factors.

Expected income: Past studies have typically used the average wage in a region as a proxy for the income that an individual might expect from moving there. Relying on population average (or median) wages as a proxy nevertheless raises a number of issues. Regions may differ in human capital and industrial bases. As a consequence, the average wage in a region might have little to do with what a specific individual could expect to earn by moving there. Todaro (1969), for instance, discusses the fact that, though urban areas have much higher average wages than rural ones, an experienced farmhand might nonetheless expect *lower* wages in the city, given the mismatch of his skills to the needs of local employers.

Dahl and Sorenson (2008) propose an alternative approach. They estimate wage equations for each region, essentially allowing the returns to various individual characteristics to vary by location. Those estimates then allow them to calculate individual-specific counterfactual wages for each location a person might choose. Such an approach, however, does not seem as useful for scientists and engineers who have highly specific training. One year of education in electrical engineering, for example, may have a very different value from one year of education in medicine, even in the same region.

To address these issues, we construct our measure of the income that an individual could expect in another region by averaging the incomes of all of those in the labor market with the same 8-digit education. We use the 77 labor markets in Denmark instead of the townships (*kommune*) to construct these averages for two reasons. First, it allows us to average over a larger number of individuals and therefore to reduce the influence of idiosyncratic income differences as a source of measurement error. Second, it accounts for the fact that individuals might commute to their jobs. In essence, this measure captures what someone with the same educational credentials would earn in a region. If no employers can fully use that education, this measure should capture the next best alternatives available.

We also assign this expected income as the income that individuals can expect to receive if they remain at their current jobs. Alternatively, one might substitute their actual income as the amount they could expect if they did not move, but that has at least one drawback: Actual income captures returns to both education and other individual characteristics, while our expected income measure depends only on education. Mixing the two could potentially bias the comparisons of the current place of employment relative to other opportunities

Distance to home: We calculat the logged distance in kilometers between each person's home address in 2005 (or 2004) and the centroid of each township to which the individual

might move (or stay) in 2006 (or 2005). Although this variable, in part, captures an individual's interest in staying close to extended family, friends and colleagues, it might also capture a number of non-social factors, such as the direct costs of commuting or moving.

Distance to parents: We locate both parents of each individual and included an indicator variable denoting their location(s) in 2005 (or 2004). We then calculate the logged distance in kilometers from each township to these locations. If the parents lived at different addresses, we average the distance from the township to each parent.

Distance to siblings: We construct a parallel measure for siblings. Our measure includes half-siblings because we identified siblings as all individuals that shared at least one parent with the focal individual. Once again, our measure averages the logged distance in kilometers from these individuals' home addresses in 2005 (or 2004) to the centroid of each township in cases with more than one sibling.

Distance to home town: We attempt to identify each individual's home town(ship). Although we cannot track where a person lived for the entire duration of his or her childhood, we can determine the secondary school from which he or she graduated. We therefore calculate this measure as the logged distance in kilometers from the location of their secondary school to the centroid of each township.

Distance to past residences: Since people also probably form relationships in every place in which they have lived, we also construct a second measure. We first identify every place that the individual has lived since 1980. We then calculate and average the logged

distance between each of these locations and every township.[6]

High school classmates: Although we could not survey individuals directly to identify their friendships, we could use the census data to construct a measure of the locations of individuals with a high probability of being friends. In particular, we construct a measure of prior migration flows by high school classmates, counting the number of members of one's high school class that live in each township.

Because they use past flows to predict future flows, measures of prior mobility have the potential to confound social preferences for unobserved factors affecting migration. To reduce this unobserved heterogeneity problem, we therefore normalize these numbers according to the movement of individuals from *other* cohorts—in this case, the class that graduated the year before and the one that graduated the year after the focal individual. If one assumes that cohorts face a relatively stable set of unobserved influences on their location choices, then this adjustment should net out this unobserved heterogeneity.

College classmates: Using the same approach and using the same adjustment for unobserved heterogeneity, we also construct a measure of the number of college classmates in each township.

Region size: We measure population in terms of the logged number of employees in the township. More populous regions offer a wider range of amenities and potential employers (Glaeser et al., 2001), but people may also prefer the lower cost of living and social integration of small towns.

