The Return to Big City Experience: Evidence from Danish Refugees*

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Abstract

This paper provides the first causal evidence of an urban wage premium. We exploit a government policy of quasi-random settlement of political refugees across labor markets in Denmark between 1986 and 1998. Refugees initially earn similar hourly wages across regions, but those placed in Copenhagen see their wages grow 30% faster with each year of experience. Greater accumulation of experience at high-wage establishments and differential sorting across occupations drive this dynamic premium. An estimated spatial model of earnings dynamics further attributes an important role to sorting on unobserved ability within cities.

Keywords: Agglomeration Economies, Urban, Regional Labor Markets, Resettlement, Wage Differentials

JEL Codes: R11, R12, R23, J31, J61

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1 Introduction

There are large wage differences across labor markets, even within countries. In particular, average wages are much higher in cities than in towns and rural areas. A central question is whether the city makes workers more productive, or whether more productive workers live in the city.

We study this question using a large natural experiment. Between 1986 and 1998, the Danish Government allocated 80,000 newly arriving refugees across counties in Denmark, without regard to labor market relevant characteristics. In this setting, we document the causal effect of being placed in a big city on lifetime wages and earnings.

In contrast, recent studies on the productive advantage of cities control for differences in worker ability across space using person fixed effects (Glaeser and Mare, 2001; D'Costa and Overman, 2014; De La Roca and Puga, 2017).[1] Under this approach, only individuals who move across locations identify the effect of cities on worker productivity. Selection into moving induces a potential source of bias in the resulting estimates.

This paper makes three distinct contributions. First, we exploit random variation of worker location to identify a causal effect of cities on worker wages and earnings, for a particular population. Second, we show that this effect is substantial and dynamic in nature, and manifests in higher returns to experience. Third, we provide evidence that a large part of the effect reflects fundamental differences in the types of firms, occupations, and industries available to workers in cities.

To proceed, we split the spatial economy of Denmark in two parts: Copenhagen, the country's capital and only big city, and the union of all remaining small cities and towns. We then exploit the quasi-random allocation of refugees across these two zones, and examine how labor market outcomes differ between the two groups. This allows us to circumvent potential biases associated with location choice when considering how living in a big city impacts refugee wages and earnings.

We then document the treatment effects of assignment to Copenhagen on lifetime wage and earnings paths. Initially, refugees earn similar hourly wages across areas. However, individuals settled in Copenhagen see their wages and earnings grow around 30% faster for every year of experience they gain, relative to their counterparts settled outside of Copenhagen.[2] This treatment effect is substantial, and comparable in magnitude to the return to an additional two years of education over a working

[1] De La Roca and Puga (2017) provide evidence of a city size earnings premium in the Spanish administrative data, which persists after controlling for unobserved heterogeneity using person fixed effects. D'Costa and Overman (2014) conduct an analysis on wage growth using a panel of British workers which also employs worker level fixed effects. Both papers are in the tradition of Glaeser and Mare (2001), who were the first to explore the urban wage premium in regressions with person fixed effects. For an excellent review of the literature on the urban wage premium, see Rosenthal and Strange (2004).

[2] This suggests that the success of assimilation is a function of the spatial distribution of refugees. Given that refugees sort mainly into big cities in the absence of dispersal policies (see Damm (2009a)), this can explain the finding of Edin et al. (2004) that dispersal policies on average lower earnings of refugees.

life.

Next, we explore the mechanisms underlying this city wage growth premium. First, we focus on employment outcomes. Refugees assigned to Copenhagen transitioned into employment at different rates depending on their initial level of education. Those with at least a high school degree did not take up employment at different rates, while those with less education were 4% less likely to ever join the labor force if assigned to Copenhagen. Conditional on joining the labor force, both groups worked the same amount of hours on average. As a result, differences in the intensive margin of labor supply and wage growth cannot explain our results.

The Danish matched employer-employee data contains detailed information on the universe of workers and establishments in Denmark. In conjunction with our random variation, we use this information to decompose the wage growth premium into contributions from firm and job characteristics. We find that accumulation of experience at high-wage firms, and differential sorting across occupations and industries explains the majority of the big city effect on wage and earnings growth. Over time, a refugee assigned to Copenhagen is increasingly likely to work at more productive firms and in skill intensive jobs than one settled outside Copenhagen. Previous literature has, for the most part, not taken a stand on the contribution of firm characteristics to the urban wage premium.[3]

While the natural experiment controls for differences in latent worker characteristics across space, a remaining question is whether the city differentially affects workers based on these characteristics. For example, high latent ability workers may be more able to take advantage of the greater presence of high-wage firms in a big city. We explore this possibility in a spatial model of earnings dynamics, following Baum-Snow and Pavan (2012). We exploit the variation of the settlement policy as an important source of identification of the distribution of latent ability among refugees. We find that higher ability workers move to more productive firms faster in the city, accounting for more than 50% of the dynamic experience premium. Using this structure, our results on the importance of the accumulation of high-wage experience can be further understood as reflecting the success of high latent ability workers in the city.[4]

Lastly, in explaining our findings we are able to dismiss several other mechanisms, including separate wage trends between locations, the effects of ethnic enclaves, and variation in educational take-up across space.

We are not the first to employ the exogenous variation associated with the Danish refugee dispersal policy in the economics literature. Damm and Dustmann (2014) study the effect of growing up in a high-crime neighborhood on the likelihood of children to themselves commit crimes using the same data. In another context, Dustmann et al. (2019) study the effect of refugee settlement on electoral

[3]See, for example, Wheeler (2006), Combes et al. (2008), Baum-Snow and Pavan (2012), Papageorgiou (2017), and Grujovic (2018). Notable exceptions are Mion and Naticchioni (2009) and Dauth et al. (2018).

[4]Using a methodology based on the framework in Abowd et al. (1999), Dauth et al. (2018) corroborate these findings.

outcomes.[5] To the best of our knowledge our paper is the first to document the causal effect of cities on refugees' lifetime economic outcomes.

Clearly, refugees are a singular population, and at first glance their usefulness for studying the sources of the urban wage premium is not clear. They may not know the language, have different preferences, and have a need to integrate into the host society. However, the mechanisms driving the differential return to experience for those allocated to Copenhagen appear to be more general. We would expect the higher presence of high-wage establishments and different occupation distributions to also impact the earnings paths of natives living in Copenhagen. While we can say less about their quantitative importance for natives, our results suggest that future studies of the urban wage premium should consider these mechanisms as fundamental sources of the dynamic advantages that cities bestow.

The paper continues as follows. Section 2 introduces the refugee dispersal program, the Danish administrative data, and the sample used throughout the paper. In Section 3, we document the treatment effect of initial allocation to Copenhagen on hourly wages, earnings, and labor supply. The remaining sections are dedicated to understanding the determinants of the city wage growth premium. First, Section 4 documents the importance of key observables: accumulation of experience at high-wage firms, occupations and industries. Second, in Section 5 we quantify the importance of sorting on unobserved ability within locations in a spatial model of earnings dynamics. Section 6 concludes.

2 Background, Data, and Sample Selection

In this Section, we describe the Danish refugee dispersal policy. Next, we discuss the construction of our sample used for estimation before clarifying our treatment of the Danish geography. Lastly, we document the persistence of assigned locations for our sample.

2.1 The Danish Refugee Dispersal Policy

Our description here follows Damm and Dustmann (2014) and Damm (2009a), which provide substantially more detail. Prior to 1986, refugees chose municipalities according to their own preference, which resulted in a small number of municipalities housing a large share of the refugee population. In 1986 the Danish government initiated a refugee dispersal policy aimed at distributing refugees across municipalities in proportion to population size. The motivation was to ensure all localities shared in the work of integrating refugees.

Under the policy, arriving refugees were housed in Red Cross reception centers located across Den-

[5] Other papers using the Danish Refugee Dispersal policy include Damm (2005), Damm (2009a), Damm and Rosholm (2010), Foged and Peri (2013), and Damm (2014). Furthermore, a similar experiment in Sweden has been exploited by Aslund and Rooth (2007) and Edin et al. (2003).

mark until receiving asylum. After being granted asylum, refugees faced no legal impediments to labor market participation. Within 10 days of the asylum decision, refugees were assigned temporary housing in one of 15 counties in Denmark. Each county assigned the refugees to a municipality within the county and helped them find permanent housing.[6] When assigning refugees to a municipality within a county the local county council had access to the birth date, marital status, number of children, and nationality of the refugee.[7] This was the only information used by the council upon assigning refugees to municipalities, and assignment was random conditional on this information. Importantly, the council did not have information on years of schooling or family income, and the council did not meet with the refugees in person. In Table 5 in Appendix A.2.1, we compare refugees assigned to Copenhagen and elsewhere, and confirm that years of schooling do not differ by initial assignment after controlling for the information available to the council.

The refugees received social assistance and Danish language courses for the first 18 months in the assigned municipality. After this, the refugees were encouraged but not forced to stay in the assigned municipality. Damm (2005) concludes that the 1986-1998 refugee program indeed succeeded in assigning refugees to municipalities in proportion to local population sizes. Our empirical strategy exploits this initial exogenous variation in two steps. First, we study the effect of initial placement in a big city on lifetime wage growth. In a second step, we use the persistence of the initial assignment to explore to what extent we can interpret our results as the return to big city experience.

2.2 Data and Sample Selection

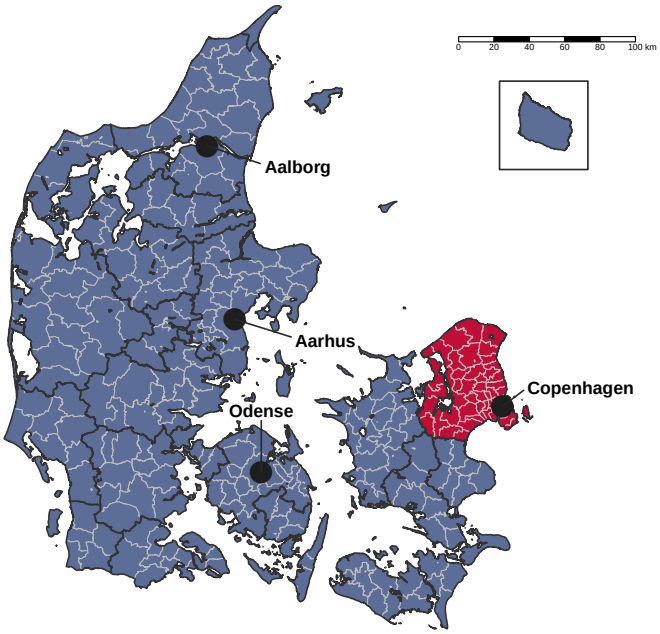
Our analysis uses administrative data provided by Statistics Denmark. Our core dataset is a matched employer-employee panel covering the entire Danish population from 1986 to 2012, including all refugees from the time of being granted asylum. The dataset includes detailed labor market information such as annual average hourly wages, annual earnings, 4-digit occupation codes, and current municipality of residence and work.[8] Additionally, for employers, we use information on detailed industry, employment, and earnings at the establishment level. We also use non-labor market information on a large set of basic characteristics such as gender, age, years of education, and family information on spouse, number of children, and age of youngest and oldest child. Finally, for refugees, we know country of origin and the year of arrival. We describe the construction of the data and all variables used in Appendix A.1.

[6] Damm (2005) reports that 90% of refugees were assisted in finding permanent housing.

[7] The council had a tendency to assign families with a large number of children to less populated municipalities as bigger houses were available in these municipalities.

[8] Annual hours worked are estimated using information on mandatory pension contributions. This is then used to construct a measure of hourly wages, potentially introducing a source of measurement error. Lund and Vejlin (2015) improve upon Statistics Denmark's estimated annual hours measure for the years 1980-2007, primarily by using additional information on time spent in sickness and leave. All results in this paper are robust to using this improved hourly wage measure.

Figure 1: Commuting Zones in Denmark



Notes: The 23 commuting zones shown in this Figure (black lines) are constructed by the authors based on 1986 commuting flows across the 271 municipalities in Denmark (light grey lines). Commuting flows are derived from the residence and work place identifier in the Danish administrative "IDA" data set (see Online Appendix for details on the IDA data). The zones are constructed so as to maximize commuting flows within and minimize commuting zones across them, following the methodology outlined in Tolbert and Sizer (1996). The Copenhagen commuting zone is highlighted in red. Commuting zones constituting the "Non-Copenhagen" assignment area are denoted in blue. Aalborg, Aarhus, and Odense are the three second-largest cities in Denmark after Copenhagen. The box in the top-right corner shows the Bornholm commuting zone, which is situated on an island to the east of the rest of Denmark. Appendix A.3.1 presents commuting zones derived from using commuting flows from other years.

Following previous papers exploiting the same experiment (Damm and Dustmann, 2014),we restrict our sample to men between the age of 19 and 55 arriving from Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia between 1986 and 1998.

Table 5 in Appendix A.2.1 shows mean characteristics for both refugees and natives. On average, refugees are younger than Danes, have fewer children, and are less likely to be married. We are missing education information for 19% of our sample, as education information was collected from a survey after arrival for refugees, while this information for Danes is based on administrative records.

2.3 The Geography of Denmark

Denmark has a single big city, Copenhagen, which houses 2.3 million people in its broader metropolitan area. The remaining 3 million people live in either three second-tier cities (Aarhus, Aalborg and Odense), smaller towns, or rural areas. The second-tier cities are an order of magnitude smaller than Copenhagen; Aarhus, the largest, contains around 250,000 people.

We use commuting flows of all Danish workers between Denmark's 271 municipalities in 1986, together with a hierarchical clustering algorithm to construct 23 Danish commuting zones.[9] These zones are shown in Figure 1, with the Copenhagen commuting zone appearing as the collection of blue municipalities in the east.[10]

In our analysis, we divide the economy into two locations: the Copenhagen commuting zone and everywhere else. In the remainder of the paper, we refer to the Copenhagen commuting zone as Copenhagen, and all remaining commuting zones as Non-Copenhagen.

2.4 Persistence of Initial Assignment

If refugees moved immediately after assignment, the policy would not be informative about the effect of being in a city on labor market outcomes. In Figure 2, we show the fraction of refugees who have never moved from their initial zone of assignment over time. 15 years after assignment, 78% have never changed zone. Refugees are less likely to leave Copenhagen, regardless of initial educational level. However, refugees with at least a high school degree are more likely to move to Copenhagen than those with less education. We discuss the implications of this persistence for the interpretation of the treatment effects in Section 3.2.

3 The Return to Big City Experience

We now document the effect of initial allocation to Copenhagen on lifetime wage and earnings paths. To do so, we segment our sample by initial allocation, and compare the two treated groups. We first examine wage- and earnings-experience profiles, and then the extensive margin of labor supply. Section 3.2 discusses the interpretation of the treatment effect on wages as return to big city experience.

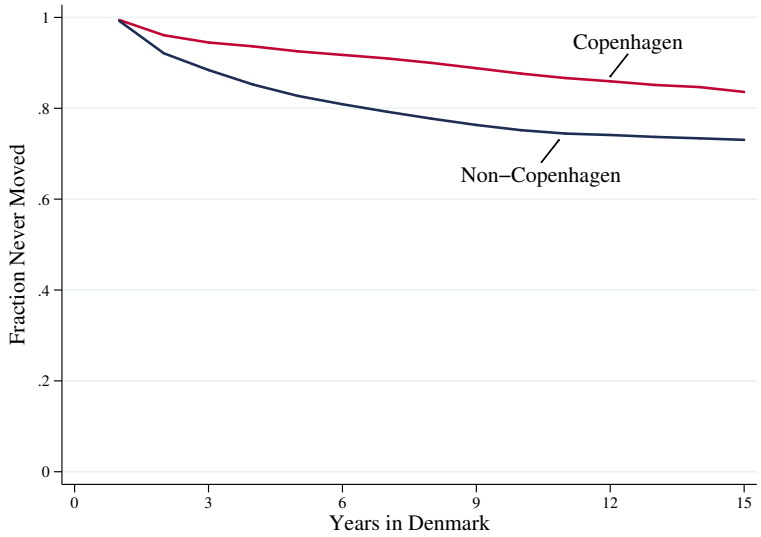
3.1 The Effects of Initial Allocation

Treatment Effects on Wages and Earnings In a linear setting, wage-experience profiles can differ in two ways as a result of initial allocation: intercept or slope. Refugees in one area could earn uniformly higher wages, or see their wages grow faster with experience. We refer to differences in intercept as the Static Treatment Effect and differences in slopes as the Dynamic Treatment Effect. These effects only condition on initial assignment, not current location. As a result, they are conceptually distinct from static and dynamic effects of cities in the literature (e.g., Glaeser and Mare (2001)). They are

[9] Tolbert and Sizer (1996) constructed commuting zones for the U.S. labor market which are widely used in the economics literature (e.g. Autor and Dorn (2013)). We follow their method to construct commuting zones for Denmark.

[10] In Appendix A.3.1, we show the commuting zones that result from using commuting flows in 1980 and 2000. There we show that our main results are robust to the choice of commuting zone delineation.

Figure 2: Persistence of Initial Assignment



Notes: The sample underlying this figure includes all refugees from the full sample whose construction is outlined in Section 2.2. This figure plots the fraction of refugees that have *never* changed assignment region (Copenhagen and Not-Copenhagen) out of all refugees assigned to a given region against the number of years since arrival in Denmark. Years in Denmark is computed as the number of years since being granted asylum. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper.

specific to our context; we explore their interpretation as "big city premia" in the next subsection.

To document these treatment effects, we estimate the following equation:

$$y_{it} = \beta_1 Exp_{it} + \beta_2 InitCph_i + \beta_3 \left(InitCph_i \times Exp_{it}\right) + \phi' \boldsymbol{X}_{it} + \epsilon_{it}. \tag{1}$$

y_{it} is either the log hourly wage or log yearly earnings in Danish Kroner, deflated by an index of Danish nominal wage growth.[11] Exp_{it} is the number of years in which worker i has undertaken paid employment prior to year t. $InitCph_i$ is an indicator variable that takes a value of 1 if the refugee is initially assigned to Copenhagen and 0 otherwise. $\mathbf{X}_{it}$ is a vector of controls that include cohort fixed effects, nationality fixed effects, and the variables relevant to the assignment of refugees.

