Dynamic Social Network Effects of Refugee Resettlement

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1. Introduction

Social networks are well-recognized as an integral factor in determining many labor market outcomes. Between 30% and 60% of jobs since the 1930s were found through informal social channels (Bewley, 1999; Ioannides and Loury, 2004), reflecting the old adage "it's not what you know but who you know." There is evidence that referrals from network members are beneficial to an individual's job search (Montgomery, 1991; Munshi, 2003; Beaman & Magruder, 2012), that an increase in network size increases welfare participation among members (Bertrand, Luttmer & Mullainathan, 2000) and that peer effects from social networks can increase weather insurance take-up (Cai, Janvry & Sadoluet, 2015). More recently, economists have turned to modeling and estimating the dynamic effects of social networks on labor markets. Beaman (2012) shows an increase in the newly-arrived refugee cohort size depresses employment rates and wages while previously arrived cohorts improve outcomes among network members. Dagnelie, Mayda & Maystadt (2018) use the universe of refugee records to show that same-origin entrepreneurs in a refugee's social network increases the probability of employment in the first 90 days while an increase in the number of previously settled refugees decreases the probability of employment. Allowing for network dynamics reveals the tension between competition and collaboration in social networks. However, causal identification of network effects is often difficult due to selective migration among cohort members. Refugee resettlement represents an attractive source of exogenous variation in cohort size because the destination is selected on observable refugee characteristics by a resettlement agent. I extend the work on refugees in dynamic social networks by leveraging the universe of U.S. refugee resettlement to identify the social network effects of resettlement on the earnings, labor supply, quality of work and welfare usage of newly-arrived refugees.

Every year the U.S. admits thousands of refugees, with as many as 97,000 resettled in 2016. The extent to which refugees integrate well into their local community is a potentially important factor for influencing future Presidential Determinations of admissions quotas (Immigration and Nationality Act § 207). Identifying the effect of such large immigrant inflows is an important first step in designing effect immigration policy. However, the literature on labor market impacts of immigration is mixed. Card (1990) shows that a large immigrant inflow from Cuba into Miami had relatively little impact on the labor market for low-skilled native workers. The surprising lack of effect may be due to imperfect substitutability between natives and immigrants (Ottaviano & Peri, 2012), but other work argues that accounting for skill and education reveals negative impacts (Borjas, 2003; 2017) perhaps due to negative sorting (Borjas, 1999). Empirically, the prediction of negative sorting due to labor market conditions does not hold for Mexican migrants (Chiquiar & Hanson, 2005) but strong migrant networks in the destination country does increase negative self-selection into migration (McKenzie and Rapoport, 2010). Social networks are a key component in the job finding process, but their formation and growth could still be endogenous to labor market conditions which makes it difficult to disentangle social effects from selective migration.

Instead, economists have used refugee placement as an exogenous shock to network size to estimate the effects of new immigration. Using International Rescue Committee [1](IRC) administrative records on adult men with no previous ties, Beaman (2012) shows that newly-arrived refugees compete for jobs with their network but that previous cohorts actually improve employment rates and wages through information sharing. Dagnelie, Mayda & Maystadt (2018) use the universe of refugee administrative data from the U.S. State Department to show that entrepreneurs in a refugee's social network improves the likelihood of employment during the first 90 days of resettlement. On the other hand, the number of previously settled refugees who are employed in the network negatively affects the same probability of employment. In this paper I use the universe of refugee admissions to construct the growth of local refugee social networks and identify the effect of an increase in network size on the earnings, quantity and quality of working hours and welfare usage of newly-arrived refugees.

2. Background on Refugee Resettlement

If refugees endogenously chose their destination clean identification of network effects would be difficult. However, refugees are placed in a community by a resettlement agent after a lengthy screening process to determine eligibility and fit. First, the United Nations High Commissioner for Refugees (UNHCR) must refer an asylum-seeker's application to the U.S. Refugee Admissions Program (USRAP) under the U.S. Citizenship and Immigration Services (USCIS) agency before traveling to the U.S. Once an individual has been referred, they apply for refugee status to show they "cannot return to their country of nationality due to a well-founded

[1] One of nine independent refugee resettlement agencies.

fear of persecution because of their religion, race, political opinion or membership in a social group." (UNHCR, 1989) They are then interviewed by a USCIS officer abroad to determine eligibility for USRAP. If their application is approved, the refugee is transferred to the care of the State Department's Bureau for Population, Refugees & Migration (PRM) for resettlement in the U.S. PRM delegates the resettlement process to one of nine independent agencies. Agencies place refugees near any relatives living in the U.S. or in a community that best matches their needs if no relatives are present (Department of State, 2018). The quality of a match is determined by a refugee's biographical information as well as any records sent by overseas resettlement agencies. In some cases, the destination is chosen in advance of the first meeting between case-worker and refugee (Beaman, 2012) which implies that the destination choice is most likely exogenous to the individual conditional on observable characteristics. Furthermore, there is often a delay between when a refugee receives their resettlement location and when they actually arrive. Therefore, any agency selection on short-term, unobservable characteristics are plausibly mitigated by unforeseen waiting periods.

3. Data

I use the Worldwide Refugee Admissions Processing System (WRAPS) database to construct refugee social networks in the U.S. by origin and resettlement city for each year between 2003-2017. WRAPS is maintained by the Refugee Processing Center (RPC) under the Department of State (DOS) Bureau of Population, Refugees and Migration (PRM) and contains the universe of U.S. refugee arrivals. Figure 1 shows the total number of refugees admitted to the U.S. over the 2003-2017 time period. The U.S. admits a large number of refugees from many different countries, however I use only flows that meet a certain likelihood of being found in survey data. I discuss the selection criteria in detail in the next section.

I observe individual characteristics from the American Community Survey (ACS) for the same time period as refugee flow data is available, 2003-2017. I focus on people aged 18-64 since they are most likely to be affected by labor market conditions. As a robustness check I estimate the model separately for those aged 65 or older (results available upon request). Table 1 shows summary statistics of the outcomes used in the main analysis. I aggregate refugee flows up from the city level to the county level since the lowest geographic unit available in both surveys are county of residence.