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[6]Since friendships within a region form over time, one would expect the intensity of attachment to a region to increase with the time lived there. We therefore experimented with weighting regions according to the time lived there (and the recency of residency). Both of these adjustments incrementally improved the fit, but we report this simpler specification for ease of interpretation and comparison.

Work region: Finally, we include an indicator variable for the township of an individual's employment in 2005 (or 2004). This variable should help to account for the fact that many people may not actively consider alternative jobs each year and therefore remain employed in the same township. Descriptive statistics for these variables appear in Table 1.

Table 1: Descriptive statistics for the choice locations

Variable	Random sample Mean	SD	Employer change Mean	SD	Estab. closings Mean	SD
Expected Ln (income)	12.983	0.174	12.967	0.193	12.954	0.179
Ln (Distance to home)	1.738	1.325	1.976	1.403	1.825	1.407
Ln (Distance to parents)	1.959	1.759	1.988	1.769	2.476	1.660
Ln (Distance to siblings)	2.146	1.823	2.101	1.827	2.165	1.859
Ln (Distance to hometown)	2.749	1.613	2.823	1.578	1.289	1.781
Ln (Distance to prior residences)	2.384	0.997	2.526	1.063	1.125	1.417
High school classmates	0.613	0.576	0.570	0.591	0.618	0.603
College classmates	0.576	0.818	0.536	0.805	0.547	0.835
Work region	0.853	0.354	0.277	0.448	0.570	0.495
Ln (Region size)	10.276	1.404	10.339	1.405	10.626	1.460
N	7,500		7,500		1,661	

4   Results

Table 2 reports the results of our first set of analyses, comparing the three samples. Across all three samples, both economic and social factors influence individuals' choices of where to work. As we move from the simple random sample (model 1) to the sample of those changing employers (model 2), we note three main differences. First, the job changers exhibit a lower likelihood of staying in the same region (captured in the *work region* variable). Given that the sample selects on movers, that result seems unsurprising. Second, they exhibit stronger preferences for densely populated regions; those that move, disproportionately move to the cities. Third, the job changers appear *less* sensitive to expected income in their choices of

locations than the population as a whole.

Table 2: Conditional logit estimates on location choice

	Random sample	Employer change	Estab. closings
Expected income	0.627**	0.326*	1.247**
	(0.228)	(0.137)	(0.454)
Distance to home	-0.577**	-0.653**	-0.608**
	(0.030)	(0.015)	(0.039)
Distance to parents	-0.052	-0.086**	-0.289**
	(0.038)	(0.019)	(0.062)
Distance to siblings	0.015	-0.008	0.076
	(0.032)	(0.016)	(0.054)
Distance to hometown	0.024	-0.009	0.189
	(0.037)	(0.019)	(0.479)
Distance to prior residences	-0.295**	-0.334**	-0.724
	(0.053)	(0.028)	(0.497)
High school classmates	1.023**	0.971**	0.985**
	(0.055)	(0.031)	(0.115)
College classmates	0.527**	0.738**	1.189**
	(0.039)	(0.031)	(0.116)
Work region	5.334**	1.115**	3.075**
	(0.038)	(0.040)	(0.104)
Region size	0.291**	0.548**	0.489**
	(0.021)	(0.012)	(0.039)
Pseudo R^2	0.83	0.47	0.64
Log-likelihood	-7,132	-21,854	-1,793
Observations	1,813,867	1,812,917	221,772
Individuals	7,500	7,500	1,661

Standard errors in parentheses.
Significance levels :   † : 10%   * : 5%   ** : 1%

By contrast, the sample of individuals employed at establishments that closed (model 3) differs in three ways from both the random sample and from job changers: First, this group places much greater weight, on average, on expected income. Second, it also values proximity to parents more highly. Third, it weights the presence of college classmates as more valuable. The sample does not, however, assign higher weights to all social factors—as one might have anticipated if the unexpectedly unemployed relied more on social support. Though the estimates do not differ dramatically, we nonetheless focus in the remainder of

the text on the results of the sample of those employed in 2004 or 2005 at establishments that closed, those moving for the most plausibly exogenous reasons.