We report the results for hourly wages in Column I.A. of Table 1. There is no significant difference in initial wages across the two locations. However, each year of experience earns a refugee assigned to Copenhagen an additional 0.81 percentage point wage increase compared to the refugees placed elsewhere.

In Column I.B., we report the results for refugees who had at least a high school degree upon arrival

[11] To construct an index of nominal wage growth, we use the entire population of native workers and apply our sample selection criteria from Section 2.2. We compute average hourly wages in each year relative to 1986. We use this index to deflate mean hourly wages and earnings for refugees. The results are robust to controlling for aggregate trends using year fixed effects.

Table 1: Regression of the Determinants of Individual Wage and Earnings Outcomes

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.284***	2.497***	2.108***	7.594***	7.836***	7.502***
	(0.142)	(0.159)	(0.126)	(0.322)	(0.370)	(0.341)
Initial Assignment to Copenhagen	0.0477	0.858	-0.892	-7.250***	-5.434**	-10.40***
	(1.013)	(0.883)	(1.356)	(1.840)	(1.903)	(2.369)
Years of Experience × Initial Assignment to Copenhagen	0.810***	0.736***	0.813***	2.137***	1.865***	2.614***
	(0.148)	(0.163)	(0.134)	(0.303)	(0.330)	(0.312)
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.056	0.062	0.055	0.155	0.158	0.156
Observations	97,402	57,994	39,408	107,297	63,870	43,427

Notes: The specification estimated in this Table is stated in Equation (1) in the text. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The definition of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the regions constructed in Section 2.3. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample whose construction is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample with at least a high-school degree. Columns II.C and II.C are based on refugees with less than a high-school degree including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

in Denmark. In Column I.C., we do the same for refugees with either less than a high school degree, or missing education information. The differential slope for wages is very similar across subgroups, and there is no significant difference in initial wages.

We repeat these regressions with log earnings in the right-hand panel. Contrary to hourly wages, earnings are initially lower in the city for both of our sub-populations. The estimated coefficient on experience implies that the city earnings catch up after about 3.5 years, and then overtake. We examine hours worked in Appendix A.2.3. There we show that yearly hours worked increase significantly with experience. The initial gap in hours worked between Copenhagen and elsewhere quickly closes for workers with at least a high-school degree, but not for those without.

In the Appendix, we consider a range of exercises to establish the robustness of the results in Table 1.

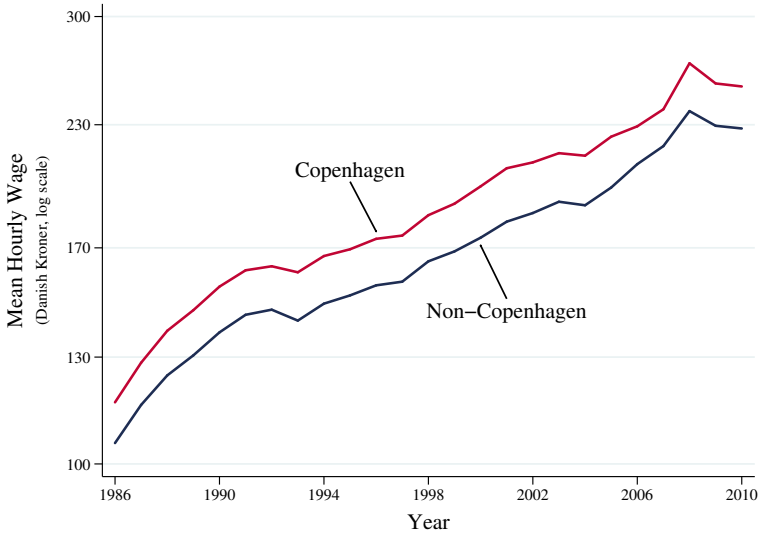
Appendix A.3.1 explores the robustness of the results to our definition of commuting zones. A different definition of commuting zones leads to changes in the geographic delineation of our treatment and control groups, "Copenhagen" and "Non-Copenhagen". Our results are robust to deriving commuting zones from commuting flows from any year for which data is available (1980 to 2010).

In Appendix A.3.2, we investigate the role of the second-tier cities in Denmark, Aalborg, Aarhus, and Odense. First, we exclude refugees assigned to these three cities, and compare assignment to Copenhagen to assignment to the rural areas of Denmark. We continue to find no Static Treatment Effect, but a larger Dynamic Treatment Effect. This accords with the intuition that being placed in the second tier cities lead to steeper wage-experience profiles relative to being placed into even smaller cities or the countryside. So once we remove these cities from the "Non-Copenhagen" stratification, the treatment effect of being assigned to Copenhagen becomes more pronounced. When we drop refugees assigned to Copenhagen from the sample and instead compare being assigned to a second-tier city to being assigned to even smaller cities or the countryside, we find a much smaller Dynamic Treatment Effect.

In Appendix A.3.3, we repeat our baseline regression non-parametrically, with dummies for 3-year experience bins. In line with a large literature (see, e.g., Lagakos et al. (2018a)), we find concavity in the returns to experience. However, the treatment effect itself is broadly linear in years of experience, and the size of the effect after 15 years is well captured by the linear model. We continue to find no static effect for wages, and a negative static effect for earnings that is not significant.

We finally rule out that differential aggregate wage trends across the two regions are driving these results. If the overall level of wages in Copenhagen were growing faster than other regions, such a trend would show up in β_3 in Equation (1), as the arriving cohorts age. In Figure 3 we plot the average hourly wage earned by all working Danes, from 1986 to 2010, split by each worker's current location in that year. Wage levels in Copenhagen and Non-Copenhagen do not systematically diverge. We

Figure 3: Wage Growth Among All Danes



Notes: The sample underlying this figure includes all male Danes between 19 and 55 years of age. Log mean hourly wage is the log of the mean of all hourly wage observations in that region and year in Denmark. The definition of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the regions constructed in Section 2.3.

infer that Copenhagen is not on a steeper overall growth path than the rest of the country.[12]

Wages and earnings are only observable for individuals who work. One driver of the dynamic treatment effect on wages and earnings could be differential selection into work across locations. We now analyze treatment effects on labor force participation and the extensive margin of labor supply.

Treatment Effects on Labor Supply Table 7 in Appendix A.2.2 shows the treatment effect for labor force participation. We regress an indicator variable for ever working by the last year in our sample (2012) on an indicator for assignment to Copenhagen, and the assignment variables from specification (1). We run the regression separately for those with at least a high school degree in Column (1), and those with less than a high school degree in Column (2).

The effect of assignment to a city on labor force participation differs markedly across education groups. For those with at least a high school degree, assignment to Copenhagen did not significantly affect participation. However, those without a high school degree saw both a statistical and economically significant effect of being assigned to the city, raising their chance of never working by almost 4%.

In Table 8 in Appendix A.2.2, we show the treatment effect on labor supply conditional on joining the labor force. We regress an indicator for current employment on a full set of dummies for time

[12]Note that this is not inconsistent with differential returns to experience in Copenhagen; simple models of lifecycle earnings with overlapping cohorts can exhibit differential wage-experience slopes across locations, but a stable aggregate city premium over time as older cohorts are replaced.

spent in Denmark and the assignment variables, conditional on having worked at least one year in our sample. Employment rates rise steadily throughout our sample period for both groups, in both locations.[13] For the educated, assignment to Copenhagen did not impact employment rates once in the labor force. However, for those with less than a high school degree, employment rates are 2% *higher*.

Together with the evidence in Table 7, this suggests that the treatment induced selection into the labor force for the less educated; they were less likely to work at all if assigned to a city, but those that did were more successful in gaining and maintaining employment. One hypothesis is that those without formal education find it particularly difficult to join the labor force in the city compared to those assigned elsewhere, and those that do join are more able than those who do not.

We do not confront this issue directly. Instead, for the remainder of the paper we focus on those with at least a high school degree, who account for 55% of our baseline sample. For these workers, we can rule out selection into the labor force as a driver of the Dynamic Treatment Effect. This allow us to focus on the role of city-level observables in explaining our results. Other forms of selection *within* a city, conditional on working, may also be a driver of the Dynamic Treatment Effect on wages and earnings. We confront this in Section 5.

3.2 Treatment Effects and the Return to Big City Experience

In the previous section, we showed that the average wage-experience profile among workers *initially assigned* to Copenhagen is steeper compared to that of those assigned elsewhere. It is tempting to make a direct inference about the size of a big city experience premium using these results. However, since some workers migrate after assignment, we cannot fully attribute their experience to the assignment region. This complicates the interpretation of the Dynamic Treatment Effect as the statistical return to experience *earned in Copenhagen.* In this section, we discuss the interpretation of the Dynamic Treatment Effect in the presence of worker relocation after assignment.

Suppose there are two city types indexed by c, big cities ($c = b$) and small cities ($c = s$), and that after demeaning all variables the log hourly wage of worker i in city c at time t is given by the following equation:

$$w_{it}^{c} = \gamma^{s} \times E_{it}^{s} + (\gamma^{b} + \theta_i) \times E_{it}^{b} + \eta_{it}^{c}, \tag{2}$$

where θ_i is a scalar indexing person i's unobserved ability, E_{it}^{c} are her years of experience accumulated in cities if type c, and γ^{c} is the causal return to this type of experience. η_{it}^{c} is a structural residual that captures other determinants of wages (e.g., good firm matches and occupation shifters), with $\mathbb{E}[E_{it}^{s}\eta_{it}]$ and $\mathbb{E}[E_{it}^{b}\eta_{it}]$ not necessarily zero.

[13] However, it is worth noting even after a considerable amount of time spent in Denmark, beyond 15 years, employment rates for refugees remain about 12% below those of natives for the same age and gender.

Throughout, we assume $\gamma^b \geq \gamma^s$ so that Equation (2) allows for a wage growth premium from working in a big city. Crucially, Equation (2) reflects that higher unobserved ability may make big city experience more valuable; it is this potential complementary between ability and big city status that introduces the selection problem central to this paper.[14] If more able workers benefit more from being in a city, and hence move there at higher rates, higher wages in a city conditional on observables could be due to the city itself, or the resulting difference in average ability across locations. We define the *causal* return to big city experience, denoted by γ, as the extra return to an additional year of experience collected in a big relative to a small city, such that $\gamma \equiv \gamma^b - \gamma^s$.

We partition the set of refugees into two subsets; $\mathcal{B}$ is the set of workers assigned to a big city, $\mathcal{S}$ that of those assigned to a smaller city. The value of the experiment is to ensure that average latent ability is the same across these groups, such that $\mathbb{E}[\theta_i \mid i \in \mathcal{B}] = \mathbb{E}[\theta_i \mid i \in \mathcal{S}] = 0$ holds.[15] This helps us overcome the initial spatial selection problem introduced by the complementarity between unobserved ability and city status.

Migration of workers across assignment regions complicates the mapping from the estimated treatment effect to the parameters of the wage process. As a benchmark, we first consider an "ideal" setting without migration by assuming, that

(A.1.) Workers never move across assignment regions.

Assumption **A.1.** guarantees that all experience is accumulated in the region of assignment. As a result, treatment effects - which condition on initial assignment only - recover the *statistical* return to big city experience. To see this, consider regressing wages on experience for workers in groups $\mathcal{S}$ and $\mathcal{B}$ separately. The difference in the OLS estimates of the experience coefficients, $\hat{\gamma}^b - \hat{\gamma}^s$, obeys

$$\text{plim } \hat{\gamma}^b - \hat{\gamma}^s = \underbrace{\gamma^b + (\sigma_E^b)^{-2}\mathbb{E}[E_{it}^b \eta_{it}]}_{\equiv \beta^b} - \underbrace{\left(\gamma^s + (\sigma_E^s)^{-2}\mathbb{E}[E_{it}^s \eta_{it}]\right)}_{\equiv \beta^s} \equiv \beta,$$

where σ_E^c is the variance of E_{it}^c.[16] We define β as the return to an extra year of experience collected in the big relative to the small city. β is the main object of interest of the paper, and we refer to it as the *return to big city experience*. It consists of both the *causal* return to big city experience, $\gamma = \gamma^b - \gamma^s$, and terms reflecting other determinants of wages which covary with experience. For example, a large

[14] The wage process in Equation (2) with potential for differences in the degree to which individuals of different types can benefit from locations is similar to others in the literature (see e.g., Baum-Snow and Pavan (2012) and De La Roca and Puga (2017)).

[15] Equation (2) provides a simple framework to think about the interpretation of the Dynamic Treatment Effect. In particular, the role of unobserved heterogeneity is reduced to a static and a dynamic role for unobserved ability in wages. Other forms of unobserved heterogeneity, including sorting on preferences for amenities, comparative advantage, and multi-dimensional types (as in Lindenlaub (2017)) are likely to be important in practice. Nonetheless, we find the parsimony of one-dimensional heterogeneity an attractive way to think about how our estimates relate to the existing literature, and what can be identified in our setting.

[16] This holds under the assumption that unobserved ability does not affect the probability of employment, i.e., $\mathbb{E}[E_{it}^s|\theta_i] = \mathbb{E}[E_{it}^s]$, and similarly for big cities b.

literature suggests that as workers gain experience they work for increasingly more productive firms, i.e., they climb a job ladder (see, e.g. Baum-Snow and Pavan (2012)). If workers climb such ladders faster in big cities, this would contribute to the *return to big city experience*, β, through the $\mathbb{E}[E_{it}^{c}\eta_{it}]$ term. This highlights that even in the "ideal" setting (under Assumption (**A.1.**)) we cannot isolate the causal return to big city experience, γ.[17]

The estimated Dynamic Treatment Effect above recovers β under Assumption (**A.1.**) However, Figure 2 shows that Assumption (**A.1.**) does not hold in the data; most, but not all workers stay in their assigned region. This changes the interpretation of the estimated Dynamic Treatment Effect. To understand how we replace (**A.1.**) with two stylized assumptions about the process of relocation. We assume that

(A.2.a.) Workers assigned to the big city remain there, and

(A.2.b.) Workers who migrate from the small to the big city do so directly upon assignment and remain there.

Figure 2 motivates these assumptions as a stylized description of the data: some workers move quickly after assignment and those assigned to Copenhagen move less.[18]

Denote by $\varkappa$ the fraction of individuals in group $\mathcal{S}$ who relocate from $\mathcal{S}$ to $\mathcal{B}$ and by $\mathcal{M}$ the set of movers. Again running separate regressions on the two assignment groups and differencing the coefficients on experience yields:

$$\text{plim}\ \hat{\gamma}^{b} - \hat{\gamma}^{s} = \beta - \underbrace{\varkappa\beta}_{\text{Migration Bias}} - \underbrace{\varkappa\mathbb{E}[\theta_i | i \in \mathcal{S} \cap \mathcal{M}]}_{\text{Selection Bias}}. \tag{3}$$

Equation (3) shows that relocation introduces two sources of bias into the interpretation of the Dynamic Treatment Effect as a measure of the return to big city experience, β.

Migration bias occurs if as long as *any* worker migrates upon assignment, i.e., $\varkappa_{sb} \neq 0$ holds. In this case, the Dynamic Treatment Effect underestimates the return to big city experience, β. The reasons is that movers in S would see faster wage growth after moving to the big city, but would still be counted in the S stratification. This would shrink the estimated wage-experience profile difference between the two assignment groups and hence the measured Dynamic Treatment Effect would underestimate the return to big city experience, β.

Second, *selection bias* arises if $\mathbb{E}[\theta_i | i \in \mathcal{S} \cap \mathcal{M}] \neq 0$, i.e., movers differ from non-movers in terms of unobserved ability. Suppose, as is common in the literature, more able workers are more likely to

[17] To isolate γ in an experiment, workers would have to be randomly assigned both across space and also across firms *within* locations over their working lifetimes.

[18] Furthermore, in Appendix A.2.4, we show that more educated workers are more likely to move to Copenhagen than less educated ones. To the extent that educational attainment covaries with unobserved ability, this further supports our stylized assumption.

Table 2: Wage-Experience Profiles, Stayers Only

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.103***	2.335***	1.937***	7.063***	7.341***	6.962***
	(0.153)	(0.168)	(0.151)	(0.329)	(0.414)	(0.326)
Initial Assignment to Copenhagen	-0.122	1.208	-1.943	-13.41***	-11.06***	-17.31***
	(0.946)	(0.765)	(1.357)	(1.897)	(2.126)	(2.345)
Years of Experience × Initial Assignment to Copenhagen	1.154***	1.050***	1.195***	3.235***	2.992***	3.638***
	(0.148)	(0.165)	(0.155)	(0.301)	(0.363)	(0.294)
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.056	0.062	0.057	0.153	0.156	0.154
Observations	75,066	43,429	31,637	82,553	47,732	34,821

Notes: The specification estimated in this Table is stated in Equation (1) in the text. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The definition of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the regions constructed in Section 2.3. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample that never relocate across assignment regions upon initial assignment. The construction of the sample is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample that never relocate across assignment regions upon initial assignment and that have at least a high-school degree. Columns II.C and II.C are based on refugees that never relocate across assignment regions upon initial assignment and that have less than a high-school degree, including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

move to the city so that $\mathbb{E}[\theta_i | i \in \mathcal{S} \cap \mathcal{M}] > 0$. These high-ability movers will nevertheless be counted into group $\mathcal{S}$, shrinking the gap in estimated slopes between the two treatment groups. As a result the Dynamic Treatment Effect further underestimates the return to big city experience.

