Economic Systems xxx (xxxx) xxx

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

Ethnic identity and economic welfare

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ARTICLE INFO

JEL Classifications:
J61
J71

Keywords:
Ethnosizer
Ethnic identity
Refugees
Wage gap

ABSTRACT

In this study, we use rich survey data to understand the determinants of labor market success across refugees of different ethnicities in Turkey. In particular, we examine individual personality traits and integration barriers by considering metrics of refugees' proximity to Turkey based on their home countries' levels of cultural distance. Using microdata, we derive a refined index called ethnosizer scale to grasp the distance of minor ethnic identities in Istanbul to the dominant identity. Utilizing this parameter, we aim to analyze how the degree of commitment to the local society's culture affects the economic welfare of refugees in Istanbul, in terms of their earnings, participation in labor markets and wage gap compared to the natives.

1. Introduction

Since the 1980s, the impact of migration has remained a topic of discussion among social scientists and policymakers. The progress of globalization, the rise of emerging countries, increasing global inequality, and wars in the Middle East have led to demographic changes. In line with the expansion of international migration, in addition to sociological studies, a stream of literature has rapidly grown on the effect of ethnic identification on economic behavior and welfare, such as participation in the labor market, income, and household ownership. To some extent, these studies are related to identity economics, pioneered by Akerlof and Kranton (2000), who suggest that social identity became a considerable determinant of economic preference and labor market outcomes. In this sense, the identity of an immigrant became a primary variable for explaining participation in economic life, business and solidarity networks, property ownership, employment, and savings behavior. The dominant characteristics of identity in society define the degree of discrimination, wage inequality, and deprivation of social rights.

Pendakur and Pendakur (2005) conduct one study in this context, finding that, among European ethnic minorities, the degree of ethnicity is positively correlated with using informal network channels to find a job. However, the result is not the same for non-European ethnic minorities. From the same perspective, Battu et al. (2005) show a direct correlation between the measurement of identity and the probability of employment. However, Battu et al. (2007) focus on the importance of the impact of oppositional identity in adopting the dominant identity. They demonstrate that the self-definition of an immigrant with respect to family, friends, religion, and language leads to adverse labor market outcomes. Similarly, Battu et al. (2011) explicitly examine the consequences of an ethnic identity for getting a job. They show that in the UK ethnic identity is highly correlated with using ethnic job-finding networks.

Likewise, Zimmermann (2007) addresses the role of ethnic identity in earnings. Using an index called ethnosizer to capture the degree of integration by immigrants, he examines the particular contribution of ethnic identity. He finds that ethnic identity matters significantly and that the findings are highly robust to the concrete model specification. Constant and Zimmermann (2009) extend this

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https://doi.org/10.1016/j.ecosys.2021.100888
Received 31 July 2020; Received in revised form 23 December 2020; Accepted 21 March 2021
Available online 7 May 2021

framework to model the labor force participation and earnings of both male and female immigrants, because they may have completely different understandings and expressions of their ethnic identity. This is based on the idea that immigrants are mostly useful in the host country when they bring talents and skills that differ from those possessed by native workers. Constant et al. (2009a) demonstrate that, rather than ethnic identity, the level of integration induces homeownership. The probability that a migrant who is integrated and assimilated will have a home is greater than that of the other characteristics of migrants. Constant et al. (2009b) conclude that the probability that migrants will be willing to acquire the citizenship of the host country is related purely to their level of integration. However, ethnic identity and self- identity influence future naturalization. Nekby and Rödin (2010) use the same methodology as Constant and Zimmerman (2009) but with intergenerational data. The specific focus is the impact of the acculturation identity on the probability of employment by the second and later generations of immigrants in Sweden.

Several studies also introduce ethnic identity as a valuable variable for explaining wage and income inequality (Mason, 2004; Neuman and Oaxaca, 2005). Zorlu (2003) points out the significant differences in wage level across the seven different ethnic identities and workers with Dutch citizenship. The wage levels are influenced more strongly by ethnicity than by gender. Neuman and Oaxaca (2005) find parallel results in the Israeli labor market. Mason (2004) also obtains empirical results on the heterogeneity of Hispanic speakers, such as Mexican and Cuban Americans, which causes adverse selection in labor market outcomes and discrimination due to skin color or phenotype.