4. **Methodology**

Absent from the microdata are refugee status indicators, so I estimate a survey respondent's probability of being a refugee using a procedure suggested by Capps et al. (2015) and refined by Evans & Fitzgerald (2017 WP). First, I estimate the number of immigrants from an origin country o who arrived in a particular year t, I_{ot}, by summing the person weights provided in the ACS across individual and counties. That is,

$$I_{ot} = \sum_{c} \sum_{i} perwt_{ioct}$$

where i indexes individual survey respondents and c indexes the county in which they reside. Next, I divide the number of refugees who arrived in year t from origin country o (as reported by WRAPS) by the estimated origin- and year-specific immigrant population which gives the "refugee concentration ratio" (RCR), a term coined by Evans & Fitzgerald. RCR can be interpreted as the estimated probability that an individual who immigrated to the U.S. from country o in year t is a refugee. I focus on individuals with an RCR of 0.70 or greater to limit measurement error from including non-refugee immigrants in the analysis. Figure 2 plots the number of refugees admitted from an origin each year and the corresponding total immigrant population, highlighting pairs with RCR ≥ 0.70. Some origin/year pairs have an RCR greater than 1 which is likely due to the survey weight underrepresenting the population. Table 2 lists the origin/year pairs I identify as having an RCR of 70% or greater. Most of the selected individuals originated from Iran, Iraq and Burma, countries that had a large number of refugees admitted to the U.S.

To identify the dynamic refugee social network effects on refugee outcomes, I estimate the following empirical specification:

$$Y_{ioct} = \alpha + \delta_0 N_{oc(t)} + \delta_1 N_{oc(t-1)} + \delta_2 N_{oc(t-2)} + \delta_3 N_{oc(t-3)} + X_{ioct}\beta + \Gamma_t \times \Omega_o + \Theta_c + \varepsilon_{ioct}$$

where Y_{ioct} is the outcome of interest for individual i from origin country o who was placed in county c in year t.[2] $N_{oc(t)}$ is the number of refugees from origin o resettled to county c in year t (per 1000 people), $N_{oc(t-1)}$ the number resettled in year $t-1$ and so on. X_{ioct} is a vector of age, age-squared, marital status, family size, number of children and education level dummies to

[2] In all regressions I pool those who arrived in the same year or a year prior to increase sample sizes and because the CPS codes immigration year as an interval.

control for observable characteristics that are relevant to the resettlement decision. Standard errors are clustered at the county level. Θ_c and $\Gamma_t \times \Omega_o$ are fixed effects for county and origin/arrival year pairs, respectively. Θ_c controls for any time-invariant county-specific omitted variables and $\Gamma_t \times \Omega_o$ control for any year of arrival-origin-specific shocks that are correlated with the number of refugees resettled to the U.S. In this model, the δ terms are the dynamic effects of a refugee's social network size on the outcome of interest. The identifying assumption is that there are no origin-specific or time-varying shocks that are correlated with the number of refugees from an individual's home country that were resettled within 3 years of their own arrival year. That is, a shock that would bias the estimates of the δ's would need to either be time-varying and common across all sending countries or be time-invariant and origin-specific. This is arguably a weak assumption since many of the large spikes in refugee arrivals are due to temporary and unexpected conflicts in the sending country.

There are still a few concerns about the exogeneity of resettlement flows. First, there is indeed selection into destination by the resettlement agent. However, the selection is on observable characteristics of the refugee since the agent must choose a location based on application data and often having not yet met the individual (Beaman, 2012). In my analysis I control for any observables that may be endogenous to the destination choice. Second, for lagged flows to be relevant measures there cannot be too much selective out-migration after being relocated to the county on record. Beaman (2012) calculates an out-migration rate of 8.8% among newly settled refugees, suggesting that selective migration may not be a prominent threat to identification.[3] Lastly, any migration that is random (relative to the outcome variable) will produce measurement error in the size of the network which would bias the coefficient estimates towards zero. In that case, the estimates serve as a lower bound on the true parameter, that is the effect of an increase in network size had there been no out-migration.

It is important to distinguish the differences in the effects identified by each of the δ's. δ_0 is the average effect of an additional refugee per 1000 in the network who arrived in the same year – that is an additional refugee cohort member per 1000 in the network. Since same-cohort refugees roughly all receive the same amount of support and have the same experience they are more likely to compete with each other for similar jobs (conditional on X_{ioct}). On the other hand,

[3] Special thanks to Anna Maria Mayda for corroborating this based on private administrative data from PRM during her time at DoS.

δ_1, δ_2, and δ_3 measure the average effect of an additional refugee per 1000 in the more tenured parts of the network. Refugees who arrive earlier have more time to find work, learn about welfare opportunities, improve their English-speaking abilities (as applicable) and generally reduce information frictions. Therefore, they are less likely to compete with recent arrivals for the same jobs, may offer better advice to recent arrivals and may even improve cultural tolerance of refugees among natives (Gehrsitz & Ungerer 2016). Hence the expected sign of δ_1, δ_2, and δ_3 is ambiguous as it depends on which effect is dominant: cooperation or competition.

5. Results

Table 3 shows results of estimating Equation 1 for single, unattached men, mirroring Beaman's sample as closely as possible. Column 1 shows that an additional refugee per 1000 in the network leads to an insignificant 0.3pp decrease in the probability of employment. The effects of previously arrived refugees are positive and increasingly significant as time between cohorts increases. An additional refugee per 1000 in the network with two years of living experience increases the probability of employment for a newly arrived refugee by 0.55pp. The effect is even stronger and more significant for additional refugees with three years of tenure; they increase the probability of employment by 0.8pp, significant at the 1% level. This pattern of sign and significance pattern is similar across other employment outcomes. Larger networks of increasing vintage increase hours worked, decrease the likelihood of working a low-skill job and increase wages of newly arrived refugees. There is very little effect on the probability of being self-employed, which is likely due to the fact that very few men in the sample are self-employed (3.55%).

Turning to welfare outcomes, there is almost no effect from social networks on welfare and SSI receipt, again perhaps because very little are receiving assistance (9.14% and 1.78%, respectively). There is a significant negative effect of the most tenured network members on the probability of Medicaid enrollment which is surprising since refugees are both eligible and encouraged to enroll by their resettlement agency.