The above analysis suggests that under the assumption that $\mathbb{E}[\theta_i | i \in S, i \to b] > 0$, we can construct an informative upper bound on the return to big city experience, β. To do so we reestimate our baseline Equation (1) only on individuals who *never move* across assignment regions. First, since these workers do not move by definition, this measure does not suffer from the first source of downward bias we identified above. Second, we remove on average high-ability individuals whose wages grow faster with experience after moving to Copenhagen. This leaves on average lower ability individuals in our Non-Copenhagen stratification than compared to the randomly selected sample. Likewise, the Copenhagen group earns all their experience in Copenhagen and contains those least likely to leave Copenhagen since it benefits them most. Jointly, this has the effect of biasing upwards our estimate of the return to big city experience, β.

The results of re-estimating our treatment regression in (1) on the stayer population are shown in

Table 2. These results accord with our simple selection story: the differential value of experience accumulated in Copenhagen is uniformly higher in the sample of stayers than in the full sample (see Table 1 above). Comparing the results in Tables 2 and 1 suggests that the *return to big city experience* lies in the range of $0.74\% - 1.05\%$ for the sample of refugees with at least high school education, a relatively tight bound.

This section suggested that experience accumulated in big cities is indeed more valuable. The richness of the Danish administrative data we used to document this, however, allows us to go further. In the next section, we try to understand which observable variables help explain the return to big city experience.

4 Observable Determinants of the Return to Big City Experience

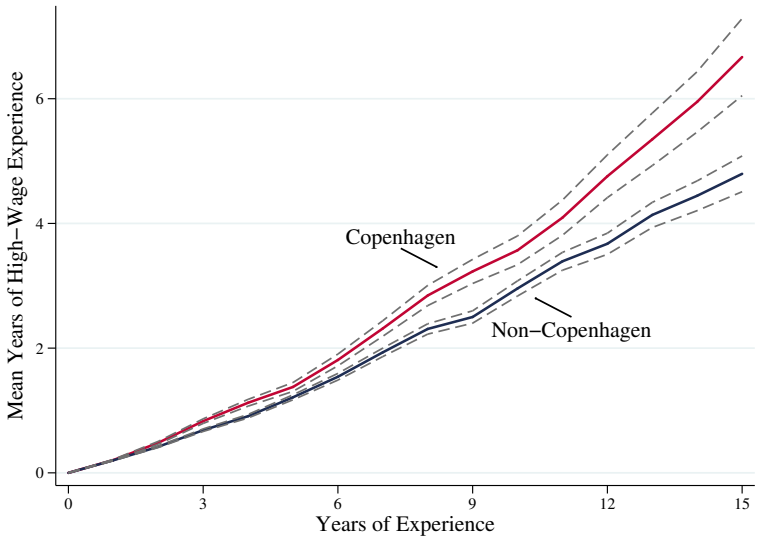
Previous research on the urban wage premium, to the best of our knowledge, has not drawn on matched employer-employee data to understand its determinants. The Danish administrative data allows us to investigate whether the type of jobs refugees work in differ across assignment regions in ways that can help explain the causal dynamic treatment affect identified above.

People who live in big cities often pursue different work than those outside. One potentially important difference is in production technologies. The urban literature has found that firms located in big cities tend to be more productive than firms elsewhere (see, for example, Combes et al. (2012)). This suggests that the experience collected at firms in Copenhagen may be fundamentally different, since it is collected at firms that are on average more productive. Part of the return to big city experience may be a return to "productive firm experience". Moreover, the larger presence of productive firms in Copenhagen could mean that workers sort towards such firms at a higher rate, which would further steepen the average wage-experience profile.

To test for both of these channels, we construct a simple measure of productivity for every Danish establishment to understand the importance of this mechanism. Each year we divide *all establishments in Denmark* into deciles based on the average hourly wage paid at the establishment.[19] For each year, we classify an establishment as high-wage if it falls into one of the top three deciles of the resulting firm-wage distribution. In line with previous findings in the urban literature, high-wage establishments tend to be large and disproportionately present in Copenhagen (see Combes et al. (2012), Mion and Naticchioni (2009), Dauth et al. (2018)). For each refugee at each point in time, we then construct years of experience at high- and low-wage establishments separately. Figure 4 shows the average years of experience at high-wage establishments by years of total labor market experience separately by assignment area. Refugees assigned to Copenhagen gradually accumulate more years

[19]The average wage is computed using all Danish hourly-wage observations at the person-year level (excluding refugees), subject to the sample selection procedure outlined in Section 2.2.

Figure 4: Average High-Wage Experience across Assignment Groups, by Years of Overall Experience



Notes: This Figure shows the accumulation of experience at high-wage firms among refugees by initial assignment area. Refugees are assigned to a group (Copenhagen or Non-Copenhagen) based on the region they are initially assigned to, not based on where they work at any point in time. The delineation of the two assignment regions, Copenhagen and Non-Copenhagen, corresponds to the that constructed in Section 2.3. The sample of refugees used includes all refugees with at least a high-school degree from our full sample whose construction is outlined in Section 2.2. Every year, the average hourly wage of all Danes at every establishment in Denmark is computed. High-wage firms are defined as establishments in the top three deciles of the resulting firm-wage distribution. For each refugee the total numbers of years worked in Denmark before the current year constitutes her experience up to the current year, the years spent at high-wage firms constitute the high-wage experience. 95% confidence intervals shown in grey.

of experience at high-wage firms compared to refugees assigned elsewhere.

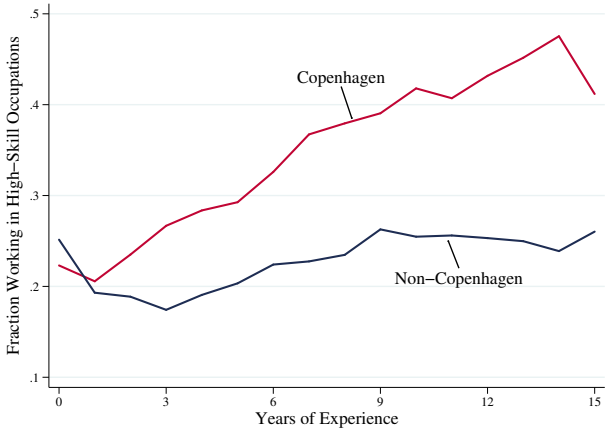
We now assess the role of these two channels in explaining the Dynamic Treatment Effect identified above. We re-estimate Equation (1) with separate controls for years of experience accumulated at high- and low-wage establishments. We keep the interaction term on overall experience only, which allows us to examine how much the *composition* of experience is driving the results above. We also include a fixed effect for whether the establishment a refugee is currently working at is a high-wage establishment. This specification is estimated in Column (2) of Table 3 (Column (1) repeats the baseline treatment regression from Table 1 above for comparison), and reduces our baseline coefficient to 0.566%, suggesting that those assigned to Copenhagen move to higher paying establishments over time, and experience at high-wage establishments is worth more in a statistical sense than experience at other establishments.

Assignment regions may also differ in the industries and occupations in which they offer opportunities. If workers sort into different occupations and industries over time as a function of their location, this could help explain differences in the return to experience across the assignment groups.

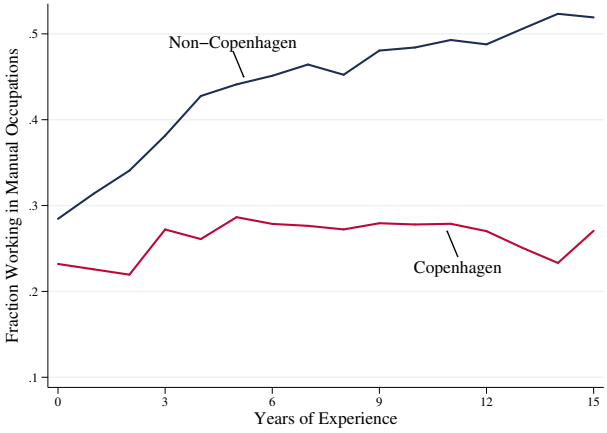
To test the importance of this channel we draw on the occupation and industry information available in the Danish administrative data. To investigate the importance of different occupations across assignment areas, we construct three broad three groups: we differentiate occupations that are low-

Figure 5: Occupations by Initial Assignment and Years in Denmark

(a) High-Skill Occupations



(b) Manual Occupations



Notes: This Figure shows the fraction of refugees working in different occupations, by initial assignment area. Refugees are assigned to a group (Copenhagen or Non-Copenhagen) based on the region they are initially assigned to, not based on where they work at any point in time. The delineation of the two assignment regions, Copenhagen and Non-Copenhagen, corresponds to the that constructed in Section 2.3. The sample of refugees used includes all refugees with at least a high-school degree from our full sample whose construction is outlined in Section 2.2. The ten 1-digit ISCO codes of occupations in the Danish administrative data are collapsed to three occupational groups, ordered by the average hourly wage of Danes working in them: (1) low-skill, (2) manual, and (3) high-skill. We then compute the fraction of workers, by assignment region, that work in either of the three occupations at different years of experience. Figure 5a shows the fraction of workers in high-skill occupations, by assignment region and years of experience, Figure 5b does the same for manual occupations, and Figure 12 for low-skill occupations.

skill, manual, and high-skill.[20] In Figure 5, we show the distribution of refugees across occupations by assignment region and years of experience. In both assignment regions, many refugees initially start their careers doing low-skill service work (e.g., cleaning, sales, or clerical support work). However, as they gain experience, refugees placed outside of Copenhagen transition predominantly into manual work, while those placed into Copenhagen move into high-skilled work. At 15 years of experience, 40% of refugees assigned to Copenhagen work in high-skill occupations compared to 27% of those assigned elsewhere.

To assess the contribution of differential sorting into occupations and industries across assignment regions we add further controls to the regression in Column (2) of Table 3. Including occupational fixed effects at the 1-digit level in Column (3) further decreases the coefficient on the Dynamic Treatment Effect to 0.354%. This is line with the descriptive patterns above: refugees assigned to Copenhagen have a higher chance of working in high-skilled jobs, and this advantage widens over time.[21] For industries, we find that workers in Copenhagen are more likely to work in skill-intensive business

[20] We use the broadest one-digit occupation categories, which comprise nine different categories. A list of these can be found in Appendix A.2.5. The three occupational groups are ordered in terms of the average wage of all Danes working in them, with low-skill workers earning the least and high-skill workers the most.

[21] With 1-digit occupation controls, a static wage premium emerges. Hence within occupations, it does appear that workers in Copenhagen earn roughly 3% higher wages. The absence of this effect in the baseline estimation is due to the fact that initially, workers are more likely to be employed in low-pay service jobs in Copenhagen, depressing the average wage.

Table 3: Mechanisms Explaining the Urban Growth Premium

	Log Hourly Wage × 100			
	A	B	C	D
Years of Experience	2.497***			
	(0.159)			
Years of Experience at High-Wage Firms		2.587***	2.165***	2.246***
		(0.121)	(0.124)	(0.138)
Years of Experience at Other Firms		2.059***	1.860***	1.570***
		(0.203)	(0.140)	(0.126)
Initial Assignment to Copenhagen	0.858	-0.241	0.597	0.580
	(0.883)	(0.676)	(0.538)	(0.533)
Years of Experience × Initial Assignment to Copenhagen	0.736***	0.566***	0.354**	0.278*
	(0.163)	(0.148)	(0.115)	(0.101)
Assignment Controls	Yes	Yes	Yes	Yes
High-Wage Establishment FE	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes
Industry FE	No	No	No	Yes
R-Squared	0.062	0.137	0.188	0.224
Observations	57,994	57,994	48,183	44,135

Notes: The specification estimated in this Table is stated in Equation (1) in the text. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. Years of Experience is decomposed into the number of years of experience accumulated at high-wage establishments and number of years accumulated at non high-wage establishments. The classification of establishments into high- and low-wage ones is explained in Section 4 in the text. The sample used for the estimates in Columns A through D includes all refugees from the full sample whose construction is outlined in Section 2.2 with at least a high-school degree. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. The industries and occupations controlled for via fixed effects are listed in Appendix A.1.2 and Appendix A.1.3, respectively. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

services, while manual jobs in agriculture and manufacturing is more frequently observed outside of the capital. The fixed effects for 1-digit industries included in Column (4) further decrease the Dynamic Treatment Effect to 0.278%.[22] We conclude that jointly, these observables account for a large fraction of the Dynamic Treatment Effect identified before and restated in Column (1).[23]

Besides the nature of jobs and firms, there could be other factors that facilitate faster wage growth for refugees in Copenhagen. We consider two such factors that appear potentially important.

First, the literature has shown that skilled wage premia tend to be higher in big cities (see, e.g.,

[22]See Appendix A.1.2 for the complete list of industries used.

[23]The order of inclusion of the different types of experience and industry and occupation fixed effects makes no qualitative difference.

Baum-Snow and Pavan (2012) and Eckert and Kleineberg (2019)). As a result, refugees assigned to Copenhagen could find it relatively more attractive to invest further in education and training. If they increased their years of education more than those assigned to Non-Copenhagen this could contribute to the estimated Dynamic Treatment Effect. The Danish administrative data provides detailed information on education take-up throughout the life of a worker. In Appendix A.2.6, we test formally whether refugees initially assigned to Copenhagen take-up more years than those assigned elsewhere. Table 9 there shows the result of a t-test of mean differences in educational take-up between the two assignment groups. The second column repeats this exercise for refugees with at least a high school degree at arrival. Differences in take-up across assignment regions are very small in both samples; about equal to an additional month of education. This suggests educational take-up differences across commuting zones are not an important driver behind the Dynamic Treatment Effect identified above. Including years of education in the specifications in Table 3 further confirms that it does not contribute to the Dynamic Treatment Effect.

Second, several papers (see, e.g., Edin et al. (2003) and Damm (2009b)) have examined the effect of being located in an ethnic enclave on employment and wage outcomes, and generally find positive effects, especially for the low-skilled. As Damm (2014) notes, before the dispersal policy was introduced, immigrants and refugees clustered in Copenhagen, suggesting ethnic enclaves may be more prevalent there. If refugees collocating with other immigrants of their own nationality in Copenhagen gradually gives them access to informal networks and employment opportunities, this would appear as differential return to big city experience. To test this channel, we include in our baseline specification controls for the ethnic composition of the municipality of assignment for each refugee, and in particular the stock of co-nationals in the year of assignment.[24] Table 15 in Appendix A.3.4 presents the estimates. Our baseline estimates for the Dynamic Treatment Effect are unchanged. Refugees assigned to ethnic enclaves receive lower wages and earnings on average, but this does not affect the estimated Dynamic Treatment Effect of being assigned to the big city.

In addition to these observable channels, dynamic selection on unobservables *within* assignment areas could be driving part the Dynamic Treatment Effect. This is conceptually distinct from the selection *across* assignment areas that the experiment helps address. First, there could be selection into who obtains experience at all. If higher ability individuals are more likely to get jobs in Copenhagen than outside, this could generate differences in the estimated Dynamic Treatment Effect.[25] Second, there could be complementarities between unobserved ability and high-wage firms, occupations, and industries. The next section details a structural model of earnings dynamics to understand the role

[24] It is worth noting that the Copenhagen commuting zone we constructed in Section 2.3 consists of about thirty municipalities, so that there is variation in these stocks across the municipalities of assignment within the Copenhagen commuting zone.

[25] Recall that by focussing our analysis on workers with at least high-school education, there are no observable differences in participation across assignment regions. However, who chooses or is forced not to participate could co-vary differently with skill across assignment areas

of such interactions between sorting across regions and jobs and unobserved ability in generating the observed differences in returns to experience across assignment regions.

5 Sorting *within* Cities and the Return to Big City Experience

We can explain a significant fraction of the Dynamic Treatment Effect by controlling for observables indexed to firm, occupation, and industry types. In this section, we quantify the role of sorting on unobserved ability *within* cities in explaining the observed differences in the wage-experience premium between assignment regions. This requires the specification of a statistical model of spatial earnings dynamics that can link observable outcomes to unobserved ability. In line Section 3.2, we consider only one-dimensional differences in unobserved ability.

Ex-ante, there are at least three reasons why sorting *within* cities may be important in our setting. Suppose that high-ability individuals have a higher return to experience, as assume in Equation 2 above.

First, there may be differences in who gets experience at all within a city and without, even with identical populations in both locations. Suppose employment rates for high-ability individuals are higher in the city.[26] This would introduce a correlation between observed experience and the likelihood that an individual is a high-ability individual, pushing up the estimated returns to experience.

Second, there could be a correlation between unobserved type and the amount of experience accumulated at a high-wage firm. If high-ability individuals are more likely to work at high-wage firms, and there are more high-wage firms in the city, we would misattribute some of the observed dynamic city premium to a firm component.

Lastly, there could be complementarities between worker type and firm type, boosting the wage for high-ability individuals when they are working at a high-wage firm. If there is differential sorting into such firms over time within the city, this could appear to raise the premium to experience earned in the big city.

In other words, we aim to distinguish mechanisms of sorting by ability and composition from mechanisms of general human capital accumulation, which may occur faster in a city. To this end, we construct and estimate a statistical model of location choice and earnings dynamics that explicitly accounts for the unobserved heterogeneity of workers. We estimate the model on our sample of refugees using a maximum likelihood strategy that exploits the quasi-random assignment of refugees across space.

[26] Given our evidence in Section 3.1 and Appendix A.2.2 that overall employment rates are not affected by assignment to the city for this population, it would also have to be the case that low-ability individuals had correspondingly lower employment rates within the city, leaving the overall employment rate unchanged.

5.1 A Model of Spatial Earnings Dynamics

In the model workers can work either in Copenhagen ($j = CPH$) or outside Copenhagen ($j = NCPH$) and be of either of low- or high- ability, indexed by $h = \{h_L, h_H\}$. Additionally, a worker can be employed at a firm of either one of two types, low- or high- productivity, indexed by $f = \{f_L, f_H\}$.[27]

In the model workers can participate in the labor market for T years before retiring. After retirement individuals live for an additional $T/2$ years at an income equal to their last annual wage before dying with certainty . Throughout their working life workers are either employed (E) or unemployed (UE) in either of the two locations. We denote by x^i_f the years of experience of worker i at firm type f and by $\mathbf{x}^i$ the vector $\{x^i_{f_L}, x^i_{f_H}\}$.