In model 3, many factors significantly predict where scientists and engineers choose to work. The more interesting information, therefore, regards the relative magnitude of these coefficients. In interpreting these magnitudes, we find it useful to convert the coefficients into dollar equivalents.[7] We do so by calculating the point at which the average individual would consider the increased utility due to an increase in their expected wage (Δ_{wage}) equally attractive to the lost utility from being further from family and friends or from being in a less attractive region (Δ_x):

$$\beta_{wage}\Delta_{wage} = \beta_x\Delta_x, \tag{3}$$

where β_{wage} and β_x are the conditional logit coefficients for, respectively, expected income and some other factor. For those variables specified in terms of logged distance, the tradeoff expected for a one unit increase in distance varies as a function of distance. One intuitive way to interpret these coefficients considers the effect of a doubling in distance:

$$\Delta_{wage} = \exp^{\frac{\beta_x \ln 2}{\beta_{wage}}} \tag{4}$$

Equation 4 produces figures in terms of percentage differences in income (because of the logging of expected income in the models), but we can convert them to average dollar equivalents by evaluating these percentage changes in income at the average expected wage. Table 3 reports these values.

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[7]We converted the values from Danish kroner to U.S. dollars using the average exchange rate for 2006: 5.94 DKK = 1 USD.

Table 3: Tradeoffs for annual income (U.S. dollar equivalents)

	Random sample	Employer change	Estab. closing
Doubling distance to home	$31,237	$104,046	$13,699
Doubling distance to parents	$2,071	$6,939	$5,937
Doubling distance to prior residences	$13,496	$35,770	$16,880
Doubling region population	$13,282	$76,308	$10,641
More high school classmates (1 SD)	$109,165	$332,990	$41,572
More college classmates (1 SD)	$69,220	$358,736	$82,925
Average wage	$70,003	$69,168	$68,138

Consider, for example, the results from model 3 (establishment closing sample). When comparing two potential jobs – one six miles from her home and the other twelve miles away (i.e. double the distance) – an individual would prefer the closer job unless the more distant job paid at least $13,699 more per year. Imagine that she also lived next door to her parents, then the more distant job would need to pay at least $19,636 ($= 13,699 + 5,937$) more for her to prefer it. These values are large. The average technical worker in Denmark earned roughly $69,000 in 2006, so the results imply that the typical individual would need to expect a substantial increase in income to justify even a short move. Longer potential moves, which would entail more than a doubling of distance, would require even larger offsetting gains in expected income.

One might worry that these values seem too large. But of course if people placed lower values on staying near to family and friends then we would expect much higher rates of geographic mobility (unless some other factor produced geographic inertia). Moreover, our estimates actually appear modest compared to those found in prior studies. For example, in one of the few other studies that attempted to estimate the gains in expected income required to move – using average per capita wages in a state to proxy for expected income – Davies et al. (2001) calculated that the average American in 1996 would only consider some

other state equally attractive if it had per capita income of at least \$170,820 more than his or her current state of residence (more than six times the average per capita income).

Though the dollar equivalents help us to understand how individuals trade off income versus other factors, they do not provide direct intuition regarding the relative importance of various factors in the choice of where to work. To assess this relative importance, in table 4, we report the regression coefficients standardized by normalizing the independent variables to have means equal to zero and standard deviations of one (Menard, 2004). We continue to focus on the estimates from the sample employed at workplaces that closed. Among this sample, the most important factor in choosing a new job is its proximity to the person's prior residences. These places probably proxy for relationships to the people living there, though people may also simply develop preferences for familiar places. Next most important is the number of college classmates in the region. Proximity to home weights next most heavily in choices of work locations, followed by region size, proximity to parents, proximity to hometown and then expected income. Among all the factors influencing the choice of locations, the potential for income gain actually ranks quite low.