Table 3 shows that social networks are indeed relevant for the population who is most likely to benefit from them – single, unattached men. This bolsters the evidence found in Beaman (2011) whose sample was only those men that were processed by a single resettlement agency.

Tables 4 and 5 extend the analysis to all men and women, single or otherwise. The signs and magnitude of lagged flows is similar to that of Table 3; more tenured refugees in the network increase the probability of employment, increase hours worked, decrease the probability of low-skill work and increase wages. The effect is much stronger for men than women, although women seem particular at risk for competition. An additional refugee per 1000 who arrived at the same time decreases women's wages by $86 on average. However, Table 5 shows that women are also much more likely to receive welfare with additional tenured network members. Both men and women are more likely to be covered by Medicaid if their own cohort is larger, which is most likely due to resettlement agencies devoting more resources to areas with large groups of newly arrived refugees. However, larger tenured networks decrease the probability of Medicaid enrollment, implying that there is perhaps cooperation among refugees who have had more time to navigate the healthcare system.

6. Robustness Checks

In this section I perform various robustness checks to rule out any alternative explanations for my findings. First, Table 6 asks if the previous results are simply a statistical artifact by regressing educational attainment on lagged flows. Since the ACS is a repeated cross-section, it is not feasible for tenured networks to have an effect on newly arrived refugees at the time of survey. Column 1 shows that there are small and insignificant impacts on male refugees at every lag. Column 2 is more concerning, with women's education being negatively impacted by an increase in the size of the network. This effect is statistically significant for the contemporaneous term and first two lags, but the coefficient with the largest magnitude is a negligible impact relative to the average education level (-0.025/11.94 = -0.21% decline in years of education).

Next, Table 7 determines if the placement decision is endogenous to local conditions. I regress the total number of refugees resettled to a county on the immigrant population rate and the unemployment rate.[4] Neither have a statistically significant effect on the number of refugees resettled which rules out an endogenous agglomeration effect.

[4] Both are calculated using the nativity and employment status variables in the ACS.

Lastly, I re-estimate the models in Tables 4 and 5 different RCR cutoff values (50-90%) in Appendix Figures A1-A6. Unsurprisingly, the coefficients of interest are relatively stable across different thresholds, but the standard errors increase as the cutoff increases (which naturally lowers the sample size). In some cases the coefficient is attenuated which is likely due to contamination by non-refugee immigrants who might respond to an immigration shock differently than refugees.

7. Conclusion

In this paper I showed the dynamic social network effects of refugee resettlement on recently arrived refugee outcomes. Unlike previous work, I use the universe of U.S. refugee resettlement between 2003 and 2017 and examine the impacts on not only refugee labor market outcomes but also welfare income, Medicaid enrollment and self-reported well-being. I find small and sometimes significant effects on employment, labor force participation and hours worked from an increase in the size of the refugee social network, particularly from additional refugees with two an three years of experience in the U.S. Distinct from most of the work on refugees I also show that networks increase Medicaid usage and decrease welfare income dependency. These effects are estimated using the universe of refugee resettlement and a more nationally representative sample of individuals than previous work that focused on county-level outcomes or individuals resettled by a single agency.

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Figures and Tables

Figure 1: U.S. Refugee Admissions

Table 1: Summary Statistics

	Mean	SD
Male	0.50	(0.50)
Age	35.04	(10.16)
Married	0.63	(0.48)
Household size (family)	3.64	(1.98)
Number of kids	1.08	(1.45)
Employed	0.48	(0.50)
Self-employed	0.04	(0.20)
Hours usually worked/week	20.14	(19.72)
Working in low skill industry	0.38	(0.48)
Wage income (Windsorized)	10,217.56	(17,807.51)
Received Welfare income	0.13	(0.34)
Received Supplemental Security Income	0.02	(0.14)
Covered by Medicaid last year	0.37	(0.48)
N	2082	