The spatial dispersal policy is modeled as initial assignment to an area. The randomness of the assignment guarantees the orthogonality of initial assignment and latent ability.

We abstract from modeling occupation and industry choices for tractability. These decisions could be modeled in an analogous way to the decision of which firm type to work for.

5.1.1 Wage Function

The wage of a worker in location j at time t, if employed, is a function of four state variables $(h^i, \mathbf{x}^i, f^i)$.[28] For notational simplicity we suppress the worker index i on these state variables for the remainder of the model section. The log wage process of a worker, conditional on receiving an offer in location j and being employed by a firm of type f, is given by

$$\ln w(h, \mathbf{x}, f) = \bar{w} + \theta_h + \psi_f + \alpha_{h,f} + \sum_p \beta_1^{h,f_p} x_{f_p} + \beta_2 \left(\sum_p x_{f_p} \right)^2 + u. \tag{4}$$

Here, θ_h denotes the component of the wage that depends on a workers' latent type, and ψ_f that component which depends on the productivity of the firm. In the empirical implementation we set $\theta_{h_L} = \psi_{f_L} = 0$. Consequently, $\bar{w}$ is the mean wage offer of low latent ability workers from low-productivity establishments controlling for experience. The term $\alpha_{h,f}$ allows for a complementarity between firm and worker types. We set $\alpha_{h_H,f_L} = \alpha_{h_L,f_L} = \alpha_{h_L,f_H} = 0$ and estimate α_{h_H,f_L}. $\beta_1^{h,f}$ denotes the return to experience at type f firms, which we allow to differ depending on the latent ability of the worker. β_2 denotes a common return to total experience squared. We also assume there is a shock to match quality u that shifts each period's wage. We assume that u is drawn i.i.d in every period from a type-I extreme value distribution with mean zero and a variance denoted by σ_u.

[27] Our model builds on the framework of Baum-Snow and Pavan (2012).

[28] The formulation and wage function we employ can be rationalized as the outcome of a general equilibrium islands model where refugees are a small fraction of the total population. Since we take employment decisions of Danes as given and the refugees in our experiment form a very small part of the overall Danish labor force, it does not seem appropriate to employ a general equilibrium framework in our context.

5.1.2 Labor Market Transitions and Worker Migration

For simplicity, we assume that workers in location j only receive job offers from firms in the same location. The arrival rate of job offers *from unemployment* for any firm type is denoted by $\underline{\lambda}_j^h$, which is indexed by the latent ability type and location j. The corresponding probability of job offers *while employed* is denoted by $\bar{\lambda}_j^h$. While on the job, workers run the risk of being exogenously separated from their job and put into unemployment with probability δ_j^h, which may differ across locations and latent ability types. Workers on the job are also subject to reallocation shocks at rate μ_j^h. In this case, the worker is separated from his job and receives a new job offer without having to pass through through unemployment.[29] Whenever a worker obtains a job offer, the probability of that offer coming from firms of type f is denoted by $\pi_j^{h,f}$, for individuals of ability h in location j.

Each period t, agents receive preference shocks for each location j denoted by η_j. η_j is drawn i.i.d. from an extreme value Type-1 distribution with mean zero and variance σ_η. If an agent decides to change labor market, she loses her current job and needs to look for a new job in the destination location. Moving between locations incurs a utility cost denoted by τ.[30]

5.1.3 Value Functions

All workers receive amenity services from location j which we denote by a_j. Differences in the cost of living are not explicitly modeled, but absorbed into amenity differences between locations. We denote the value of unemployment benefits by b.

We denote the value of being employed in location j by $V_t^E(j, h, \mathbf{x}, f \mid u, \eta_j, \eta_{j'})$, and that of being unemployed by $V_t^{UE}(j, h, \mathbf{x} \mid \eta_j, \eta_{j'})$.[31] Both are conditional on realized location and match specific shocks, i.e., $\{u, \eta_j, \eta_{j'}\}$. Here t indexes the years of labor market participation, employed or unemployed, by a given individual since arrival in Denmark.[32] These value functions, for employed workers,

$$V_t^E(j, h, \mathbf{x}, f \mid u, \eta_j, \eta_{j'}) = a_j + \ln w(\cdot) + \rho \max_{j,j'}\{\bar{U}_{t+1}^E(j, h, \mathbf{x'}, f) + \eta_j, \bar{U}_{t+1}^{UE}(j', h, \mathbf{x'}) - \tau_j + \eta_{j'}\},$$

[29] This shock is necessary to match transition probabilities across firm types. In the data a worker may move from a high-wage firm to a low-wage firm, which is hard to rationalize without forced mobility.

[30] Given that we interpret firms as establishments, the same firm can never be located in two regions and hence moving necessitates a "firm" change. It is conceivable that workers search for job in other other regions and move there upon finding one. However, this is empirically indistinguishable given our data from workers moving to another region and finding a job there immediately upon arrival.

[31] Unemployed workers do not have a current firm type f, since they are not associated with an establishment in the data.

[32] Time matters since workers are finitely lived.

and unemployed workers,

$$V_t^{UE}(j,h,\mathbf{x} \mid \eta_j,\eta_{j'}) = a_j + \ln b + \rho \max_{j,j'}\{\bar{U}_{t+1}^{UE}(j,h,\mathbf{x}) + \eta_j, \bar{U}_{t+1}^{UE}(j',h,\mathbf{x}) - \tau_j + \eta_{j'}\},$$

can be expressed as a function of $\bar{U}_t^E$ and $\bar{U}_t^{UE}$, which denote the continuation values of being in location j at the *beginning of next* period, net of idiosyncratic location preferences and conditional on current period labor market status. $\mathbf{x}'$ denotes the vector of firm type specific experience of the worker in the next period. Depending on the current firm type f, $\mathbf{x}'$ increments one of the components of $\mathbf{x}$ by one. ρ is a yearly discount rate. Using the properties of the Type-I Extreme distributed location shock we obtain the following expression for the expected value of being employed conditional on the match specific shock:

$$\begin{aligned}\bar{V}_t^E(j,h,\mathbf{x},f \mid u) &\equiv \mathbb{E}_{\eta_j,\eta_{j'}} V_t^E(j,h,\mathbf{x},f \mid u,\eta_j,\eta_{j'}))\\ &= a_j + \ln w(\cdot) + \frac{\rho}{\sigma_\eta}\log\left[\exp\left(\sigma_\eta \bar{U}_{t+1}^E(j,h,\mathbf{x'},f)\right) + \exp\left(\sigma_\eta \bar{U}_{t+1}^{UE}(j',h,\mathbf{x'}) - \sigma_\eta \tau_j\right)\right].\end{aligned}$$

Further, the value of being unemployed is given by

$$\begin{aligned}\bar{V}_t^{UE}(j,h,\mathbf{x}) &\equiv \mathbb{E}_{\eta_j,\eta_{j'}} V_t^{UE}(j,h,\mathbf{x} \mid \eta_j,\eta_{j'}))\\ &= a_j + \ln b + \frac{\rho}{\sigma_\eta}\log\left[\exp\left(\sigma_\eta \bar{U}_{t+1}^{UE}(j,h,\mathbf{x})\right) + \exp\left(\sigma_\eta \bar{U}_{t+1}^{UE}(j',h,\mathbf{x}) - \sigma_\eta \tau_j\right)\right].\end{aligned}$$

Using these expressions, $\bar{U}_t^E(j,h,\mathbf{x},f)$ and $\bar{U}_t^{UE}(j,h,\mathbf{x})$ are a function of expected value and transition rates, only:

$$\begin{aligned}\bar{U}_t^E(j,h,\mathbf{x},f) &= \delta_j^h \bar{V}_t^{UE}(j,h,\mathbf{x})\\ &+ (1-\delta_j^h)\Big[\mu_j^h\{\pi_j^{h,f}\mathbb{E}_u \max\{\bar{V}_t^E(j,h,\mathbf{x},f \mid u), \bar{V}_t^{UE}(j,h,\mathbf{x})\}\\ &+ \pi_j^{h,f'}\mathbb{E}_u \max\{\bar{V}_t^E(j,h,\mathbf{x},f' \mid u), \bar{V}_t^{UE}(j,h,\mathbf{x})\}\}\\ &+ (1-\mu_j^h)\big[(1-\bar{\lambda}_j^h\pi_j^{h,f'})\mathbb{E}_u \max\{\bar{V}_t^E(j,h,\mathbf{x},f \mid u), \bar{V}_t^{UE}(j,h,\mathbf{x})\}\\ &+ \bar{\lambda}_j^h\pi_j^{h,f'}\mathbb{E}_{u,u'} \max\{\bar{V}_t^E(j,h,\mathbf{x},f \mid u), \bar{V}_t^{UE}(j,h,\mathbf{x}), \bar{V}_t^E(j,h,\mathbf{x},f' \mid u')\}\big]\Big],\end{aligned} \tag{5}$$

and

$$\bar{U}_t^{UE}(j,h,\mathbf{x}) = (1-\underline{\lambda}_j^h)\bar{V}_t^{UE}(j,h,\mathbf{x}) + \underline{\lambda}_j^h \sum_p \pi_j^{h,f_p}\mathbb{E}_u \max\{\bar{V}_t^E(j,h,\mathbf{x},p \mid u), \bar{V}_t^{UE}(j,h,\mathbf{x})\}. \tag{6}$$

In the expression for $\bar{U}_t^E$, f' denotes the opposite firm type of f, i.e. if f' is low than f denotes high and vice versa. In the expression for $\bar{U}_t^E$, the first term represents the value of being exogenously

separated and entering unemployment. The second and third lines capture the expected value of receiving a reallocation shock, while the fourth and fifth show the expected value of being hit by no shock and receiving no offers, and getting an offer for a new job, respectively. The distributional assumption on the random component of wages allows an analytical expression for the maximized values in Equation (5) and Equation (6).[33]

5.1.4 Initial Transition into Work

In Section A.2.2, we discussed the time it takes for refugees to integrate into Danish society before joining the labor force.[34] In the data, the fraction of refugees coded as "Not in the labor Force" (NILF) starts out very large and gradually falls off as refugees start to work. The transition from NILF into the labor force differs from the other labor market transitions and we treat it in a distinct way.

In the model, refugees start in an initial state (NILF) and receive random shocks that allow them to escape it. It is impossible to return to the initial state. This accords with the data; less than 1% of refugees return to NILF after joining the labor force for the first time. Refugees cannot move while they are in the initial state and receive unemployment benefits, denoted by b as above.

Refugees in NILF receive job offers at rate ϱ_j^h. This offer rate depends on both unobserved type and location. Conditional on an offer, $\pi_j^{h,f}$ is the probability that it is made by a firm of type f, as above. The value from being in the NILF state is given by:

$$
\begin{aligned}
W_t = \varrho_j^h \Big[& \pi_j^{h,f_L} \mathbb{E}_u \max\{\bar{V}_t^E(j,h,0,f_L \mid u), a_j + \ln b + \rho W_{t+1}\} \\
& + \pi_j^{h,f_H} \mathbb{E}_u \max\{\bar{V}_t^E(j,h,0,f_H \mid u), a_j + \ln b + \rho W_{t+1}\} \Big] + (1-\varrho_j^h) \left[a_j + \ln b + \rho W_{t+1}\right].
\end{aligned}
$$

This concludes the description of the model. The next section describes the construction of the estimation of all model parameters using a Maximum Likelihood strategy that makes use of the exogenous variation induced by the natural experiment.

5.2 Maximum Likelihood Estimation

We construct a longitudinal panel that contains the establishment type, the hourly wage, and the location for all refugees between 1986 and 2010.[35] In this data, we compute overall experience and

[33] The Online Appendix contains the derivation of all equations in this section and the analytical expression for Equations (5) and (6).

[34] Refugees undertake Danish language classes, participate in other integration programs, and receive social assistance.

[35] We define firm types as in Section 4. We use the full sample of all Danes for any given year to calculate average hourly wages paid at each establishment. Then we split the population of establishments into those whose average wage falls into the top three deciles of the national establishment distribution and the rest. The establishments in the top three deciles in each year are what we refer to as high-productivity establishments.

firm type specific experience counts for each worker at each point in their labor market careers. The shocks in the model imply that randomness plays an important role in determining the sequences of labor market states of individual workers. The estimation strategy is to choose all parameters of the model to maximize the likelihood of observing the life paths for all workers in our sample in terms of firm types, hourly wages, locations, and experience stocks by firm type.

Latent ability, h, is the only unobserved state variable. Following Baum-Snow and Pavan (2012), we construct the model implied probability of observing the life-path of every agent in the data conditional on model parameters and the agent's latent type. We denote the tuple of labor market outcomes of worker i at time t by Y_t^i. Y_t^i consists of a wage, if observed, the location of the worker, and the type of labor market transition that the worker has experienced between periods $t-1$ and t. Let $\mathbf{Y}_t^i$ denote the collection of these tuples for worker i, t years after her arrival in Denmark, so that $\mathbf{Y}_t^i = \{Y_1^i, \ldots, Y_t^i\}$.

$\mathbf{Y}_T^i$ then describes the entire life path of labor market outcomes for worker i. $P(\mathbf{Y}_T^i \mid h; \theta)$ denotes the probability of observing a given path for worker i, conditional on her latent ability type and the entire set of parameters of the model, summarized in the vector θ. We can then decompose $P(\mathbf{Y}_T^i \mid h; \theta)$ as follows

$$P(\mathbf{Y}_T^i \mid h; \theta) = P(Y_1^i \mid h; \theta) \times \prod_{t=2}^{T} P(Y_t^i \mid Y_{t-1}^i, h; \theta).$$

$P(Y_t^i \mid Y_{t-1}^i, h; \theta)$ is the model-implied probability of observing an individual making a given location and firm type transition between $t-1$ and t as well as the likelihood of the observed wage at time t. All individuals are in the NILF state at the beginning of the first period, thus $P(Y_1^i \mid h; \theta)$ is the probability of making a transition from NILF to the observed labor market state at the end of period one.

The overall contribution of worker i to the likelihood function is the weighted average of the conditional likelihoods,

$$L(\theta) = \chi_L P(\mathbf{Y}_T^i \mid h_L; \theta) + (1 - \chi_L) P(\mathbf{Y}_T^i \mid h_H; \theta),$$

where χ_L denotes the fraction of low latent ability workers in our refugee sample. . The natural experiment facilitates the estimation of χ_L. The randomness of the initial assignment implies that χ_L does not differ among refugees assigned to Copenhagen and Non-Copenhagen nor over time.

Since types are randomly assigned initially, we can construct the log likelihood function simply by summing $L(\theta)$ across all workers i in our sample

$$\mathcal{L}(\theta) \equiv \sum_i \log \left[\chi_L P(\mathbf{Y}_T^i \mid h_L; \theta) + (1 - \chi_L) P(\mathbf{Y}_T^i \mid h_H; \theta) \right]. \tag{7}$$

We do not observe all workers for the same length of time T. Workers that arrive in later years are not observable for an entire T years. The maximum likelihood strategy accommodates this conveniently: we simply record the contribution to the likelihood of all workers in all the periods for which we

observe them and hence maximize the sum of the observed data.[36]

5.3 Estimation Results and Model Fit

Tables 16 and 17 in Appendix A.4.1 show the estimated parameter values . The estimation suggests a strong separation of high- and low-ability types. The high-type fixed effect for wages is estimated at 27 log points. This is emphasized in Figure 16 in Appendix A.4.2, which shows simulated wage densities for both types compared to the wage density in the data. Given the proportion of high-types is estimated at 48%, they account for almost all the mass in the upper quantiles of the wage distribution in the data.

The job-ladder parameters largely show a pattern that accords with intuition. As suggested by our results in Section 4, the probability of a job offer from a high-wage firm is higher in Copenhagen. The difference is even more pronounced for a high-ability worker; the big city allows high-type workers to climb sort towards high-type firms particularly fast. Job finding rates from unemployment are somewhat lower in the city, particularly for low-ability workers.

Using the estimated parameters, we simulate labor market life paths for 10^5 agents to construct a synthetic panel of workers. The panels in Figure 6, compare moments in the data to the same moments computed in the simulated panel. The model does a good job of fitting important patterns in the data.

Figures 6a and 6b show the persistence of the initial location assignment and high-wage firm experience profiles in data and the simulated panel. The difference in high-wage experience accumulated over time is matched well, while the level is not. Figure 6c shows the wage-experience profiles by initial allocation. The broad pattern is correct, though the size of the dynamic premium is less in our simulated model than in the actual data. One of the reasons is the absence of occupations and industries in our model which Section 4 found to explain a significant part of the Dynamic Treatment Effect. Figure 6d shows the state transitions in both simulated and actual data. With the exception of the probability of leaving unemployment the model approximates the data well.