Table 4: Standardized coefficient estimates

	Random sample	Employer change	Estab. closing
Distance to prior residences	-.294	-.355	-1.026
College classmates	.431	.594	.993
Distance to home	-.765	-.916	-.855
Region size	.408	.770	.714
High school classmates	.589	.574	.594
Distance to parents	-.091	-.152	-.480
Distance to hometown	.038	-.014	.337
Expected wage	.109	.063	.223
Distance to siblings	.027	-.015	.141

But do all individuals place similar weights on the same factors? Tables 5 and 6 explore

how the weights that individuals assign to expected income and other factors differ by gender and marital status. The first table estimates the models within four subgroups of the random sample: married men, married women, single men and single women. The second table replicates these models using those employed at establishments that closed.

In table 6, the subsamples for both married and single women become somewhat small and therefore our estimates in those groups have fairly wide standard errors. Subject to that caveat, we note a number of interesting differences across groups: First, men appear to place much greater weight on potential income than women, or at least than married women. Married men also appear far less rooted to their current work regions. Interesting, these differences may contribute to the gender wage gap, as men systematically opt to move more often for higher paying jobs. Second, married men appear to value living near their parents less highly, possibly because, in couples, proximity to the wife's parents come first. Third, single men exhibit a preference for being *more distant* from their siblings. Fourth, both married men and married women place higher value on being in regions with larger numbers of their high school classmates. Fifth, single women interestingly place the greatest value on living in more densely populated areas.

Our estimation approach has at least one potential weakness. As noted above, the conditional logit model assumes an equal probability of choosing each region, net of the observed characteristics (the IIA assumption). We assessed the sensitivity of our results to this assumption in two ways. First, we ran tests of the sensitivity of the results to the removal of each of the regions from the choice set. Although these tests suggested that our models do not violate the IIA assumption, monte carlo simulations have found that such tests can generate false negatives even in large samples (Cheng and Long, 2007). We therefore re-estimated models 1 through 3 using the mixed logit, which does not assume IIA, with ran-

dom coefficients for each of the independent variables (Train, 2003).[8] Since the mixed logit produced similar average coefficients, we have reasonable confidence that the IIA assumption does not prove problematic in these models.

Table 5: Conditional logit estimates on location choice (random sample)

	Married Men	Married Women	Single Men	Single Women
Expected income	0.369	0.603	0.779*	0.697
	(0.392)	(0.593)	(0.380)	(0.569)
Distance to home	-0.621**	-0.889**	-0.431**	-0.526**
	(0.049)	(0.084)	(0.051)	(0.079)
Distance to parents	-0.006	-0.147	-0.014	-0.274*
	(0.059)	(0.107)	(0.064)	(0.115)
Distance to siblings	-0.014	0.076	0.074	-0.089
	(0.051)	(0.091)	(0.055)	(0.090)
Distance to hometown	-0.023	0.053	0.066	0.106
	(0.058)	(0.102)	(0.062)	(0.106)
Distance to prior residences	-0.256**	0.049	-0.515**	-0.162
	(0.087)	(0.149)	(0.089)	(0.145)
High school classmates	0.935**	1.323**	1.055**	0.845**
	(0.085)	(0.139)	(0.096)	(0.175)
College classmates	0.407**	0.796**	0.518**	1.217**
	(0.064)	(0.127)	(0.055)	(0.153)
Work region	5.453**	5.364**	5.247**	5.189**
	(0.060)	(0.100)	(0.065)	(0.118)
Region size	0.320**	0.306**	0.237**	0.318**
	(0.033)	(0.056)	(0.035)	(0.066)
Pseudo R^2	0.84	0.84	0.81	0.82
Log-likelihood	-2,831	-985	-2,492	-778
Observations	775,408	273,819	574,609	190,031
Individuals	3,160	1,161	2,372	807

Standard errors in parentheses.
Significance levels : †: 10% *: 5% **: 1%

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[8]The mixed logit nevertheless comes at a cost, in terms of the time required to estimate the models. Even with exclusive access to a state-of-the-art server, the estimation of all of our models using the mixed logit would have required several weeks of computer time.