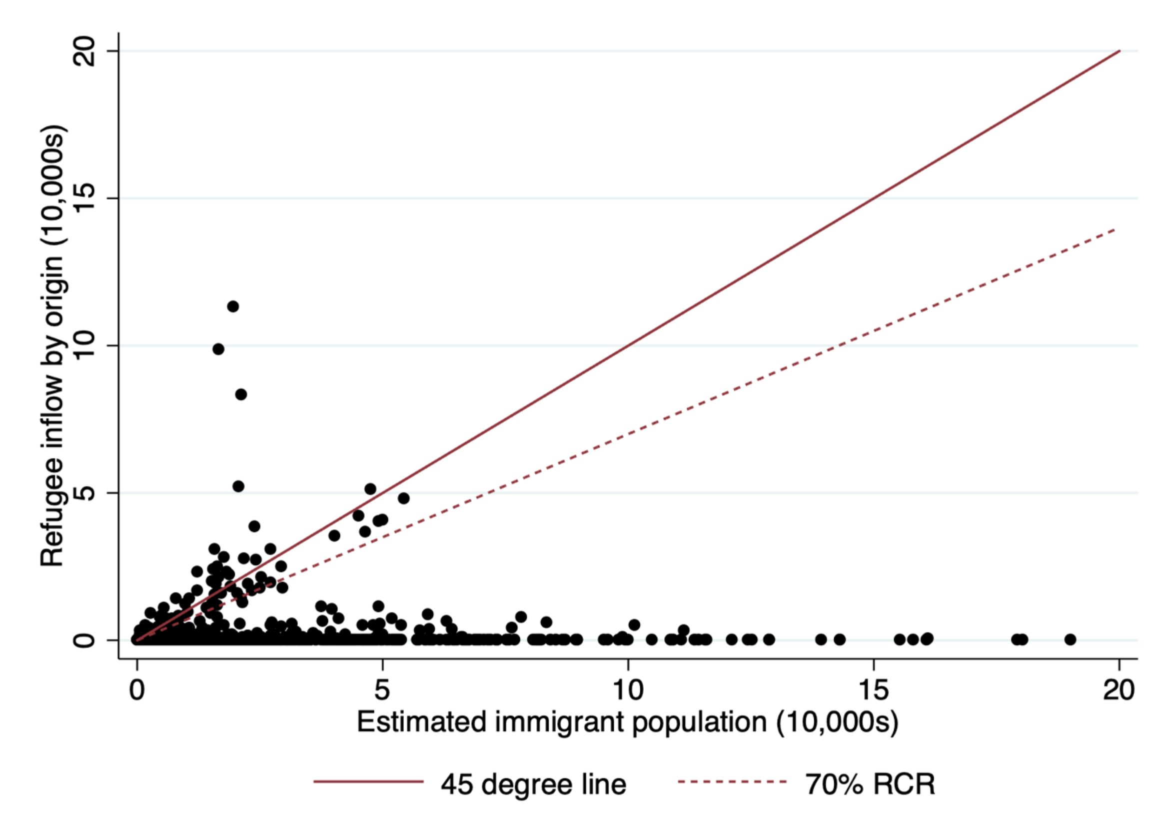

Figure 2: Refugee & Immigrant Flows

Table 2: Country-Year Pairs Used

Country	Years Used	Refugee Inflow by County		N
		Mean	SD	
Afghanistan	2005	33.00	(34.73)	4
Armenia	2006	2,489.50	(1,497.01)	12
Azerbaijan	2004	40.50	(57.28)	2
Bhutan	2011-2016	244.81	(224.62)	114
Burma (Myanmar)	2006-2011, 2013- 2016	301.38	(283.12)	324
Eritrea	2005	8.67	(14.15)	3
Iran	2004-2016	15,537.41	(33,086.90)	765
Iraq	2007-2010, 2012-2016	1,354.39	(1,986.19)	591
Laos	2004, 2005	185.56	(381.86)	9
Latvia	2005	0.00	(.)	1
Liberia	2004	124.13	(128.67)	15
Moldavia	2005	118.67	(98.37)	6
Sierra Leone	2004	11.20	(11.80)	5
Somalia	2004-2007, 2009, 2011-2014	402.55	(580.74)	128
Sudan	2012	9.50	(10.61)	2
Syria	2016	1,043.44	(2,030.86)	39
Dem. Rep. of Congo	2012, 2014, 2015, 2016	181.84	(215.38)	62
Total				2082

Table 3: Effects for Single Men With No Children

	(1) Employed	(2) Hours worked per week	(3) Self-employed	(4) Low skill work	(5) Wage Income
Panel A: Labor Market Outcomes					
Number of refugees resettled in year t	-0.00301	-0.104	-0.00113	-0.00203	-106.3**
	(0.00246)	(0.0824)	(0.00141)	(0.00159)	(50.95)
Number of refugees resettled in year t-1	0.00450	0.229	-0.00342*	0.00554**	198.5
	(0.00373)	(0.143)	(0.00198)	(0.00273)	(162.3)
Number of refugees resettled in year t-2	0.00552*	0.0269	-0.00190	0.00295	27.39
	(0.00307)	(0.103)	(0.00168)	(0.00257)	(84.29)
Number of refugees resettled in year t-3	0.00803***	0.299***	-0.000550	-0.00158	240.5***
	(0.00214)	(0.0641)	(0.000898)	(0.00248)	(59.64)
Mean of Dependent Variable	0.520	22.52	0.0355	0.406	10986
N	394	394	394	394	394

	(6) Received Welfare	(7) Received SSI	(8) Covered by Medicaid
Panel B: Welfare Outcomes			
Number of refugees resettled in year t	-0.000198	-0.000321	0.00294
	(0.00172)	(0.000351)	(0.00184)
Number of refugees resettled in year t-1	-0.000867	0.000997	0.00187
	(0.00246)	(0.00101)	(0.00256)
Number of refugees resettled in year t-2	0.000544	-0.000858	-0.00128
	(0.00182)	(0.00170)	(0.00217)
Number of refugees resettled in year t-3	0.000551	-0.000365	-0.00316**
	(0.00117)	(0.000542)	(0.00134)
Mean of Dependent Variable	0.0914	0.0178	0.246
N	394	394	394

Table 4: Labor Market Outcomes, Full Sample

	(1) Employed	(2) Hours worked per week	(3) Self-employed	(4) Low skill work	(5) Wage Income
Panel A: Men					
Number of refugees resettled in year t	0.000335	0.0062	0.001059	0.000733	-52.66
	(0.000922)	(0.039731)	(0.000648)	(0.000768)	(47.40)
Number of refugees resettled in year t-1	0.001399	-0.0226	-0.001085	0.004185***	-68.22
	(0.001303)	(0.064592)	(0.001082)	(0.001328)	(75.53)
Number of refugees resettled in year t-2	0.001377	-0.0087	-0.001220	0.001942	4.91
	(0.001269)	(0.041718)	(0.000741)	(0.001178)	(41.94)
Number of refugees resettled in year t-3	0.003367***	0.1309***	-0.000983*	-0.001804*	138.11***
	(0.001119)	(0.041672)	(0.000578)	(0.001036)	(42.52)
Mean of Dependent Variable	0.546	25.57	0.062	0.449	13499.91
N	1038	1038	1038	1038	1038
Panel B: Women					
Number of refugees resettled in year t	-0.000374	-0.0143	0.001603***	0.000246	-85.78**
	(0.000892)	(0.033888)	(0.000274)	(0.000930)	(34.16)
Number of refugees resettled in year t-1	-0.000059	-0.0658	-0.000712	0.000821	-62.66
	(0.001454)	(0.051650)	(0.000472)	(0.001055)	(64.14)
Number of refugees resettled in year t-2	0.000912	-0.0067	-0.001722***	0.000364	50.34
	(0.000815)	(0.037318)	(0.000457)	(0.000969)	(33.50)
Number of refugees resettled in year t-3	0.001350*	0.0864***	0.000888**	-0.000742	18.96
	(0.000740)	(0.032583)	(0.000435)	(0.000895)	(24.68)
Mean of Dependent Variable	0.321	13.45	0.032	0.248	6045
N	1044	1044	1044	1044	1044