5.4 Structural Decomposition of the Dynamic Wage Premium

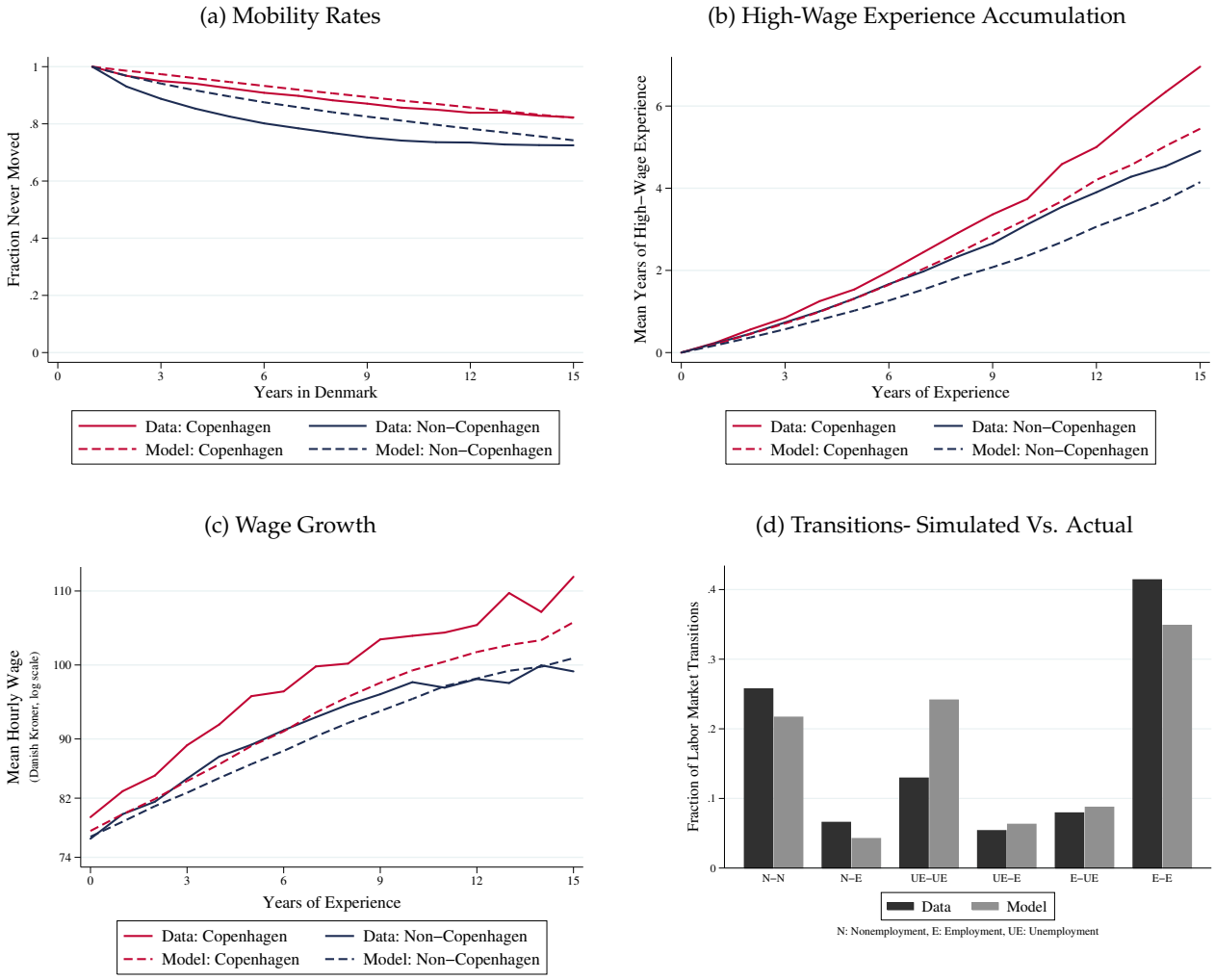
We now come to the central result of this last Section: quantifying the contribution of sorting on unobserved ability in generating the Dynamic Treatment Effect.

We consider three different scenarios of the estimated model. These are:

Scenario A (Transitions): We shut down job-ladder differences across types, to study the contribution of the Copenhagen's employment effects on high- and low-ability workers compared with Non-

[36]The Online Appendix contains a detailed derivation of the likelihood function and its components, as well as details on the mechanics of the estimation. The Online Appendix is available upon request from the authors.

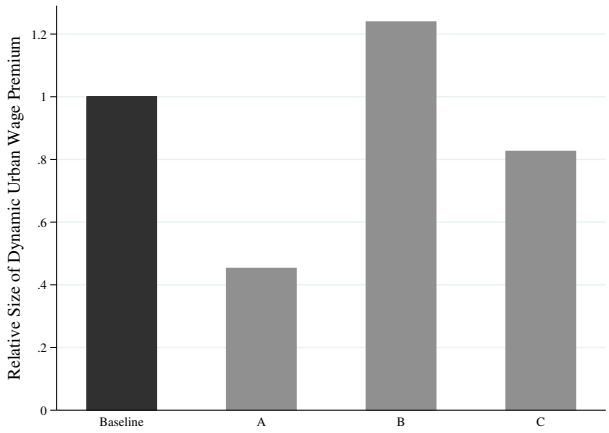
Figure 6: Model Fit



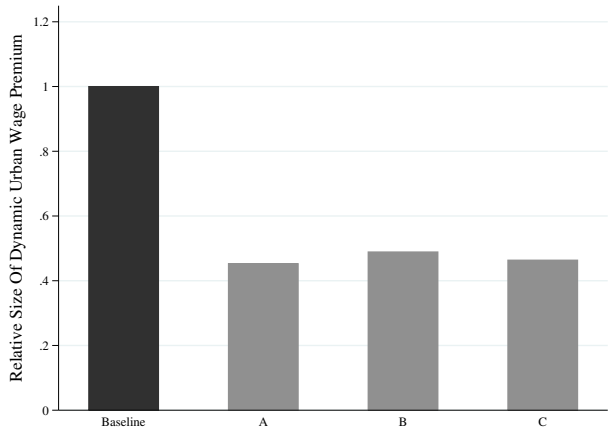
Notes: All panels in this figure compute the same objects in the data and in model simulated data. The data sample underlying this figure includes all refugees with at least high-school education from the full sample whose construction is outlined in Section 2.2. The "model data" is generated by simulating 10^5 agents using the parameters estimates in Appendix A.4.1. In the model generated data, we start the same fraction of simulated agents off in Copenhagen and Non-Copenhagen assignment area as in the data. The delineation of the two assignment regions, Copenhagen and Non-Copenhagen, corresponds to the that constructed in Section 2.3. Figure 6a plots the fraction of refugees that have *never* changed assignment region (Copenhagen and Not-Copenhagen) out of all refugees assigned to a given region against the number of years since arrival in Denmark. Years in Denmark is computed as the number of years since being granted asylum. Figure 6b shows the accumulation of experience at high-wage firms among refugees by initial assignment area. Refugees are assigned to a group (Copenhagen or Non-Copenhagen) based on the region they are initially assigned to, not based on where they work at any point in time. Every year, the average hourly wage of all Danes at every establishment in Denmark is computed. High-wage firms are defined as establishments in the top three deciles of the resulting firm-wage distribution. For each refugee the total numbers of years worked in Denmark before the current year constitutes her experience up to the current year, the years spent at high-wage firms constitute the high-wage experience. 95% confidence intervals shown in grey. Figure 6c shows the wage-experience profile for refugees allocated to Copenhagen and Non-Copenhagen separately. Figure 6d shows the fraction of all labor market transition in the data and the simulated data that occur between the three labor market states: (1) Nonemployment (N), Employment (E), and Unemployment (NE).

Figure 7: Dynamic Premium Decomposition

(a) Individual Effect of each Scenario



(b) Cumulative Effect of all Scenarios



Notes: The "model data" is generated by simulating 10^5 agents using the parameter estimates in Appendix A.4.1. In the model generated data, we start the same fraction of simulated agents off in the Copenhagen and Non-Copenhagen assignment areas as in the data. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. The estimated specification underlying this Figure is given in Equation (1) in the text. To construct the Figure we estimate this specification on various different simulated data sets. The data sets are differ by the parameters they allow to be indexed by latent ability. Define the following restrictions: (Baseline) all parameters as in Appendix A.4.1, (A) all job ladder parameters set to their average value across latent ability types within regions, (B) the returns to experience equalized across latent ability types in the wage process in Equation 4, and (D) the complementarity between high-wage firm and high-ability individuals switched off in the wage process in Equation 4. Figure 7a shows the estimated value of the interaction term between return to experience and placement into Copenhagen in Equation (1), β_3, for scenarios (A)-(C) relative to the β_3 estimated from the Baseline simulated sample. Figure 7b shows the estimated value of the interaction term between return to experience and placement into Copenhagen in Equation (1), β_3, for scenarios (A), (A,B), and (A,B,C) relative to the β_3 estimated from the Baseline simulated sample.

Copenhagen. We set these parameters to the average of their respective values for the two latent ability groups (weighted by χ_L).[37]

Scenario B (Returns to Experience): We force the returns to experience for different firms to be the same across worker types, again by setting them equal to their average values across types.

Scenario C (Complementarities): We force the estimated complementarity between high-types and high-wage firms, α_{h_H,f_H}, to be zero, so that $\alpha_{h,f} = 0 \ \forall h, f$.

For each one of these scenarios we simulate a panel of 10^5 workers and estimate the baseline specification in (1) on this simulated data, conditioning only by initial location. In Figure 7, we report the Dynamic Treatment Effect of assignment to Copenhagen for each scenario relative to the Dynamic Treatment Effect in the full structural model. The left panel shows each scenario individually, the right panel we combine Scenarios A, B, and C sequentially in the order in which they are introduced above.

Figure 7a reveals mobility differences across types to be the most important channel, explaining

[37] More precisely, we force job finding rates $\underline{\lambda}_j^h$ and $\bar{\lambda}_j^h$, job destruction rates δ_j^h, firm type f offer probabilities $\pi_j^{h,f}$, and reallocation shocks μ_j^h to be the same across worker types within each location j.

around 54% of the baseline treatment effect in the full model. As shown in Figure7b, shutting down the other two channels does almost nothing further. This is intuitive, since these two channels are dependent on the differential job ladder structure to operate. Differential returns to experience across types and complementarities will only show up as part of the premium if the city sorts high- and low-ability workers into different firms than would occur outside.

Copenhagen does not only allow all workers to gain more experience at high-wage firms than they would elsewhere, but it allows high-ability workers to sort into high-wage firms faster, and to stay there once they have arrived. This suggests that at least part of the explanatory power of conditioning on firm type Section (3) above comes from the latent type of the workers. In Copenhagen it is more likely that a worker observed at a high-wage firm is herself of high ability. Since sorting is inherently a dynamic process, this shows up as a differential return to experience between Copenhagen and Non-Copenhagen.

6 Conclusion

This paper showed that refugees who were quasi-randomly assigned to a big city had a significantly steeper wage-experience profiles than others who were assigned to smaller cities and the countryside.. Both wages and earnings of refugees placed into Copenhagen grew about 30% faster with each year of experience relative to their peers assigned elsewhere.[38] We did not find evidence for a static urban wage premium in hourly wages among refugees.

Under a set of plausible assumptions, we showed how to translate this treatment effect into a tight upper and lower bound on the causal return to big city experience. In particular, our calculations suggest that the return to big city experience lies between 30-45% in our context.[39]

We find that controlling for the gradual sorting of workers across establishments, occupations, and industries explains much of the return to big city experience. The productivity distribution of firms within a city and the occupations and industries prevalent there seem to differ in important ways from more rural areas and generate substantial differences in return to experience across space.

A structural analysis of selection and sorting into different establishments *within* the big city suggests that the unobserved ability of workers matters for these patterns. We find that the return to big city experience for our population is at least partially reflects that cities allow high-ability workers to quickly climb the job ladder into more productive firms.

[38] To obtain this number, we divide the coefficient on the interaction of experience and initial assignment to Copenhagen by the coefficient on years of experience in Table 1.

[39] To obtain the latter number, we divide the coefficient on the interaction of experience and initial assignment to Copenhagen by the coefficient on years of experience in Table 2.

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A Appendix

This Appendix contains additional materials and supporting evidence for the findings in the main body of the paper.

Section A.1 describes details of the sample construction using administrative data files from the Statistics Denmark. It also includes lists of the occupations and industries used throughout the paper.

Section A.2.1 compares refugees to natives and refugees assigned to Copenhagen to those assigned elsewhere along a set of observable dimensions important to our analysis. In Sections A.2.2 and A.2.3, we examine employment rates and hours worked among the two assignment groups. Section A.2.5 offers a comparison of the occupational composition of the workforce in Copenhagen and Non-Copenhagen among natives relative to refugees. Section A.2.6 investigates differences in educational take-up by refugees upon arrival in Denmark. Section A.2.7 presents estimates of the urban wage premium in Denmark for all Danes.

The next sections present a series of robustness checks on the baseline specification presented in Equation (1). In Section A.3.1, we explore the robustness of our results to alternative commuting zone definitions; in Section A.3.2 we present results using different definitions of the treatment and control groups; Section A.3.3 we allow for non-parametric treatment effects for wages and earnings; Section A.3.4 includes controls for ethnic enclaves.

Sections A.4.1 and A.4.2 report the structural model parameters and provide additional information on model fit.

An Online Appendix is available upon request from the authors. It contains an exhaustive list of the variables extracted from the Danish administrative data and detailed derivations of the expressions in the statistical model in Section 5.

A.1 Data Appendix

A.1.1 Details on the Construction of the Data Set

The matched employer-employee data panel used throughout the paper draws on five sources from within the universe of Danish data registers:

1. Information from *ida*, a Danish matched employer-employee dataset constructed by Statistics Denmark.

2. Information on firms' sales and purchases from firm-level VAT data administered by the Danish tax authorities.

3. Between country migration information from Statistics Denmark dataset *epersoner*.

4. Family data (e.g., number of children and age of children) from the Statistics Denmark dataset *familie*.

5. Income data including total yearly labor market earnings from the Statistics Denmark dataset *indh*.

The *ida* data We use three sub-panels within *ida*: *ida-p*, *ida-n*, and *ida-s*. *ida-p* contains basic characteristics for individuals aged between 15-74 residing legally in Denmark on the 31st of December in a given year. The unit of observation in *ida-p* is person-year. We keep information from *ida-p* on gender, age, municipality of residence, and years of education.[40] *ida-n* contains labor market information constructed using annual tax filings obtained from the Danish tax authorities. The unit of observation in *ida-n* is person-year. *ida-n* contains all workers' employment relations. For a given individual, Statistics Denmark defines the job with highest earnings on November 28th of a given year as the individual's primary employment relation. We retain information on an individual's primary employment to construct hourly wages and annual earnings, and the employer's firm identifier. *ida-s* contains information on all physical workplaces within a firm in Denmark. Employment which takes place at changing locations is said to take place at a fictitious workplace, which Statistics Denmark do not keep information on.[41] The unit of observation in the (aggregated) *ida-s* is a firm-year. We retain information on industry of the workplace and whether or not the workplace is in the public sector.

The *VAT* data Data on sales and purchases at the firm level are obtained from the Statistics Denmark panels *moms* and *momm*, which are constructed from firm VAT accounts from the Danish Tax Authorities. Firms settle VAT either monthly, quarterly, or yearly depending on size of revenue. *moms* covers the period 1995-2000 and contains annual sales and purchases. *momm* is a monthly panel starting in 2001.[42] We aggregate *momm* data to a yearly frequency.[43] The unit of observation is firm-year.

The *epersoner* data The dataset contains cross-sectional information on all individuals living in Denmark by 1st of January.[44] We retain information on an individual's earliest migration to Denmark. Following Damm and Dustmann (2014), our sample of refugees includes all individuals migrating from Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. The unit of observation is a person-year.

[40] The information on years of education is an exception; for refugees who have not studied in Denmark, the information on years of education stems from a survey conducted by Statistics Denmark (see Damm (2009a) for details).

[41] Approximately 3-5% of workers are working at a fictitious workplace.

[42] Statistics Denmark impute VAT for firms who settle VAT either quarterly or yearly.

[43] As all firms settle VAT at least on a yearly frequency then aggregation of *momm* data is not affected by imputation of monthly and/or quarterly VAT.

[44] Recall that the population of *ida-p* is all individuals living in Denmark by December 31st. Thus in order to merge *ida-p* and *epersoner*, we match a *ida-p* person-year+1 observation with a matching *epersoner* person-year observation.

The *familie* data Information on an individual's family is gathered every year on January 1st.[45] Family information is obtained from Danish social-security register (CPR). We retain information on spouses, which enables us to link individuals in our datasets together into families. Furthermore, we retain number of children, age of oldest child, age of youngest child, and marriage status. The unit of observation is person-year.

The *indh* data Data on total yearly labor market earnings is obtained from Danish tax authorities by Statistics Denmark.

A.1.2 List of Industries

The following industry codes are used in the Danish microdata and employed throughout the paper whenever industry fixed effects are applied:

A: Agriculture, forestry, and fishery, B: Winning and quarrying, C: Manufacturing, D: Electricity, gas, steam, and air-conditioning supply, E: Water supply, sewerage contractors, waste management, and remediation activities, F: Construction ,G: Wholesale and retail trade, repair of motor vehicles and motorcycles, H: Transport and storage, I: Accommodation and food service activities, J: Information and communication, K: Financial and insurance activities, L: Real estate activities, M: Professional, scientific, and technical activities, N: Administrative and support service activities, O: Public administration and defense, compulsory social security, P: Education, Q: Human health and social work activities, R: Arts, entertainment, and recreation, S: Other service activities, T: Activities of household as employers, undifferentiated goods- and services-producing activities of households for own use, U: Activities of extraterritorial organizations and bodies, X: Unknown

A.1.3 List of Occupations

The Danish micro-data features detailed 4-digit occupation codes. For the period between 1992 and 2010, the first digit of these codes coincides with International Standard Classification of Occupations (ISCO) 1-digit codes, which we list in the first column of Table 4.

We use the full sample of Danish males to compute average hourly wages by 1-digit occupation for every year between 1992 and 2010. Then we rank occupations according to their average wage for each year. In Column 3 of Table 4, we list the average rank of each occupation across the years 1992-2009. The description of the occupation in Column 1 and the detailed ranking based on the wages in Column 2, naturally suggests a coarser classification of the nine occupations into three comprehensive

[45] As for observations in *epersoner* we have to merge family data onto our other data sources by matching a person-year+1 observation with a person-year observation from *familie*.