Table 6: Conditional logit estimates on location choice (establishment closing sample)

	Married Men	Married Women	Single Men	Single Women
Expected income	1.340†	0.763	1.364†	2.334
	(0.758)	(0.711)	(0.766)	(1.803)
Distance to home	-0.680**	-0.602**	-0.533**	-0.730**
	(0.064)	(0.106)	(0.063)	(0.135)
Distance to parents	-0.128	-0.371*	-0.464**	-0.384†
	(0.096)	(0.172)	(0.103)	(0.217)
Distance to siblings	-0.038	0.090	0.215*	0.036
	(0.081)	(0.158)	(0.096)	(0.193)
Distance to hometown	-0.281	0.616	1.272	0.013
	(0.702)	(1.657)	(1.525)	(2.894)
Distance to prior residences	-0.318	-1.592	-1.621	-1.939
	(0.587)	(1.888)	(1.250)	(3.419)
High school classmates	1.347**	1.007**	0.630**	0.220
	(0.161)	(0.349)	(0.203)	(0.439)
College classmates	1.389**	0.947**	1.149**	0.542
	(0.167)	(0.356)	(0.198)	(0.483)
Work region	2.618**	3.466**	3.293**	3.579**
	(0.168)	(0.284)	(0.177)	(0.293)
Region size	0.479**	0.491**	0.511**	0.623**
	(0.058)	(0.105)	(0.068)	(0.144)
Pseudo R^2	0.62	0.67	0.65	0.72
Log-likelihood	-757	-252	-600	-160
Observations	88,654	33,098	75,530	24,490
Individuals	670	230	574	187

Standard errors in parentheses.

Significance levels : $\dagger : 10\%$ $* : 5\%$ $** : 1\%$

5 Discussion

Explanations for the relative economic prosperity of some regions relative to others have often pointed to the concentration of scientists and engineers as an important factor. These individuals represent the engines of innovation. The benefits of their innovations may moreover remain rooted in the regions in which those individuals live and work for a number of reasons—they may require complementary assets, involve a large degree of tacit knowledge or fall under the protections of intellectual property rights.

Both social scientists and policy makers have thus been quite interested in the movements

of these individuals, particularly across international borders. Politicians and bureaucrats have promoted immigration policies favorable to these technical workers. Social scientists, meanwhile, have bemoaned the potential brain drain effect of these migrations on the home countries of these individuals.

We nevertheless have limited understanding to date of why these individuals move and the movements of these technical workers within countries. We offer early evidence on both of these questions by exploiting an unusually rich data source, covering all residents of Denmark, and by developing a methodology for estimating expected incomes in each region specific to the individual, on the basis of regional differences in the returns to education. We have further refined prior research by identifying a sample of individuals who choose new employers for reasons exogenous to their own preferences and abilities, and consequently where selection bias does not plague the results: those employed at workplaces that close.

Our results reveal that Danish technical workers place very high weights on social factors when considering where to work. From most to least important, those educated as scientists and engineers care about proximity to past places they have lived, proximity to their college classmates, proximity to their current residence, population, proximity to high school classmates, proximity to their parents, proximity to their hometown, and income. For the typical Danish technical worker, therefore, social factors swamp economic considerations in their choices of where to work.

Although we interpret these findings as primarily reflecting individuals' preferences for being near to family and friends, two other factors might contribute to our results. First, family and friends may serve as sources of information on job opportunities and the prevailing wages in other regions. Individuals therefore may move near to them because those are the regions in which they have the best information about the available jobs. Second, because

individuals know with relative certainty the locations of their loved ones but not necessarily the prevailing wages in all regions, their weights may in part reflect a discounting of this more noisy information.

Though we believe that the unusual quality of the data justifies focusing on the Danish case, one might worry that our results would not extrapolate to other countries, particularly ones such as the United States where people have more recent roots in regions. Two facts, however, suggest otherwise. First, within geographic units of similar size (i.e. within state mobility in the U.S.), Danes appear as mobile as Americans (if not more so). Second, estimates of how Americans trade off gains in expected income against moving have found even lower sensitivity to expected income (Davies et al., 2001; Kennan and Walker, 2003; Bayer and Jussen, 2006), hinting that Americans may value family and friends *more* highly on average and therefore exhibit less mobility than Danes.