Table 5: Welfare Outcomes, Full Sample

	(1) Received Welfare	(2) Received SSI	(3) Covered by Medicaid
Panel A: Men			
Number of refugees resettled in year t	0.000055	-0.000154	0.003529***
	(0.000599)	(0.000226)	(0.000649)
Number of refugees resettled in year t-1	-0.000058	0.000341	-0.002207***
	(0.000876)	(0.000299)	(0.000682)
Number of refugees resettled in year t-2	0.000170	-0.000421	-0.001651**
	(0.000620)	(0.000426)	(0.000695)
Number of refugees resettled in year t-3	0.000700	-0.000009	0.000621
	(0.000508)	(0.000117)	(0.000622)
Mean of Dependent Variable	0.149	0.017	0.363
N	1038	1038	1038
Panel B: Women			
Number of refugees resettled in year t	0.000975	-0.000285	0.004334***
	(0.000615)	(0.000247)	(0.000680)
Number of refugees resettled in year t-1	-0.002090***	-0.000529*	-0.002857***
	(0.000790)	(0.000283)	(0.001047)
Number of refugees resettled in year t-2	0.002548***	0.000909*	0.000976
	(0.000399)	(0.000469)	(0.000840)
Number of refugees resettled in year t-3	0.002032***	-0.000632	0.000736
	(0.000323)	(0.000637)	(0.000894)
Mean of Dependent Variable	0.118	0.021	0.384
N	1044	1044	1044

Table 6: Education Falsification

	(1) Men	(2) Women
Number of refugees resettled in year t	-0.00337	-0.01734***
	(0.00678)	(0.00534)
Number of refugees resettled in year t-1	-0.00874	-0.01381*
	(0.01091)	(0.00786)
Number of refugees resettled in year t-2	-0.00669	-0.02549***
	(0.00982)	(0.00813)
Number of refugees resettled in year t-3	0.00593	-0.01393
	(0.00676)	(0.00949)
Mean Education Level	12.63	11.94
N	1033	1035

Table 7: Endogeneity of Refugee Resettlement

	(1)	(2)
	Refugees Resettled	
Immigrant Population Rate	28.66	
	(26.54)	
Unemployment Rate		-27.59
		(22.24)
Mean Refugees Resettled	341	
Mean of Independent Variable	10.48	6.97
N	4879	

Note: year and county fixed effects included.