Table 4: Description of Occupation Codes and Classifications

		Wage Rank	
ISCO Description (Code)	Type	Decile	Coarse
Managers (1)	High-Skill	1	1
Professionals (2)	High-Skill	2	1
Technicians and associate professionals (3)	High-Skill	3	1
Clerical support workers (4)	Low-Skill	8	3
Service and sales workers (5)	Low-Skill	9	3
Skilled agricultural, forestry and fishery workers (6)	Manual	5	2
Craft and related trades workers (7)	Manual	4	2
Plant and machine operators and assemblers (8)	Manual	6	2
Elementary occupations (9)	Low-Skill	7	3

Notes: The Danish International Standard Classification of Occupations (DISCO) 1-digit codes used throughout the paper and shown in this table are the Danish implementation of the international used ISCO occupation codes . The sample used to construct wage ranks in this table includes all male Danes between 19 and 55 years of age. We compute the average hourly wage for each 1-digit DISCO occupation for each year and average across all years in the sample. The coarse occupation ranking is the authors own grouping obtained by grouping 1-digit DISCO occupations with similar wage ranks together into three groups.

groups listed in Column 3: high-skill, low-skill, and manual professions. We list these "coarse" wage ranks in Column 4 of Table 4.

In regressions throughout the paper we use the nine 1-digit codes to control for occupation fixed effects. In the estimation of the finite mixture model in Section 5 and for some of the graphs in the mechanism section, we employ the coarse ranking.

A.2 Additional Descriptive Statistics

This Section provides additional empirical analysis referenced in the main part of the paper.

A.2.1 Descriptive Statistics for Refugees

In this Section, we compare refugees to a cross-section of Danes with respect to some observables important to our analysis. We also compare refugees initially assigned to Copenhagen to those assigned elsewhere.

The first two columns of Table 5 shows the comparison of natives and refugees. The group of natives is the 1990 cross-section of Danish males in our matched employer-employee dataset after applying the same sample selection criteria as for our baseline sample described in Section 2.2. We find that the refugees are on average younger when they arrive and enter the labor market than the average Dane. Accordingly, they are less likely to be married and have less, younger children. As Table 5 shows,

Table 5: Descriptive Statistics - Natives and Refugees

	Natives	Refugees		
	1990 Cross-section	All	Copenhagen	Non-Copenhagen
Mean				
Age	36.72	28.24	28.67	28.08
Number of children	0.68	0.54	0.47	0.57
Age of youngest child	7.43	3.46	3.63	3.40
Age of oldest child	10.01	7.27	7.20	7.30
Fraction				
Married	47%	28%	28%	28%
Missing education	0%	19%	19%	19%
10 years of education	31%	27%	23%	28%
12 years of education	50%	34%	34%	34%
More than 12 years of education	17%	20%	23%	19%
Observations	1,335,545	20,493	5,530	14,963

Notes: The sample underlying the descriptive statistics of natives is a cross-section of all men aged between 19-55 who were either employed or unemployed in year 1990. The sample underlying the descriptive statistics of refugees includes all refugees from the full sample whose construction is outlined in Section 2.2. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper.

for a fraction of refugees it was not possible to determine their level of education upon arriving in Denmark. The education information for natives is derived from administrative records and contains virtually no missing observations.

We now compare refugees assigned to Copenhagen and refugees assigned elsewhere in the first year they appear in data. The last two columns of Table 5 show descriptive statistics for the two groups of refugees. Recall that council officers observed age, nationality, and number of children when assigning refugees to municipalities. We confirm that larger families where assigned to Non-Copenhagen more often, as it was easier to house large families outside Copenhagen.

The council officers assigning refugees to municipalities did not observe refugees' education levels. Here we test for significant differences in years of education between refugees assigned to Copenhagen and Non-Copenhagen upon arrival in Denmark.

We regress years of education on a dummy for whether the refugee where assigned to Copenhagen or not. Additionally, we control for the assignment variables known to the council officers. . Table 6 presents the result.[46] Even after accounting for the information available to the council officers, we

[46]The sample used consists only of refugees without missing information in the first year they appear in the dataset, which is a larger fraction of the sample than the 19% for whom we never observe educational information from Table 5. We test and reject the possibility that the fraction of refugees for whom education information ism missing differs between Copenhagen and Non-Copenhagen.

Table 6: Regression of Initial Years of Education on Assignment Variables

	Years of Education at Arrival		
	A	B	C
Initial Assignment to Copenhagen	0.164***	0.0980	0.0245
	(0.0491)	(0.0571)	(0.0454)
Indicator for Maritial Status	0.213***	0.145*	0.130*
	(0.0617)	(0.0691)	(0.0623)
Number of children	-0.121***	-0.0549*	-0.0607**
	(0.0218)	(0.0247)	(0.0214)
Age	0.431***	0.233***	0.216***
	(0.0191)	(0.0243)	(0.0177)
R-squared	0.171	0.080	0.061
Observations	11,812	7,386	4,426

Notes: The dependent variable in all columns is log years of eduction at arrival. The dependent variable in all columns are scaled by a factor of 100 for presentational purposes. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. Sample A consists of all refugees from the full sample whose construction is outlined in Section 2.2 The sample in Column B is restricted to refugees with at least a high-school degree. Column C consists of refugees with less than a high-school degree. Refugees with missing education information are dropped from the regression. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

Table 7: Labor Force Participation

	Indicator for Never Employed	
	A	B
Initial Assignment to Copenhagen	0.00200	0.0367***
	(0.00810)	(0.00886)
Age at Arrival	0.0184***	0.0195***
	(0.000776)	(0.000521)
Number of Children at Arrival	0.0385**	-0.0278
	(0.0109)	(0.0146)
Indicator for Maritial Status at Arrival	-0.0732***	-0.0285**
	(0.0103)	(0.00814)
Nationality FE	Yes	Yes
Cohort FE	Yes	Yes
R-squared	0.145	0.177
Observations	11,129	9,432

Notes: The dependent variable is an indicator taking a value of 1 if the individual never took up paid employment between 1986-2012. The sample underlying this Table contains all refugees from the full sample whose construction is outlined in Section 2.2. The sample of Column A consists of the subsample of all refugees with at least a high-school degree. Column B consists of the subsample of all refugees with less than a high-school degree and those with missing information on years of education. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of the initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

find a statistically significant difference of 0.16 years of educational attainment between assignment groups. This amounts to an average difference of two months of accumulated education between those assigned to Copenhagen and Non-Copenhagen, with those in Copenhagen slightly more educated.

A.2.2 Treatment and Employment Rates

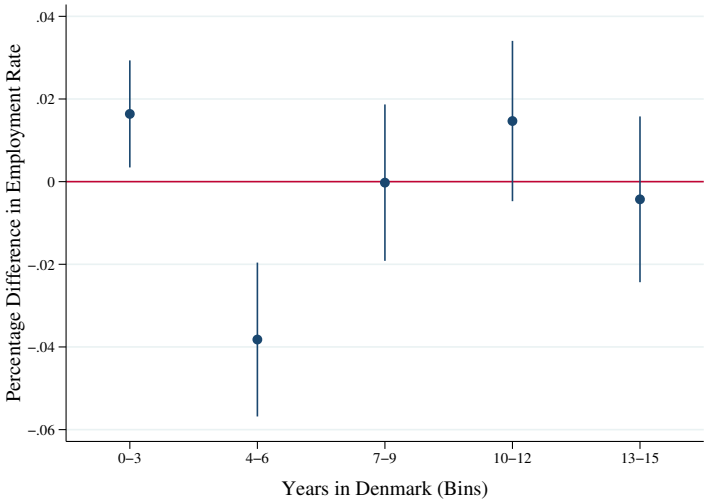
In this Section, we assess the effect of assignment to Copenhagen on employment rates, conditional on having joined the labor force. Table 7 shows the treatment effect for labor force participation. We regress an indicator variable for ever working by the last year in our sample (2012) on an indicator for assignment to Copenhagen, and the assignment variables known to the council offers deciding the municipalities of the refugees. Column 1 of Table 7 presents results for refugees with at least a high-school degree, Column 2 for those with less than a high school degree. Location of assignment has no affect on participation for workers with at least a high-school degree.

Table 8: Employment Rates by Initial Assignment

	Employment Rate	
	A	B
Initial Assignment to Copenhagen	0.00992*	0.0125*
	(0.00388)	(0.00544)
$3 \leq$ Years in Denmark <6	0.252***	0.231***
	(0.00411)	(0.00488)
$6 \leq$ Years in Denmark <9	0.378***	0.318***
	(0.00418)	(0.00501)
$9 \leq$ Years in Denmark <12	0.492***	0.396***
	(0.00429)	(0.00519)
$12 \leq$ Years in Denmark <15	0.575***	0.466***
	(0.00445)	(0.00544)
Assignment Controls	Yes	Yes
Nationality FE	Yes	Yes
Cohort FE	Yes	Yes
R-squared	0.266	0.246
Observations	97,009	69,295

Notes: The dependent variable in both columns is in indicator variable taking the value 1 of the individual is in paid employment in a given year. The sample underlying Column A contains all refugees from the full sample with at least a high-school degree whose construction is outlined in Section 2.2. The sample underlying Column A contains all refugees from the full sample with less than a high-school degree whose construction is outlined in Section 2.2. Years in Denmark is years since arrival in Denmark, binned into three year bins. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

Figure 8: Non-Parametric Employment Rate Differences between Assignment Groups



Notes: We regress an indicator variable taking the value 1 of the individual is in paid employment in a given year on assignment controls, 3-year experience bins, and 3-years experience bins interacted with a dummy variable that takes the value 1 if a refugee is initially assigned to Copenhagen. The plots the coefficients on the interaction between initial placement and experience bins for the various bins. The sample underlying the estimates contains all refugees from the full sample with at least a high-school degree whose construction is outlined in Section 2.2. The underlying sample of Column A consists of refugees with at least a high-school degree whereas Column B consists of refugees with less than a high-school degree. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Nationality and cohort fixed effects are also included. Cohort fixed effects control for year of arrival in Denmark. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. 95% confidence bounds shown in blue.

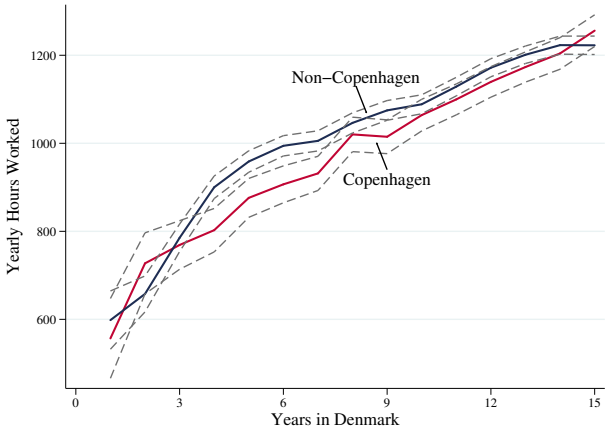
In Table 8, we regress an indicator for being employed on the assignment variables, and 3-year dummy bins for time spent in Denmark. We restrict the sample to those who work for at least one year in our data.

In the first column we report the results for those with at least a high school degree. We see that assignment to Copenhagen had no significant impact on average employment rates over the lifetime of the refugees for this group. This is not true for those without a high school degree; controlling for the assignment relevant characteristics, and conditional on joining the labor force, employment rates are 2% higher if initially assigned to Copenhagen.

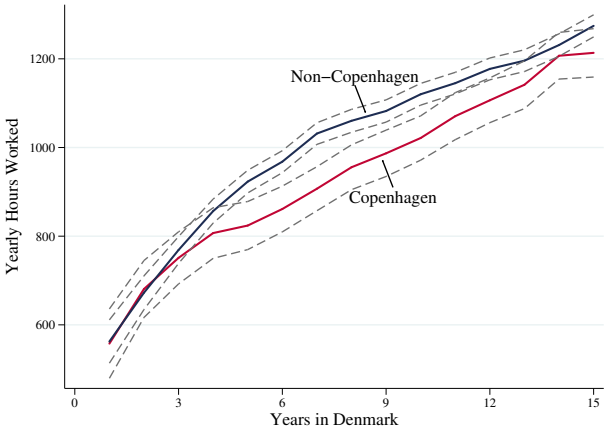
For workers with a high school degree, we interact placement in Copenhagen with the years in Denmark bins, to understand more precisely the zero effect estimated in Table 8. The estimated coefficients are reported in Figure 8. For most years, the estimated coefficients are not significantly different from zero, suggesting that selection out of employment does not interact systematically with location of initial assignment for this group.

Figure 9: Mean Yearly Hours Worked by Education at Arrival and Assignment Region

(a) At least High School at Arrival



(b) Less than High School at Arrival



Notes: The sample underlying the estimates contains all refugees from the full sample whose construction is outlined in Section 2.2. Average hours worked are taken across all observations in the sample, conditional on employment. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. Figure 9a shows average hours worked per year for all refugees with at least high school education and conditional on a given amount of years spent in Denmark. Years in Denmark is defined as the time since asylum was granted and the refugee started appearing in the labor market data. Figure 9b shows average hours worked per year for all refugees with less than high school education and conditional on a given amount of years spent in Denmark. Years in Denmark is defined as the time since asylum was granted and the refugee started appearing in the labor market data.

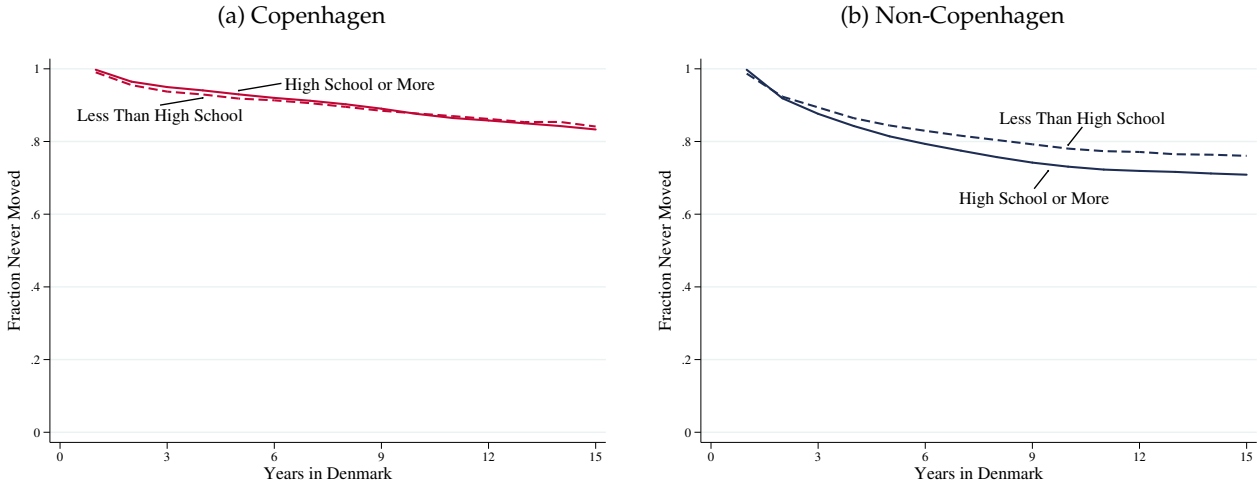
A.2.3 Hours Worked

In this section, we investigate the treatment effect of assignment to the city on hours worked, conditional on working. Figure 9 shows average hours worked conditional on working that year, by assignment region and years in Denmark. Refugees with at least high school education assigned to Copenhagen initially work less hours before catching up to those assigned outside Copenhagen. This is accords with our finding that there is a static negative earnings premium from being assigned to Copenhagen (see Table 1).

A.2.4 Persistence of Initial Allocations by Education Type

In this Section, we replicate Figure 2 from the main body of the text separately for workers with less than high school and more than high school education. The two panels in Figure 10 show the results. Panel 10a shows that both education groups are similarly likely to move out of Copenhagen after being initially placed there. However, as Panel 10b demonstrates, more educated workers are more likely to move to Copenhagen after having been assigned elsewhere.

Figure 10: Persistence of Allocation by Educational Attainment and Assignment Region



Notes: The sample underlying this figure includes all refugees from the full sample whose construction is outlined in Section 2.2. The geographic delineations of the two assignment regions, Copenhagen and Non-Copenhagen, correspond to the those constructed in Section 2.3 in the main body of the paper. For refugees with at least high school education, Figure 10a shows the the fraction of refugees that have *never* changed assignment region (Copenhagen and Not-Copenhagen) out of all refugees assigned to a given region against the number of years since arrival in Denmark. Figure 10b does the same for refugees with less than high school education.