More recent research, for example, Lehmer and Ludsteck (2011), employs decomposition and quantile regression methods, further differentiating immigrants in Germany by their origin in a range of countries within and outside Europe. Similarly, in the Italian labor market, Dell'Aringa et al. (2015) show that contrary to the natives, work experience among migrants does not have statistically significant returns. Using the European Union Statistics on Income and Living Conditions (EU-SILC) data for Austria, Grandner and Gstach (2015) compare the wages of immigrants and native workers, using the Oaxaca-Blinder Approach (1973) and the quantile regression approach of Machado and Mata (2005). They find a wage gap between native workers and migrants of between 15 percent and 25 percent that disadvantages migrants. Wage inequality between the host and immigrant population occurs in many countries in Europe. The majority of migrants within the European Union (EU) face income disadvantages, which tend to be even more pronounced for migrants from non-EU countries than for migrants from EU member states (Lehmer and Ludsteck, 2015). In Austria, which has a higher share of foreigners than Germany, Hofer et al. (2017) show a wage gap between immigrants and native workers.

In this article, using a survey conducted in Turkey, in particular in Istanbul, we explore the question of whether the integration process of refugees in that city, who mostly arrived over the past decade, influences the economic outcomes of the labor market, such as the job position, income level, and the wage gap. This is critical because the economic outcomes for refugees have vital implications, especially in the countries that are migration recipients, such as Turkey, which has a potential labor force numbering two million refugees, mainly from Syria, Iraq, Afghanistan, Pakistan, and Turkic Republics, such as Turkmenistan, Kyrgyzstan, Uzbekistan. In this sense, we contribute to the literature by studying a city that has been highly affected by refugee flows because of the crisis in Syria and developments in other poor countries in the Middle East and other regions nearby. This study concerns the country that has harbored the largest refugee population in the past decade. In this way, we aim to fill a gap in the literature, which until now has not had a comparable analytical study about refugees in Turkey.

Our data cover household and labor-related characteristics that are relevant for understanding the determinants of labor market success across groups. We consider a rich set of control variables for typically unobservable labor market influences. In particular, we examine individual personality traits and integration barriers by taking into account the metrics of refugees' proximity to Turkey. Hence, we do not consider refugees in Turkey as a homogeneous group but, rather, take into account differences based on the country of origin. This allows us to address whether the welfare differentials of refugees arise from their personal traits or from their refugee status.

To empirically measure the ethnic identity of refugees and analyze its impacts on their economic welfare, we employ a concept called an ethnosizer developed by Constant et al. (2009), which is used to measure the intensity of people's ethnic identity with respect to the society in their host country and country of origin (source/home country). This measurement uses information on their language, culture, social interactions, history of migration, and ethnic self-identification. The ethnosizer can be either one-dimensional or the two-dimensional: the former shows the degree of identity commitment to the home or host country, whereas the latter allows simultaneous intensification of commitment to the host and source countries. In addition to these identity measures, we also employ other parameters of discrimination to see whether they have any economic impact on the welfare of refugees.

In this way, we analyze the relationship between the economic welfare of refugees and the integration level (or commitment), and discrimination defined by various concepts concerning the ethnicity of refugees. To do this, we focus on how the income level of refugees is related to their ethnic status, controlling for other variables. Using information from our sample data on migration in Istanbul, we also focus on refugees' employment status. To do this, we use various probit models to analyze the impact of ethnic identity, controlling for the main determinants of the employment status of refugees in Istanbul. The wage gap between the refugees and local workers is another important issue we address in the paper. It is important to analyze whether wage differentials are due to observable differences in, for example, human capital endowments or to unobservable influences, that is, ethnic discrimination. In this sense, we also have an opportunity to test the human capital theory in the context of refugees in Turkey. This is essential for revealing structural and persistent disadvantages experienced by these groups. To consider the heterogeneous effects observed across the entire wage gap distribution, we also apply quantile regression models. Thus, we examine whether trends emerge in wage gaps in various quantiles of wage gaps between refugees and native workers.

The remainder of this paper proceeds as follows. In Section 2, we quantify the identity of the refugees in Istanbul using the ethnosizer concept. Section 3 explores the analytical links between the ethnic identities of refugees and their economic welfare in the context of income level and the probability of employment for the refugees in Istanbul and wage gaps between the refugees and the

native workers in Istanbul. Section 4 concludes.

2. Ethnosizing the refugees in Istanbul

2.1. Stylized facts on the refugees in Istanbul

In our sample, all migrants are refugees. The terms "migrant" and "refugee" are often used interchangeably, but it is important to distinguish between them as there is a legal difference. Simply speaking, migrants have chosen to move, and refugees are those who have been forced to flee their home. Migrants may move for any number of reasons. Some of them move to be closer to their family or for economic reasons.

The ongoing war in Syria since 2011 and the civil war and insecurity in northern Iraq and Afghanistan caused mass migration waves to Turkey over the past decade. According to monthly statistics published by the UNHCR the number of registered migrants in Turkey as of March 2019 was as follows; 3.6 million Syrians, 170,000 Afghans, 142,000 Iraqis, 39,000 Iranians, 5700 Somalis, and 11,700 people from other countries.