Appendix

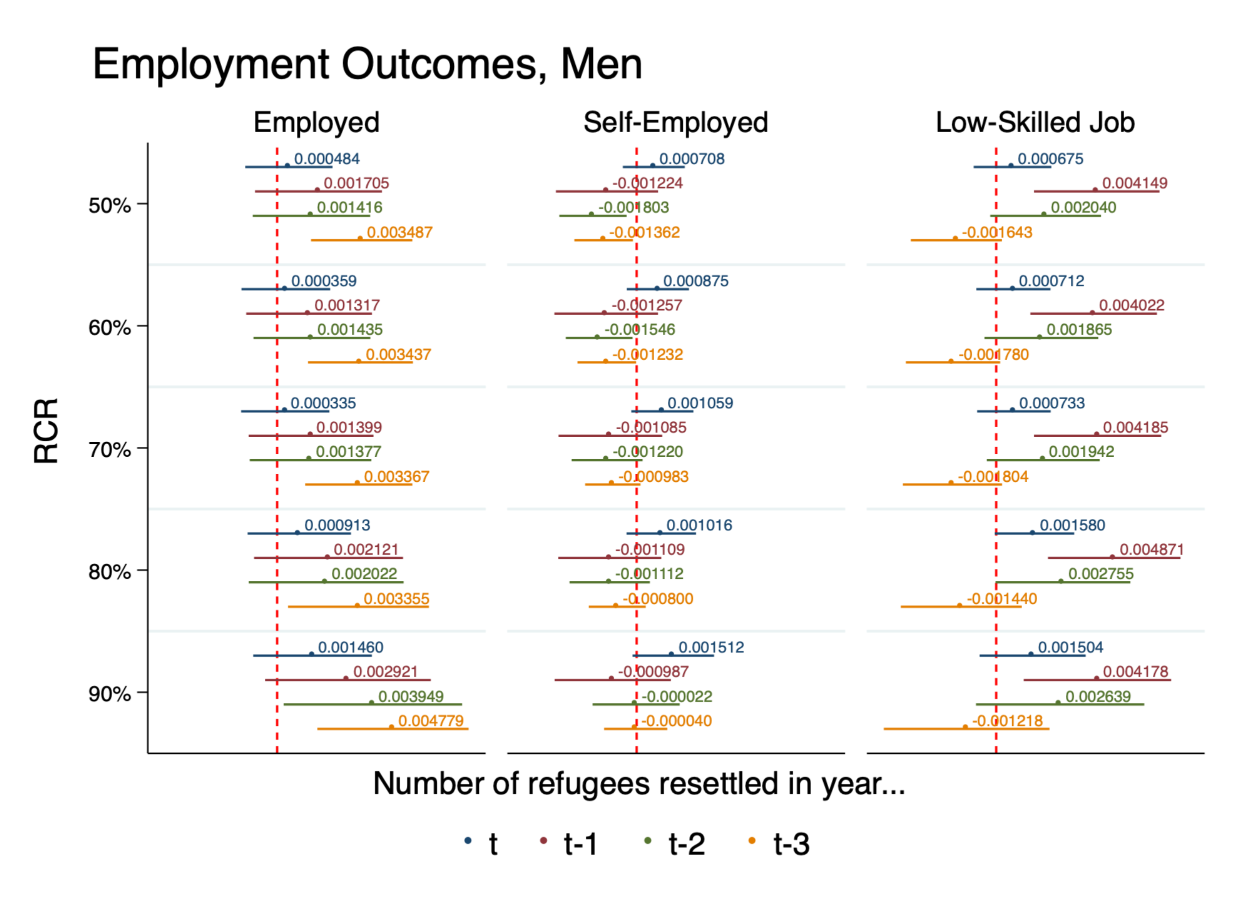

Figure A 1: RCR Cutoffs -- Employment, Men

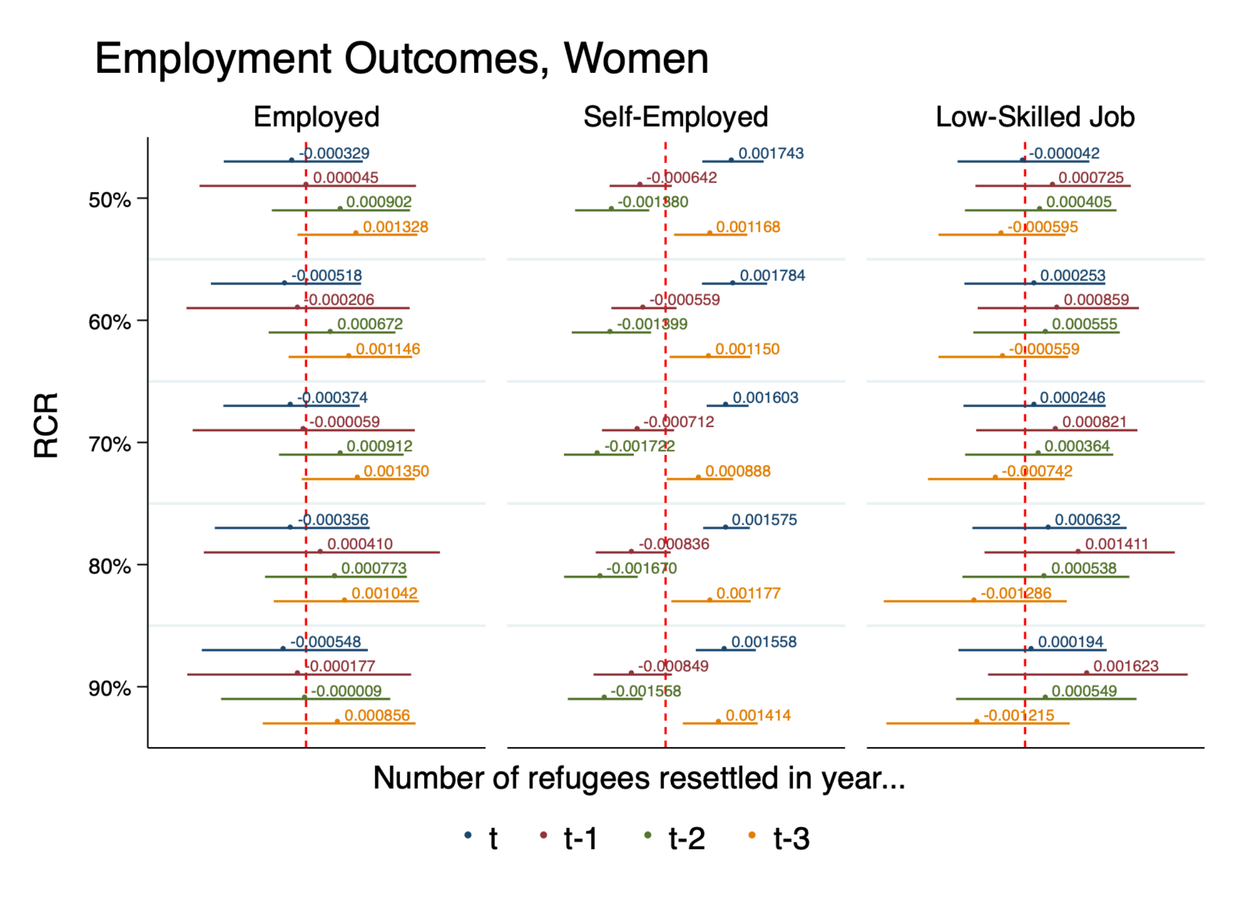

Figure A 2: RCR Cutoffs -- Employment, Women