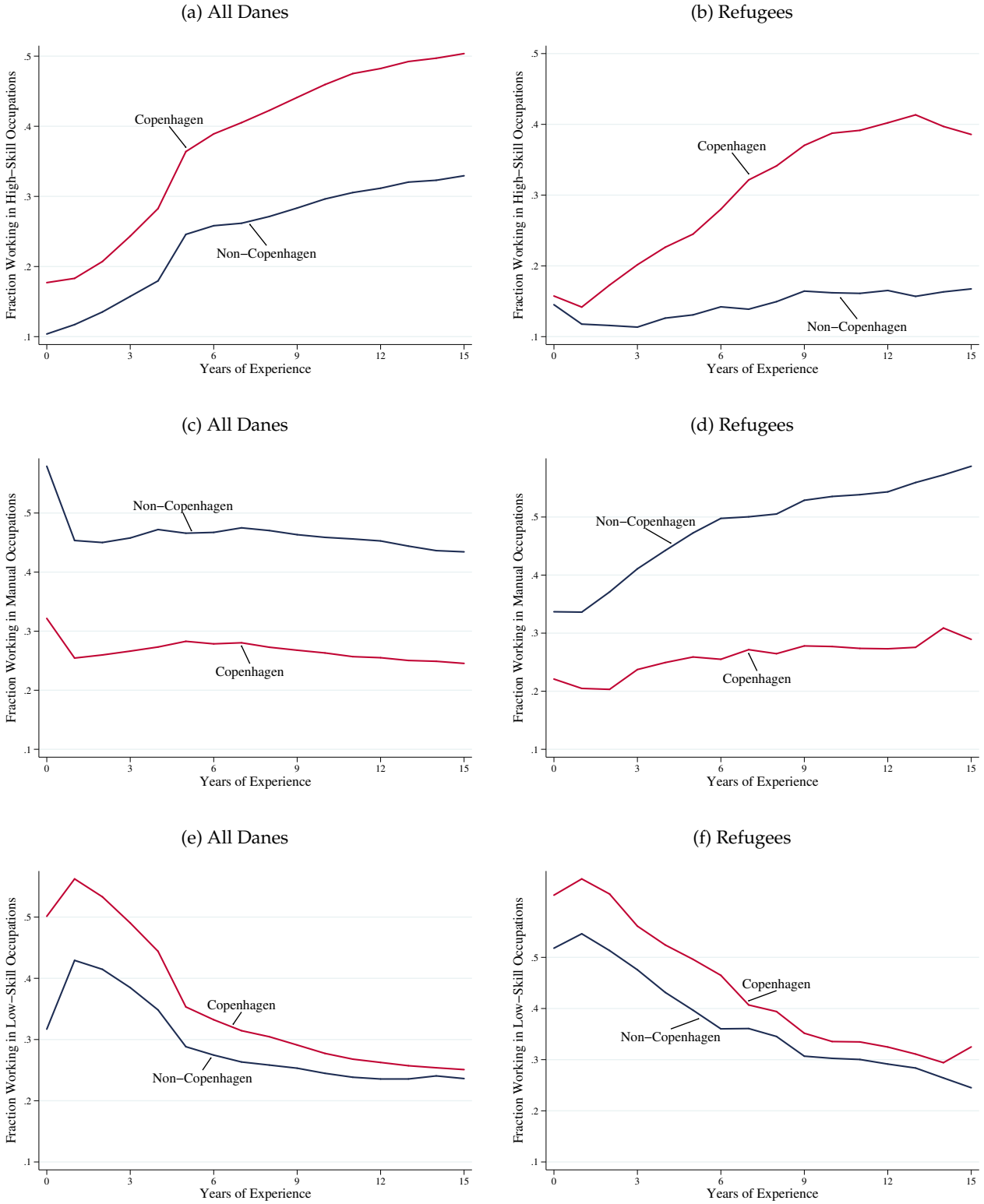
A.2.5 Occupation Distributions Across Space

The left panel of Figure 11 shows the distribution of all Danish men across the coarse occupation groups, for 5, 10, and 15 years of labor market experience, by their *current* location (Copenhagen versus non-Copenhagen). The left panel of Figure 11 shows that in Copenhagen the fraction of people doing manual work is much lower than outside of Copenhagen. The flip-side of this is that outside Copenhagen the fraction of people doing low-skill and high-skill work is persistently lower than in Copenhagen.

The right panel of Figure 11 shows the same graphs for our male refugee sample. It differs from Figure 5 in that the location specification is not based on *initial* allocation but on *current* location for direct comparability with the left hand panel.[47] Like for the native population there are substantially more refugees employed in manual work outside of Copenhagen than in Copenhagen for all years of experience. Differentially from the Danish population, less refugees in both locations work in high-skill occupations regardless of the years of experience. The fraction of low-skill workers is higher for both workers in Copenhagen and outside, however it declines substantially with refugees outside Copenhagen moving mainly into manual occupations, while in Copenhagen refugees seem to make the transition from low-skill into high-skill occupations, whose share increases by almost 20%.

[47] Figure 2shows that *current* location coincides for a majority of refugees with their location of *initial* allocation. This explains the similarity of the right panel of Figure 11 with Figure 5.

Figure 11: Natives and Refugees by Occupations, Locations, and Experience

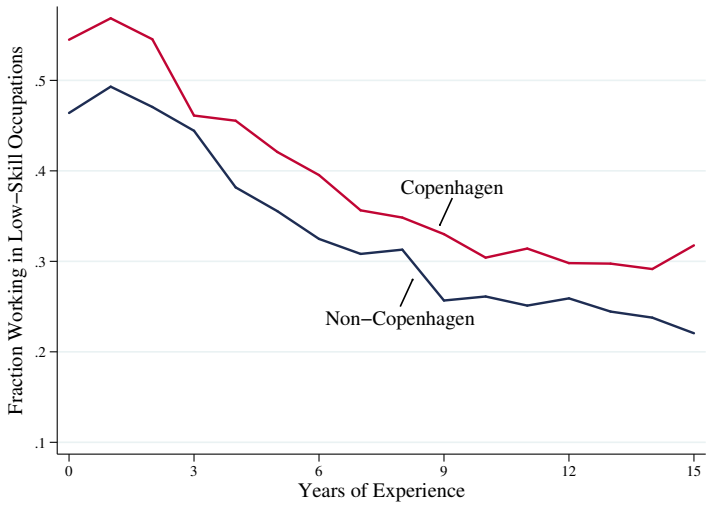


Notes: The sample for natives underlying the figures on the left hand side includes all male Danes between 19 and 55 years of age. The sample of refugees used in the figures on the right hand side includes all refugees with at least a high-school degree from our full sample whose construction is outlined in Section 2.2.The delineation of the two assignment regions, Copenhagen and Non-Copenhagen, corresponds to the that constructed in Section 2.3. The ten 1-digit ISCO codes of occupations in the Danish administrative data are collapsed to three occupational groups, ordered by the average hourly wage of Danes working in them: (1) low-skill, (2) manual, and (3) high-skill. We then compute the fraction of workers, by assignment region, that work in either of the three occupations at different years of experience. Figures 11a, 11a, and 11a show the fraction of Danes in occupations of type (1), (2), and (3) respectively, by assignment region and years of experience respectively. Figures 11b, 11d, and 11f show the fraction of refugees in occupations of type (1), (2), and (3) respectively, by assignment region and years of experience respectively.

Overall, a majority of refugees work in low-skill occupations in sectors such as janitorial services and retail. From there they move on into higher paying occupations that differ by location: outside Copenhagen manual careers are more common, while within Copenhagen workers predominantly move into various high-skill occupations.

Figure 12 shows the fraction of refugees working in low-skill occupations by *initial assignment*.

Figure 12: Occupations by Initial Assignment and Years in Denmark: Low-Skill Occupations



Notes: This Figure shows the fraction of refugees working in different occupations, by initial assignment area. Refugees are assigned to a group (Copenhagen or Non-Copenhagen) based on the region they are initially assigned to, not based on where they work at any point in time. The delineation of the two assignment regions, Copenhagen and Non-Copenhagen, corresponds to the that constructed in Section 2.3. The sample of refugees used includes all refugees with at least a high-school degree from our full sample whose construction is outlined in Section 2.2. The ten 1-digit ISCO codes of occupations in the Danish administrative data are collapsed to three occupational groups, ordered by the average hourly wage of Danes working in them: (1) low-skill, (2) manual, and (3) high-skill. We then compute the fraction of workers, by assignment region, that work in either of the three occupations at different years of experience. Figure 12 shows the fraction of workers in low-skill occupations, by assignment region and years of experience.

A.2.6 Educational Take-Up

In this Section, we test whether refugees initially assigned to Copenhagen take-up more years of education than refugees assigned elsewhere.

Table 9 shows the result of a t-test of mean differences in educational take-up after assignment between the two assignment groups. The second column repeats this exercise for only those who had at least a high school degree upon arrival. In both cases, difference in take-up across areas are very small, equivalent to about an extra month of schooling in the full sample. This suggests that differences in educational take-up across assignment regions are not an important driver behind the Dynamic Treatment Effects identified in Section 3.1.

Table 9: T-test of Differences in Take-Up of Additional Years of Education

	Sample	
	A	B
Years of Additional Education	0.0772*	0.0942**
	(0.0309)	(0.0309)
No Take-Up of Additional Education	-0.0171*	-0.0246**
	(0.00720)	(0.00750)
Less than Two Years of Additional Education	0.00584	0.0114*
	(0.00524)	(0.00465)
Two to Four Years of Additional Education	0.00400	0.00381
	(0.00364)	(0.00479)
Four to Six Years of Additional Education	0.00726	0.00937*
	(0.00408)	(0.00397)
Observations	11,812	7,386

Notes: Years of Additional Education is the years of additional education at the latest observation of an individual. All other variables are coded as an indicator of whether the individual took up a certain number of years of education. The sample of Column A consists of all refugees of the baseline sample. Column B consists of refugees with at least a high-school degree. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

A.2.7 Comparing Danish Urban Wage Premia to the Literature

In this section, we compare the urban wage premium among Danes to the urban wage premium estimated in De La Roca and Puga (2017), a seminal paper in the urban literature. Table10 replicate the fixed effect regressions of Table 1 in De La Roca and Puga (2017) for the full Danish population between the years 2004 and 2009 (as in their sample). Table 10 shows the results for earnings and reveals a similar size elasticity for wage residuals in Column 2. Including person fixed effects does not reduce this elasticity as much as in De La Roca and Puga (2017).

In Table 11, we replicate Table 2 from De La Roca and Puga (2017) for both wages and earnings. We find very similar results for earnings, including the premium for experience in the two biggest cities (Aarhus and Copenhagen). Repeating the same exercise for hourly wages, reduces the value of big-city experience, suggesting at least part of the effect may be coming from permanently increased hours after working in the big city.[48]

[48] De La Roca and Puga (2017) do not show results for hourly wages.

Table 10: Replication of De La Roca and Puga (2017) Table 1

	Log Earnings A	Earnings Residuals B	Log Earnings C	Earnings Residuals D
Experience	0.127***		0.0863***	
	(0.000346)		(0.00376)	
Experience Squared	-0.00322***		-0.00331***	
	(0.0000136)		(0.0000287)	
Tenure	0.167***		0.173***	
	(0.000305)		(0.000468)	
Tenure Squared	-0.00898***		-0.0105***	
	(0.0000206)		(0.0000388)	
Very High-Skill Occupation	0.486***		0.0540***	
	(0.00272)		(0.00421)	
High-Skill Occupation	0.269***		0.115***	
	(0.00232)		(0.00383)	
Medium-Skill Occupation	0.186***		0.0224***	
	(0.00180)		(0.00269)	
Low-Skill Occupation	0.0295***		-0.0623***	
	(0.00162)		(0.00207)	
University Education	0.190***		0.527***	
	(0.00190)		(0.00758)	
Secondary Education	0.0304***		0.0369***	
	(0.00122)		(0.00376)	
Log Area Population		0.0539***		0.0459***
		(0.00794)		(0.0106)
Constant		-0.625***		-0.523***
		(0.0847)		(0.113)
Worker FE	No		Yes	
R-squared	0.382	0.273	0.761	0.132
Observations	2,598,703	125	2,598,703	125

Notes: This Figure replicates Table 1 in De La Roca and Puga (2017) for the full sample of all Danish workers between 2004 and 2009 (the years used in De La Roca and Puga (2017)).

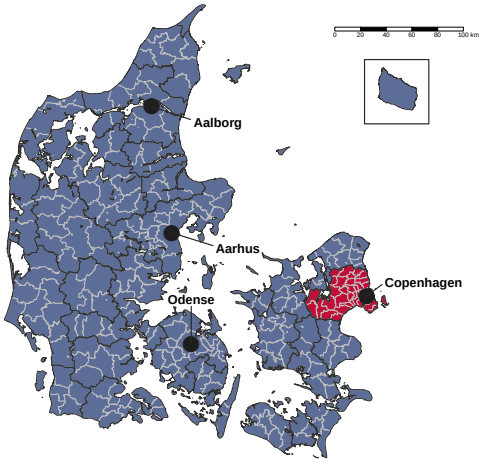
Table 11: Replication of De La Roca and Puga (2017) Table 2

	Log Earnings A	Log Hourly Wage B
Experience 2 Biggest	0.0319***	0.00841***
	(0.00180)	(0.000947)
Experience 2. Biggest × Exp.	-0.000587***	0.000121**
	(0.0000733)	(0.0000382)
Experience 3-5 Biggest	0.0251	0.0100
	(0.0129)	(0.00667)
Experience 3-5 Biggest × Exp.	-0.000699	-0.000148
	(0.000378)	(0.000192)
Experience	0.0727***	0.0466***
	(0.00379)	(0.00198)
Experience Squared	-0.00286***	-0.00165***
	(0.0000348)	(0.0000183)
Experience 2 Biggest × Now in 5 Biggest	0.00876***	0.000594
	(0.00108)	(0.000551)
Experience 2 Biggest × Now in 5 Biggest × Experience	-0.000608***	-0.000112***
	(0.0000576)	(0.0000298)
Experience 3-5 Biggest × Now in 5 Biggest	0.0107***	0.00816***
	(0.00300)	(0.00147)
Experience 3-5 Biggest × Now in 5 Biggest × Experience	-0.000814***	-0.000533***
	(0.000170)	(0.0000827)
Experience Out Top 5. × Now in 5 Biggest	0.00803***	-0.00295*
	(0.00219)	(0.00117)
Experience Out Top 5. × Now in 5 Biggest × Experience	-0.000162	0.000370***
	(0.000138)	(0.0000729)
Tenure	0.173***	0.000986***
	(0.000468)	(0.000233)
Tenure Squared	-0.0105***	-0.0000442*
	(0.0000389)	(0.0000176)
Very High Skill Occupation	0.0524***	0.0375***
	(0.00421)	(0.00226)
High Skill Occupation	0.112***	0.0333***
	(0.00382)	(0.00209)
Medium Skill Occupation	0.0204***	-0.0131***
	(0.00269)	(0.00144)
Low Skill Occupation	-0.0633***	-0.0338***
	(0.00207)	(0.00112)
University Education	0.526***	0.542***
	(0.00758)	(0.00434)
Secondary Education	0.0441***	0.326***
	(0.00377)	(0.00220)
R-squared	0.761	0.760
Observations	2,598,703	2,589,002

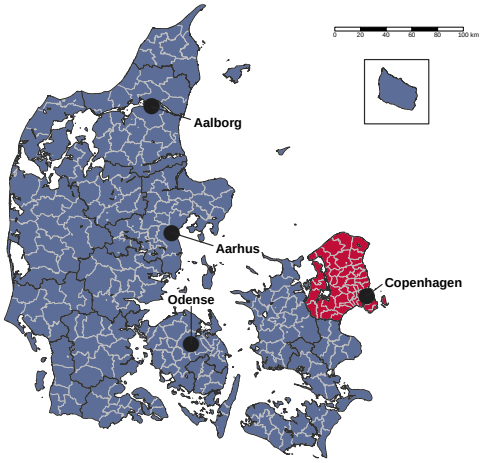
Notes: The left column of Figure replicates Table 2 in De La Roca and Puga (2017) for the full sample of all Danish workers between 2004 and 2009 (the years used in De La Roca and Puga (2017)). The right column of Table 2 runs the same specification as in Table 2 in De La Roca and Puga (2017) but with the dependent variable replaced by log hourly wages.

Figure 13: Alternative Commuting Zone Delineations

(a) Commuting Zones in Denmark, 1980



(b) Commuting Zones in Denmark, 2000



Notes: This map shows commuting zones in Denmark (black lines) constructed based on 1980 data (left) and 2000 data (right). The zones are constructed by the authors based on commuting flows across the 271 municipalities in Denmark (light grey lines) for the respective year. Commuting flows are derived from the residence and work place identifier in the Danish administrative "IDA" data set (see Online Appendix for details on the IDA data). The zones are constructed so as to maximize commuting flows within and minimize commuting zones across them, following the methodology outlined in Tolbert and Sizer (1996). The Copenhagen commuting zone is highlighted in red. Commuting zones constituting the "Non-Copenhagen" assignment area are denoted in blue. Aalborg, Aarhus, and Odense are the three second-largest cities in Denmark after Copenhagen. The box in the top-right corner shows the Bornholm commuting zone, which is situated on an island to the east of the rest of Denmark.

A.3 Robustness Exercises for Treatment Regressions

In this Section, we examine the robustness of the main empirical results in Table 1 to alternative specifications.

A.3.1 Alternative Commuting Zone Definition

The commuting zones underlying that from the two assignment regions were constructed using commuting flows between Danish municipalities in 1986. In theory we could have used commuting data from any year where such data is available, i.e. 1980-2010.Depending on the year, resulting commuting zones delineation change significantly., As Denmark becomes more integrated across municipalities commuting flows intensify, resulting in less and less commuting zones. To illustrate this, we plot the computed commuting zones for 1980 and for 2000 in Figure 13.

As Figure 13 shows, the number of commuting zones decreases markedly between 1980 and 2000. However, for our analysis only the delineation of the Copenhagen commuting zone relative to all other commuting zones is important. Beyond 1986, this delineation does not change. We reestimate our main specification using only the 1980 commuting zone. The 1980 Copenhagen commuting zone is a smaller than the 1986 delineation. Table 12 presents the estimates of the baseline regression in

Table 12: Wage-Experience Profiles, 1980 Commuting Zone

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.282***	2.484***	2.118***	7.654***	7.905***	7.547***
	(0.123)	(0.147)	(0.112)	(0.273)	(0.319)	(0.304)
Initial Assignment to Copenhagen	-1.013	-0.415	-1.606	-8.696***	-6.006**	-13.50***
	(0.954)	(0.877)	(1.260)	(1.441)	(1.734)	(1.739)
Years of Experience Initial Assignment to Copenhagen	1.076***	1.015***	1.037***	2.410***	2.005***	3.176***
	(0.132)	(0.149)	(0.126)	(0.250)	(0.280)	(0.273)
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.057	0.062	0.055	0.155	0.158	0.157
Observations	97,402	57,994	39,408	107,297	63,870	43,427

Notes: The specification estimated in this Table is stated in Equation (1) in the text. Relative to the estimates in Table 1, estimates in this table use the commuting zones constructed from commuting flows in 1980 instead of 1986. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample whose construction is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample with at least a high-school degree. Columns II.C and II.C are based on refugees with less than a high-school degree including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

Equation 1 for this alternative commuting zone delineation. The reported coefficients are larger than those presented in the body of the paper. This accords with intuition; the 1980 Copenhagen commuting zone consists of the urban core of the city of Copenhagen, whereas the 1986-2010 Copenhagen commuting zone includes Northern Zealand, which is not itself a major center of employment.