The fact that individuals weight social factors much more heavily than economic ones in deciding where to work and live nonetheless has important implications for both research and public policy. Most immediately, it suggests that labor markets operate at quite local levels. Since even relatively large differences in income are insufficient to entice most individuals to move, the set of jobs realistically of interest to the typical individual would include only those in a relatively restricted geographic radius from his or her home. It further suggests that even very large differences in wages across regions can persist indefinitely. If individuals rarely move to higher paying regions to arbitrage these wage differentials, then the primary force for equilibration comes from companies moving to regions with lower wages. But even from the side of the employer, investments in physical plant and the training of existing employees – who themselves would prefer not to move – strongly anchor existing firms to their current locations.

References

Bayer, Christian and Falko Jussen. 2006. "A generalized options approach to aggregate migration with an application to U.S. federal states." Working paper, University of Dortmund.

Bhagwati, Jagdish N. and Koichi Hamada. 1974. "The brain drain, international integration of markets for professionals and unemployment." *Journal of Development Economics* 1:19–42.

Borts, George H. 1960. "The equilization of returns and regional economic growth." *American Economic Review* 50:319–347.

Cheng, Simon and J. Scott Long. 2007. "Testing for IIA in the multinomial logit model." *Sociological Methods and Research* 35:583–599.

Dahl, Michael and Olav Sorenson. 2008. "The social attachment to place." Working paper, University of Aalborg.

Davies, Paul S., Michael J. Greenwood, and Haizheng Li. 2001. "A conditional logit approach to U.S. state-to-state migration." *Journal of Regional Science* 41:337–360.

Dumont, Jean-Christophe and Georges Lemaitre. 2005. "Counting immigrants and expatriates in OECD countries: A new perspective." OECD Social Employment and Migration Working Papers, No. 25.

Galor, Oded and Daniel Tsiddon. 1997. "The distribution of human capital and economic growth." *Journal of Economic Growth* 2:93–124.

Glaeser, Edward L., Jed Kolko, and Albert Saiz. 2001. "Consumer city." *Journal of Economic Geography* 1:27–50.

Gmelch, George. 1980. "Return migration." *Annual Review of Anthropology* 9:135–159.

Kennan, John and James R Walker. 2003. "The effect of expected income on individual migration decisions." Technical report, NBER Working Papers 9585.

Levin, Sharon G. and Paula E. Stephan. 1999. "Are the foreign born a source of strength for U.S. science?" *Science* 285:1213–1214.

McFadden, Daniel. 1974. "Conditional logit analysis of qualitative choice behavior." In *Frontiers of Econometrics*, edited by P. Zarembka, pp. 105–142. New York: Academic Press.

Medawar, Jean and David Pyke. 2001. *Hitler's Gift: The True Story of the Scientists Expelled by the Nazi Regime*. New York: Arcade Publishing.

Menard, Scott. 2004. "Six approaches to calculating standardized logistic regression coefficients." *American Statistician* 58:218–223.

Romer, Paul M. 1986. "Increasing returns and long-run growth." *Journal of Political Economy* 94:1002–1037.

Scott, Darren M, Paul A Coomes, and Alexei I Izyumov. 2005. "The location choice of employment-based immigrants among U.S. metro areas." *Journal of Regional Science* 45:113–145.

Sjaastad, Larry A. 1962. "The costs and returns of human migration." *Journal of Political Economy* 70:80–93.

Sørensen, Jesper B. and Olav Sorenson. 2007. "Corporate demography and income inequality." *American Sociological Review* .

Stephan, Paula E. and Sharon G. Levin. 2001. "Exceptional contributions to U.S. science by foreign-born and foreign-educated." *Population Research and Policy Review* 20:59–79.

Todaro, Michael P. 1969. "A model of labor migration and urban unemployment in less developed countries." *American Economic Review* 59:138–148.

Train, Kenneth. 2003. *Discrete Choice Methods with Simulation*. Cambridge University Press.

Vroom, Victor H. 1964. *Work and Motivation*. New York: Wiley.

Westerlund, Olle. 1998. "Internal migration in Sweden: The effects of mobility grants and regional labour market conditions." *Labour* 12:363–388.

Wirth, Louis. 1938. "Urbanism as a way of life." *American Journal of Sociology* 44:3–24.