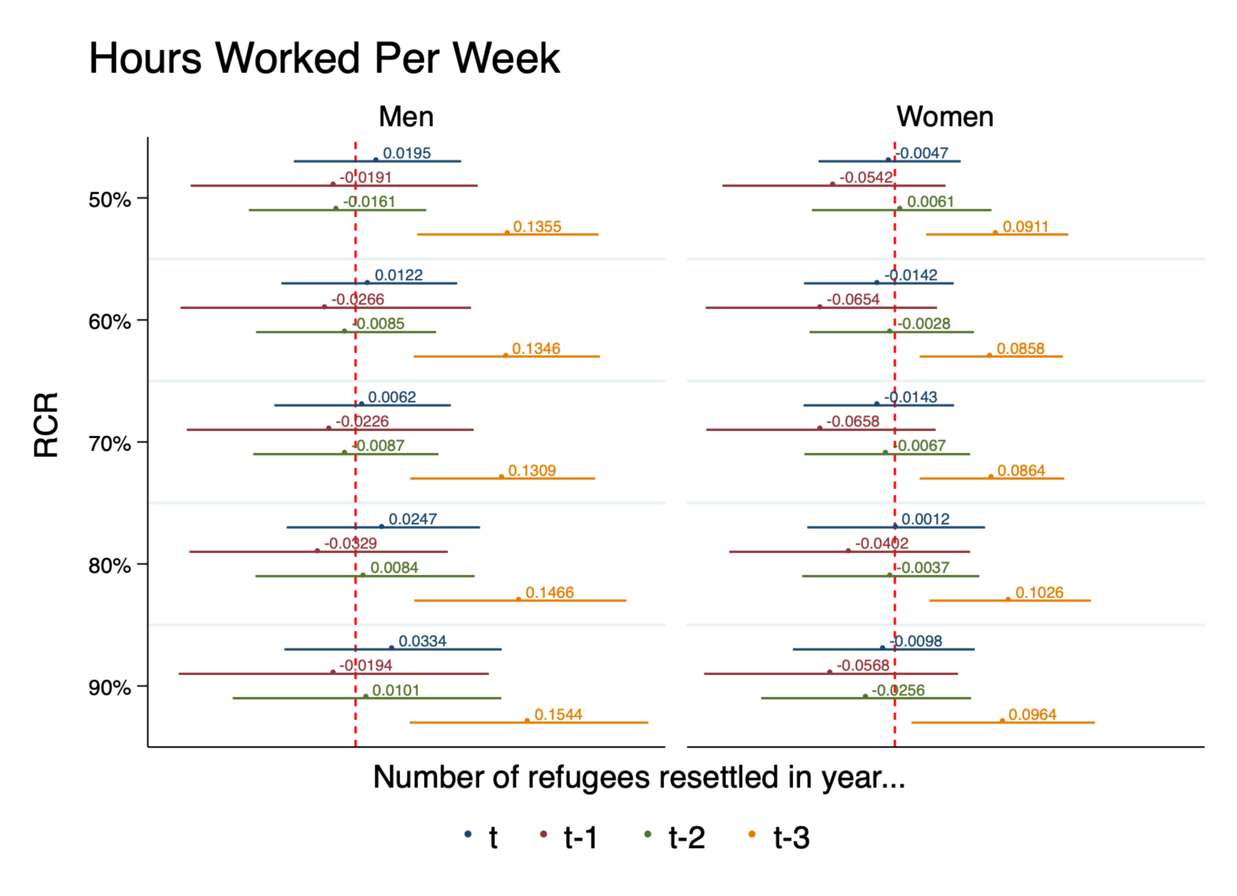

Figure A 3: RCR Cutoffs -- Hours Worked Per Week

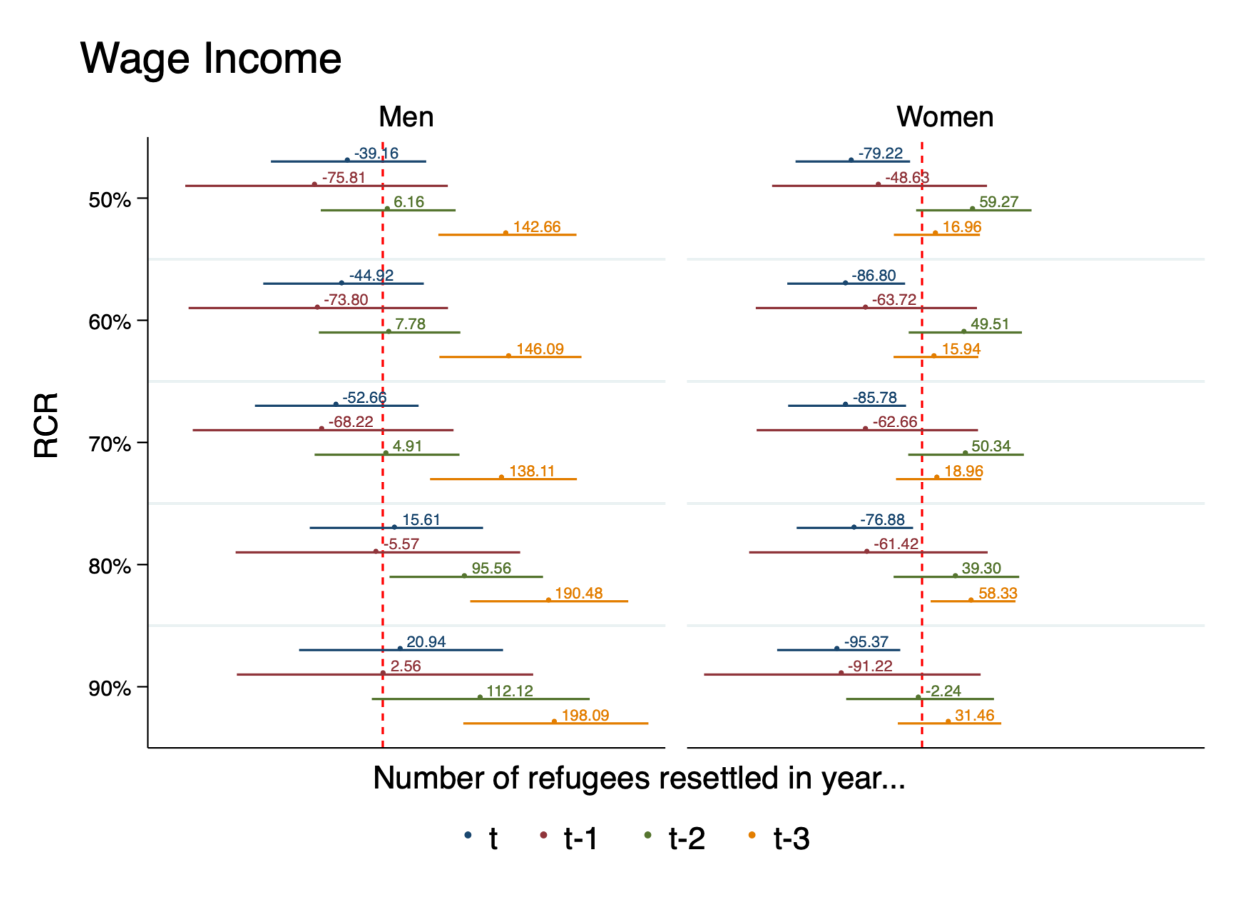

Figure A 4: RCR Cutoffs -- Wage Income