A.3.2 Alternative Treatment and Control Groups

Table 1 compares refugees assigned to Copenhagen to those assigned to any other municipality in Denmark. Here we consider alternative definitions of the assignment regions. Table 13 presents results where "Non-Copenhagen" excludes the commuting zones containing the three second-tier cities of Aarhus, Aalborg, and Odense, which are dropped from the analysis. This analysis produces the differential treatment of being assigned to Copenhagen relative to a rural area. We find a moderately larger Dynamic Treatment Effect for hourly wages and earnings than in the baseline. This accords with the intuition that the second tier cities increased the slope of the wage-experience profile of the Non-Copenhagen group when they were included in the Non-Copenhagen assignment group.

Table 13: Wage-Experience Profiles, No Small Cities

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.131***	2.311***	2.036***	7.335***	7.410***	7.515***
	(0.165)	(0.186)	(0.127)	(0.443)	(0.449)	(0.450)
Initial Assignment to Copenhagen	-1.562	-0.688	-2.659	-9.315**	-8.550***	-10.94*
	(0.927)	(0.815)	(1.530)	(2.539)	(2.119)	(3.803)
Years of Experience × Initial Assignment to Copenhagen	0.991***	0.960***	0.928***	2.393***	2.259***	2.692***
	(0.121)	(0.144)	(0.102)	(0.378)	(0.379)	(0.413)
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.054	0.060	0.052	0.158	0.159	0.162
Observations	67,128	40,828	26,300	73,889	44,957	28,932

Notes: The specification estimated in this Table is stated in Equation (1) in the text. Relative to the estimates in Table 1, here individuals initially assigned to Aarhus, Aalborg, or Odense are dropped. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample whose construction is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample with at least a high-school degree. Columns II.C and II.C are based on refugees with less than a high-school degree including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

Table 14: Wage-Experience Profiles, No Copenhagen

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.204***	2.370***	2.036***	7.605***	7.703***	7.586***
	(0.127)	(0.156)	(0.116)	(0.371)	(0.387)	(0.425)
Initial Assignment to a Small City	-3.848*	-4.178**	-3.254	-4.892	-7.620**	-1.004
	(1.659)	(1.197)	(2.185)	(2.917)	(2.508)	(4.232)
Years of Experience × Initial Assignment to a Small City	0.466	0.590*	0.304	0.585	0.962	0.126
	(0.252)	(0.277)	(0.246)	(0.456)	(0.491)	(0.577)
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.054	0.058	0.058	0.150	0.152	0.154
Observations	75,615	43,625	31,990	83,062	47,931	35,131

Notes: The specification estimated in this Table is stated in Equation (1) in the text. Relative to the estimates in Table 1, here individuals initially assigned to Copenhagen are dropped. "Treatment" is instead defined as being assigned to one of the three "small cities" in Denmark: Aarhus, Aalborg, and Odense. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample whose construction is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample with at least a high-school degree. Columns II.C and II.C are based on refugees with less than a high-school degree including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

In Table 14 we drop the refugees assigned to Copenhagen from the analysis, instead comparing those assigned to one of the commuting zones containing the three second-tier cities of Aarhus, Aalborg, or Odense, to those assigned to any of the remaining Danish commuting zones. The dynamic premium is smaller (and not significant), again according with intuition.

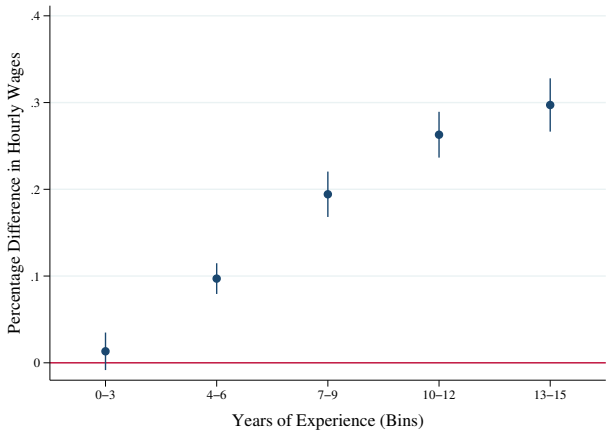
A.3.3 Non-Parametric Treatment Effects

In this Section, we re-examine the evidence in Section 3.1 non-parametrically. We re-estimate the specification in Equation (1) for hourly wages using dummies for 3-year bins of experience, and the interaction of these bins with being initially placed in Copenhagen. Figure 14 presents the results by plotting the bin dummies against years of experience. In line with most studies, we find concavity in the effects of raw experience on wages (see e.g., Lagakos et al. (2018b)). We continue to find no significant difference for initial wages for those placed in Copenhagen, and the size of the Dynamic Treatment Effect after 18-20 years is in line with that implied by the linear regressions.

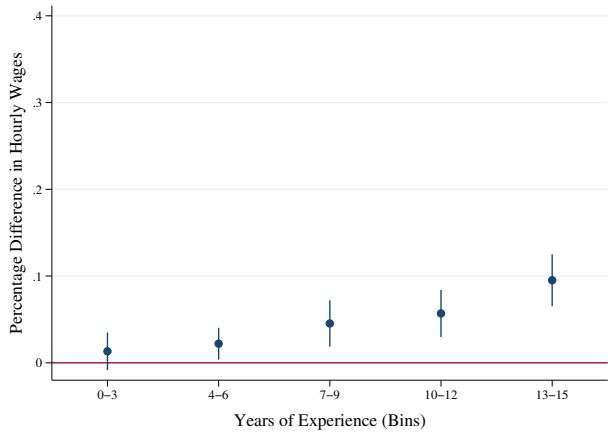
In Figure 15 we report the same regression for yearly earnings. As in Table 1, we continue to find a

Figure 14: Non-Parametric Coefficients for Wages

(a) Coefficients for Experience



(b) Interaction Terms with $InitCph_i$



Notes: The specification estimated in this Table is a modified version of the Equation (1) in the text with log hourly wages as outcome variable. Here we include three year bins of experience, and the interaction of these bins with being initially assigned to Copenhagen. The Figure shows the coefficients on the experience in dummies and on the interaction terms with initial placement into Copenhagen. The sample underlying the estimates includes all refugees from the full sample whose construction is outlined in Section 2.2 with at least a high-school degree. We control for nationality, assignment, and cohort fixed effects. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. 95% confidence intervals shown.

small negative initial premium, but this is no longer statistically significant.

A.3.4 Effects of Ethnic Enclaves

Damm (2014) reports that prior to the Danish dispersal policy, immigrants and refugees were overwhelmingly clustered in Copenhagen and the other larger cities. In this Section, we investigate whether the larger presence of other refugees from one's country in certain municipalities can explain part of the estimated treatment effects. We re-estimate our main specification in Table 15 including a control for the presence of co-nationals of the refugee at the municipality level. In particular, we compute the stock of foreign-born residents in each municipality every year, for each of the nationalities studied in the paper. Then, for every refugee, we construct a variable that records the number of co-nationals residing in their municipality of assignment in their year of arrival, and include this in the regression. Table 15 suggests ethnic enclaves are not an important explanation for differential wage-experience profiles across assignment regions. The estimate for the Dynamic Treatment Effect is virtually the same as that reported in Table 1.[49]

[49] We also re-estimated these regressions with the ethnic stock *in each year* as a control, instead of year of arrival, addressing concerns that refugees could sort into ethnic enclaves over time, and that this might assist them with employment opportunities. The results, available on request from the authors, are almost identical to those in Table 15.

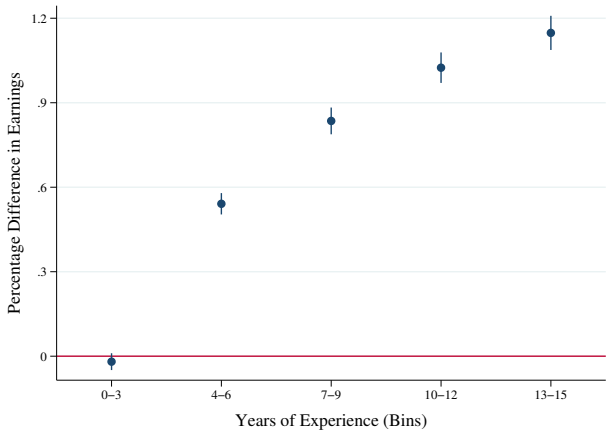
Table 15: Controls for Ethnic Enclaves

	Log Hourly Wage × 100			Log Earnings ×100		
	I.A	I.B	I.C	II.A	II.B	II.C
Years of Experience	2.314***	2.521***	2.132***	7.664***	7.890***	7.565***
	(0.137)	(0.154)	(0.126)	(0.307)	(0.357)	(0.336)
Initial Assignment to Copenhagen	0.130	0.964	-0.870	-7.041***	-5.169**	-10.33***
	(0.883)	(0.759)	(1.286)	(1.711)	(1.745)	(2.365)
Years of Experience × Initial Assignment to Copenhagen	0.776***	0.702***	0.790***	2.051***	1.778***	2.550***
	(0.147)	(0.162)	(0.132)	(0.294)	(0.324)	(0.301)
Log Size of Ethnic Stock	-0.958***	-1.071*	-0.596***	-2.393***	-2.633**	-1.681**
	(0.244)	(0.408)	(0.146)	(0.579)	(0.855)	(0.515)
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.057	0.063	0.055	0.157	0.160	0.157
Observations	97,402	57,994	39,408	107,297	63,870	43,427

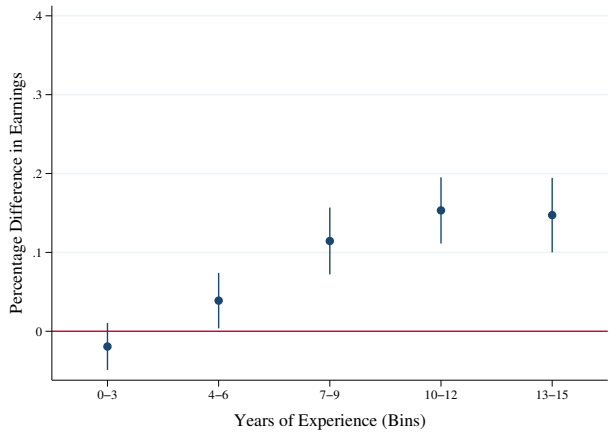
Notes: The specification estimated in this Table is a modified version of the one stated in Equation (1) in the text. Here additional controls are added for log size of ethnic stock, a variable that records for each refugee the number of co-nationals of the residing in their municipality in the year of assignment. The dependent variables in all columns are scaled by a factor of 100 for presentational purposes. The sample underlying the estimates of columns I.A and II.A includes all refugees from the full sample whose construction is outlined in Section 2.2. The estimates in Columns I.B and II.B are based on the subset of refugees from the full sample with at least a high-school degree. Columns II.C and II.C are based on refugees with less than a high-school degree including individuals with missing education information. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. *** indicates significant at the 1 percent level, ** indicates significant at the 5 percent level, * indicates significant at 10 percent level.

Figure 15: Non-Parametric Coefficients for Earnings

(a) Coefficients for Experience



(b) Interaction Terms with $InitCph_i$



Notes: The specification estimated in this Table is a modified version of the Equation (1) in the text with annual earnings as outcome variable. Here we include three year bins of experience, and the interaction of these bins with being initially assigned to Copenhagen. The Figure shows the coefficients on the experience in dummies and on the interaction terms with initial placement into Copenhagen. The sample underlying the estimates includes all refugees from the full sample whose construction is outlined in Section 2.2 with at least a high-school degree. We control for nationality, assignment, and cohort fixed effects. Nationality fixed effects for refugees' origin country's are: Lebanon, Iran, Iraq, Somalia, Sri Lanka, Vietnam, Afghanistan, and Ethiopia. Assignment controls are age at arrival, number of children at arrival, and marital status at arrival. Cohort fixed effects control for year of arrival in Denmark. Robust standard errors clustered at the level of initial commuting zone. 95% confidence intervals shown.

A.4 Model Estimation

This Section provides details on the estimation of the model in Section 5.

A.4.1 Structural Parameter Estimates

Tables 16 and 17 present the parameter estimates of our maximum likelihood estimation. We allow all relevant parameters to differ by unobserved type The only parameters we fix exogenously are the discount rate, ρ, and the log unemployment benefit b, which we set to 0.98 and 3.5 respectively. Two parameters, a_{NCPH} and τ_{NCPH}, are normalized.

A.4.2 Model Fit

Figure 16 shows the density of wage observations for the actual and simulated data. The simulated data are split by worker type. Our estimates suggests that high-ability workers account for almost all of the mass in the right tail of the wage distribution.

Table 16: Estimates of Model Parameters: Base and Wage

Base Parameters			Wage Parameters		
Description	Parameter	Estimate	Description	Parameter	Estimate
Amenity in NCPH	a_{NCPH}	0 -	Base wage	$\bar{w}$	4.075 (0.002)
Amenity in CPH	a_{CPH}	-0.062 (0.003)	High-type fixed effect	θ_{h_H}	0.269 (0.002)
Moving cost to CPH	τ_{NCPH}	1 -	High firm type fixed effect	ψ_{f_H}	0.095 (0.003)
Moving cost to NCPH	τ_{CPH}	6.823 (0.073)	H-H Complementarity	α_{h_H,f_H}	0.089 (0.003)
S.D. of moving cost shock	σ_η	0.967 (0.008)	Return to Exp. for L-type at L-firm	$\beta_{f_L}^{h_L}$	0.026 (0.003)
S.D. of match quality shock	σ_u	5.816 (0.029)	Return to Exp. for H-type at L-firm	$\beta_{f_L}^{h_H}$	0.012 (0.001)
Fraction of L types	χ_L	0.518 (0.009)	Return to Exp. for L-type at H-firm	$\beta_{f_H}^{h_L}$	0.035 (0.001)
			Return to Exp. for H-type at H-firm	$\beta_{f_H}^{h_H}$	0.024 (0.001)
			Quadratic on Experience	β_2	-0.0005 (0.637)

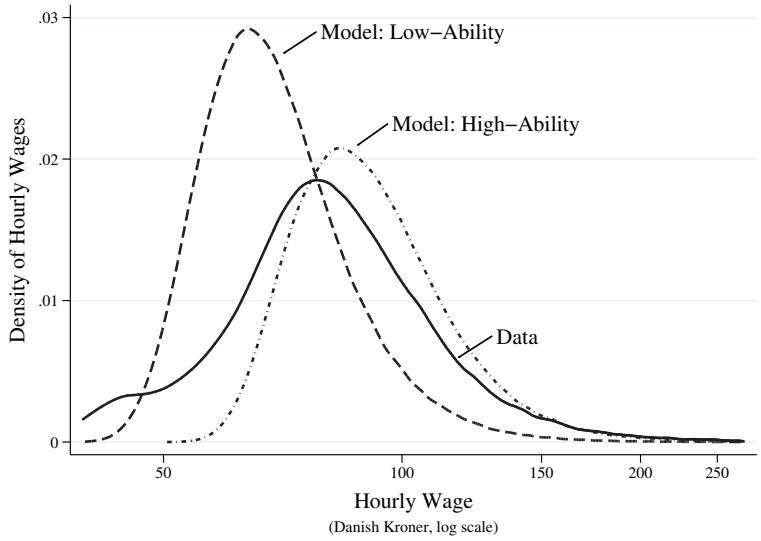
Notes: This Table shows base parameters and parameters relating to the wage process for the model in Section 5 in the main body of the text. The parameters are estimated using a Maximum Likelihood strategy outlined in Section 5.2 in the main body of the paper. The sample underlying the estimates is the full sample of refugees with at least high school education, whose construction is outlined in Section 2.2.

Table 17: Estimates of Model Parameters: Transition Parameters

	Copenhagen		Non-Copenhagen	
Description	Parameter	Estimate	Parameter	Estimate
Destruction rate for L-type	$\delta^{h_L}_{CPH}$	0.254 (0.008)	$\delta^{h_L}_{NCPH}$	0.283 (0.005)
Destruction rate for H-type	$\delta^{h_H}_{CPH}$	0.194 (0.003)	$\delta^{h_H}_{NCPH}$	0.200 (0.002)
Reallocation shock for L-type	$\mu^{h_L}_{CPH}$	0.295 (0.013)	$\mu^{h_L}_{NCPH}$	0.397 (0.021)
Reallocation shock for H-type	$\mu^{h_H}_{CPH}$	0.210 (0.013)	$\mu^{h_H}_{NCPH}$	0.220 (0.021)
Job-finding rate for L-type	$\underline{\lambda}^{h_L}_{CPH}$	0.201 (0.012)	$\underline{\lambda}^{h_L}_{NCPH}$	0.251 (0.034)
Job-finding rate for H-type	$\underline{\lambda}^{h_H}_{CPH}$	0.240 (0.007)	$\underline{\lambda}^{h_H}_{NCPH}$	0.311 (0.005)
Low-firm offer prob. for L-type	$\pi^{h_L}_{CPH}$	0.762 (0.012)	$\pi^{h_L}_{NCPH}$	0.826 (0.011)
Low-firm offer prob. for H-type	$\pi^{h_H}_{CPH}$	0.682 (0.012)	$\pi^{h_H}_{NCPH}$	0.815 (0.011)

Notes: This Table shows parameters relating to the transition parameters of the model in Section 5 in the main body of the text. The parameters are estimated using a Maximum Likelihood strategy outlined in Section 5.2 in the main body of the paper. The sample underlying the estimates is the full sample of refugees with at least high school education, whose construction is outlined in Section 2.2.

Figure 16: The Wage Distribution in Simulated and Actual Data



Note: The data sample underlying this figure includes all refugees with at least high-school education from the full sample whose construction is outlined in Section 2.2. The "model data" is generated by simulating 10^5 agents using the parameter estimates in Appendix A.4.1. The Figure shows the wage density plots of simulated wages for high- and low-ability refugees in the model and for all refugees in the data.