According to a report by the Marmara Municipalities Union's Center (Erdoğan, 2017), if all the unregistered migrants and the migrants registered in another city but living in Istanbul are added together, the Syrian population in Istanbul totals approximately 600,000. Although 33 percent of the migrants with a residence permit in Turkey live in Istanbul, they reside in districts that are relatively undeveloped, such as Bağcılar, Başakşehir, Esenyurt, Fatih, Küçükçekmece, Sultangazi, and Zeytinburnu. The number of non-Syrian migrants from Afghanistan, Iraq, Iran, and Pakistan is about 300,000. Since 2011, Turkey has maintained an open-door policy, accepting around 850,000–900,000 Afghan, Iraqi, Iranian, and Pakistani migrants. While almost half of these refugees reside in Turkey, rest of them have been in Turkey as a transit country to Europe (Erdoğan, 2017).

This study is mainly based on a comprehensive survey we conducted in 2019 on the migrant population in Istanbul, using a questionnaire and face-to-face interviews in the districts with the largest refugee population: Bağcılar, Esenyurt, Fatih, Küçükçekmece, Sultanbeyli, and Sultangazi (Erdoğan, 2017, 3). To avoid missing or erroneous inferences in questions and answers, the surveys were conducted by people who speak the native language of the respondents. Because our concern focuses on issues in the labor market, we target mostly respondents who are active in the labor market.

The survey respondents reflect the composition of the migrants in Istanbul. They consist of 517 heads of households who were refugees from Syria (246), Afghanistan (85), Iraq (57), Georgia (99), and Pakistan (30), with a total of eight different ethnic identities: Arabs (51.3 %), followed by Afghans (15 %), Uzbeks (8%), Georgians (7.2 %), and Kurds and Pakistanis (5.8 %). There is a smooth distribution of three ethnic identities—Arab (58.2 %), Afghan-Pakistani (20.9 %), and post-Soviet (20.9 %)—which we called geographic ethnicity. Among the Syrian refugees, 43 percent come from Aleppo, 25 percent from Damascus, 3 percent from İdlib, and 2 percent from Latakia. Among Afghan refugees, the majority (23 %) come from Kabul. 10 % of the Pakistanis come from Lahore and 9% of them are from Karachi. The refugees from post-Soviet countries come mainly from Batum and Tiflis in Georgia, and Samarkand in Uzbekistan. This information shows that the sample predominantly came from cities.[1]

Females make up around 30 percent of the sample, and males comprise the rest. The average age of the respondents is thirty. Whereas 40 percent of them are between 16 and 25 years old, almost 50 percent are 26−45. The mean number of years of education is 9.4, which equals more than a secondary school degree. In general, 15 percent of the migrants in the sample have a bachelor's degree. Among the three geographic ethnicities, Arabs have the highest education. Post-Soviet refugees have the highest rate of having a high school degree, at 33 percent, compared with only 4 percent among Afghan and Pakistani refugees. The refugees are predominantly Muslim, which is similar to the population in Turkey, at about 92 percent, of which 91 percent are Sunni; this is because the refugees in Turkey come mainly from Middle Eastern countries and Turkic republics, where they predominate. The only Christians in the sample come from Georgia.

Next, we examine the indicators associated with the economic circumstances of the refugees. First, we focus on their total income and its composition, shown in Table 1. Most of the refugees in the sample (about 65 %) earn income from a regular salary, and 28 percent are paid irregular wages (daily wages). Only 7 percent stated that they obtained income from entrepreneurial activities. Table 1 shows that the average annual income from various economic activities is about TL 34,867 (6,226.25 USD[2]) Their average annual income from a regular salary is TL 24,254 (4331 USD), nearly the average annual regular income in 2019 for a worker receiving the monthly minimum wage in Turkey of about 24,000 TL (4285.7 USD). Income from irregular wages and entrepreneurial income (by trade) is relatively low.

The table also shows that the refugees' average income from social benefits is quite low, compared with the average in Turkey. Only 2 percent of the respondents said that they receive social benefits, a result similar to that by the Metal-Iş. (2017), which found that only 3 percent of Syrian refugees received social benefits. A report by the AFAD (Disaster and Emergency Presidency), however, asserts that the rate is quite high. It found that 36 percent of the Syrian refugees received cash assistance from nongovernmental organizations (NGOs), whereas 30 percent declared that they receive benefits only from the government (AFAD, 2017, 9). Our survey also asks the respondents about the wage gap between them and Turkish workers with whom they work at the same jobs, and they reported an

[1] The report written by the AFAD in 2017 has the same distribution of home cities. More than half the Syrian refugees came from Aleppo, 11% came from Hama, and 6% from Latakia (AFAD, 2017, 9).