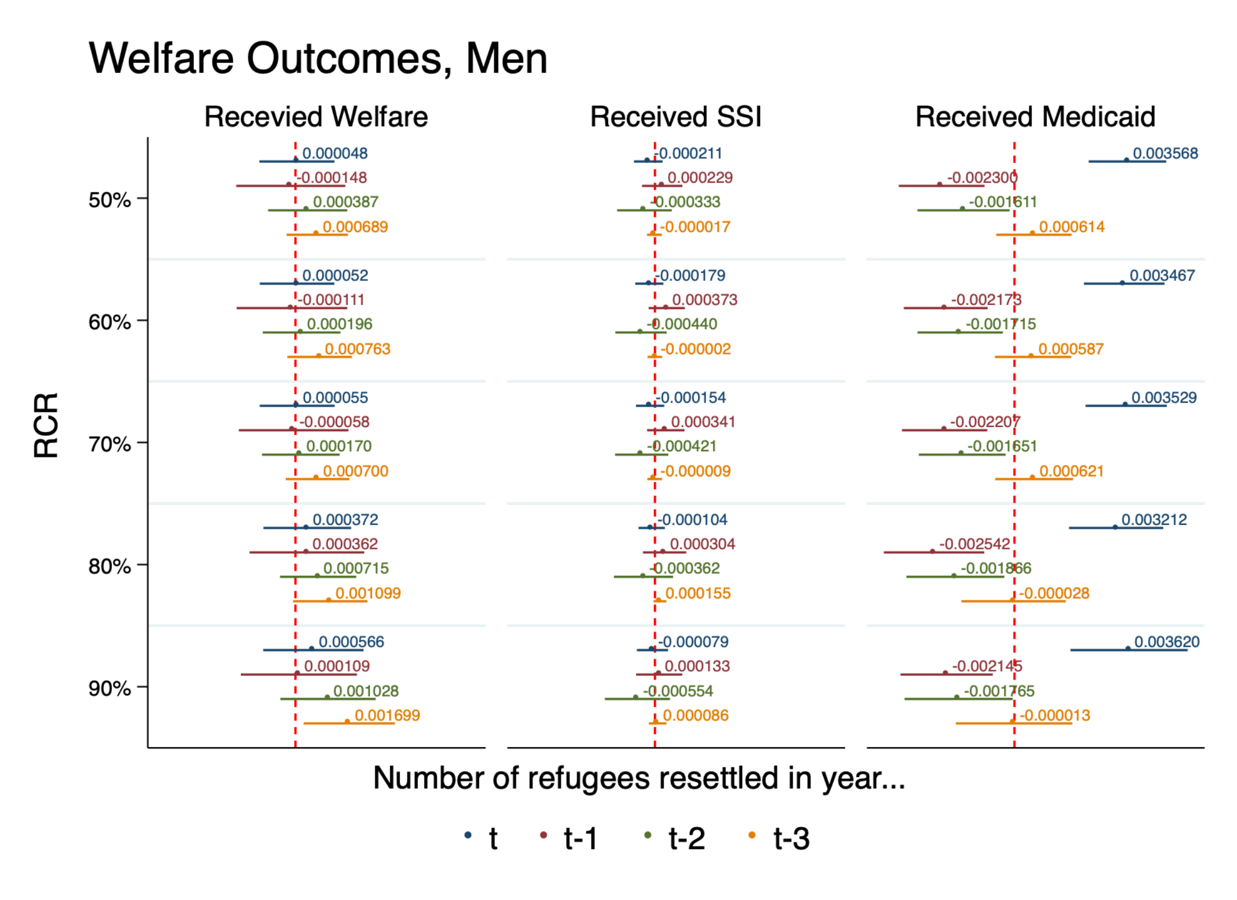

Figure A 5: RCR Cutoffs -- Welfare Outcomes, Men

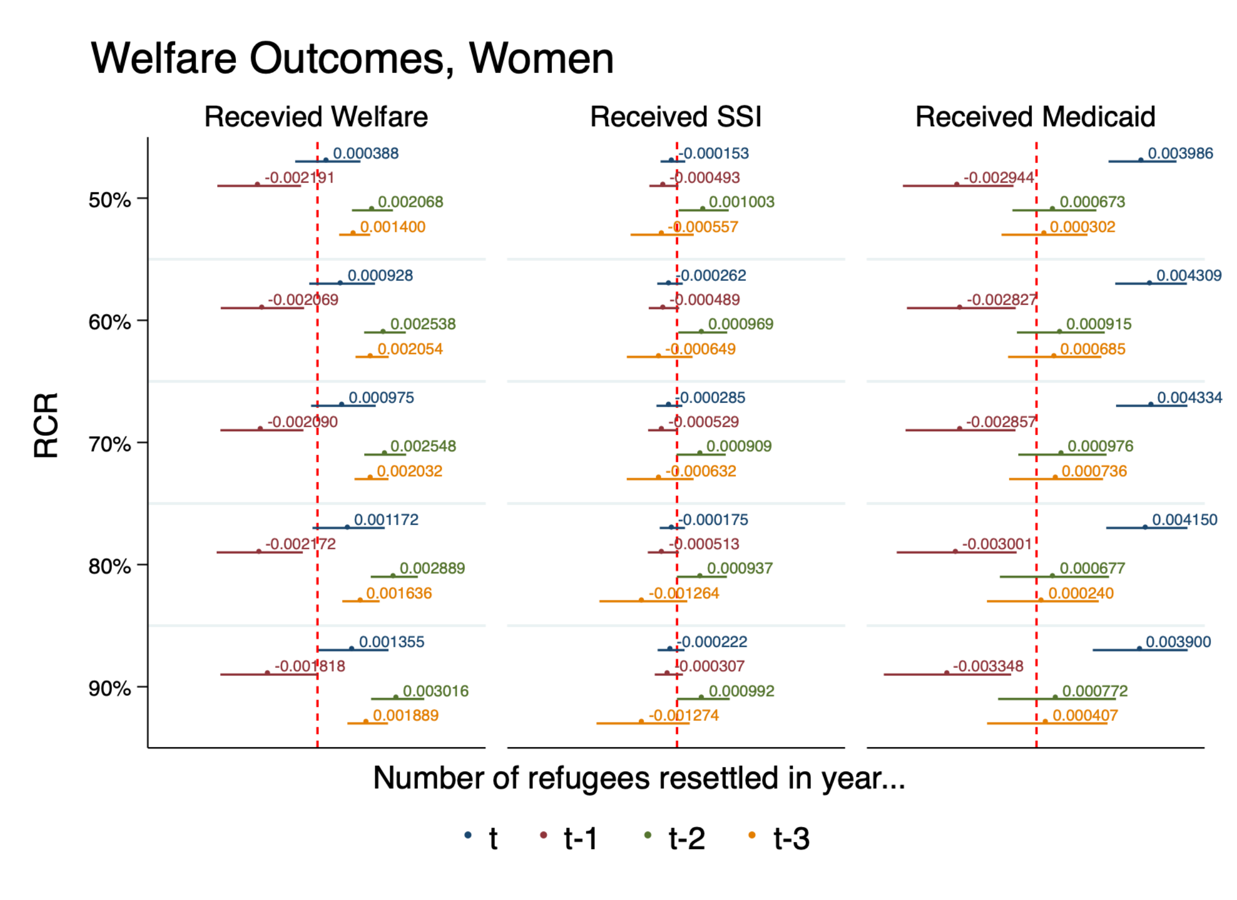

Figure A 6: RCR Cutoffs -- Welfare Outcomes, Women