[2] 1 USD is approximately equals to TL 5.6. https://www.tcmb.gov.tr/wps/wcm/connect/EN/TCMB+EN/Main+Menu/Statistics/Exchange+Rates/Indicative+Exchange+Rates

Table 1
Distribution of Refugees by Income, Social, and Work Status.

Variable	Mean	Std. dev.	Share (%)
Total income (yearly)	34,867	24,803	
Income from salary (yearly)	24,253	26,308	65
Wage	5760	13,015	26
Income from trade	4124	15,269	7
Income from social benefits	163	1513	0.5
Income from other channels	533	3222	1.5
Monthly income	2905	2066	
Wage gap (monthly)	459	534	
Working hours (weekly)	53	27	
Have a work permit	13		
Job status			
Unemployed			19.7
Unskilled blue-collar worker			31.1
Services			15.6
Skilled blue-collar worker			9.7
Skilled white-collar worker			9.6
Other			14

average gap of TL 459, that is, they earn around 25–30 percent less than the native workers. We look at this wage gap in more detail in the following sections.

In terms of the work status of refugees living in Istanbul, we see that only 13 percent have permission to work. Because Syrians hold a privileged status as refugees under the Temporary Protection Law, most of the refugees who have a work permit are Syrians. Approximately 67 percent of the refugees in the sample work without permission. Having a work permit does not make a difference in the income of the refugees in Istanbul. According to the Turkish Statistical Institute's Household Labor Force Survey (2017), which includes only citizens, the average working hours in Istanbul are 47 hours per week. But for the refugees in our sample, it is higher: they work an average 53 h that is, 6 h- more than the native workers. 40 percent of the respondents in the sample reported that they work more than 60 h per week. In terms of the weekly working hours by geographic ethnicity, whereas 65 percent of the Afghans and Pakistanis and 61 percent of the post-Soviet refugees work more than 60 h per week, only 23 percent of the Arab refugees do so.

With respect to the job status of the refugees in our sample, Table 1 shows that about 20 percent are unemployed, which is about 6.2 percentage points higher than the general unemployment rate in Istanbul in 2019 of about 12.5 percent. Those who are working are divided by occupation. About 31.1 percent, the majority, are unskilled blue-collar workers in textiles, construction, and recycling. The next largest group of refugees work as caregivers and in services, 15.6 percent. Refugees who are certified professionals or obtained a professional title after graduating from university (lawyer, teacher, nurse, etc.) are considered skilled white-collar workers, comprising 9.6 percent; and the skilled blue-collar workers make up 9.6 percent. The remainder work in trade and sales and work as craftsmen.

2.2. Quantifying the ethnic identity of the refugees in Istanbul

To empirically measure the ethnic identity of refugees and analyze its impacts on their economic welfare, we benefit from a concept called ethnosizer developed by Constant et al. (2009), which is an index used to measure the intensity of people's ethnic identity with respect to their host and source countries. This measurement uses information on language, culture, social interactions, history of migration, and ethnic self-identification. There are two types of ethnosizer: one-dimensional and two-dimensional. In the former, a stronger commitment to the host country necessarily implies a weaker connection to the country of origin and vice versa. But the latter is another ethnosizer measurement that allows simultaneous intensification of connections to the host and home countries.

To generate the measurement of ethnic identity as a linear construct of refugees' commitment to the culture and society of origin and devotion to the host society, we select variables with information on their personal attachment to the Turkish culture and society. We divided the selected variables into five categories: (1) language, (2) culture, (3) social interaction, (4) year of migration, and (5) ethnicity. Table 2 lists the specific variables in each category. The level of commitment to the home and host society are designed on a vector normalized from 0–1. It represents the minimum to a maximum commitment with a linear structure. We seek to reveal one and two-dimensional ethnosizer in terms of these five categories, and each category has the same weight in the construction of the indices.

We construct one-dimensional and two-dimensional enthosizer indexes for the five categories as shown in Table 2. Using the one-dimensional ethnosizer, we first define a language ethnosizer based on three parameters, (1) a refugee's self-assessment of written Turkish, (2) a refugee's self-assessment of spoken Turkish, and (3) the language mostly used in daily life. The answers for 1 and 2 are scored as follows: very good (0), good (0.25), fair (0.50), weak (0.75), and not at all (1). The third parameter is scored based on how close the refugee's native language is to the languages mostly used in Turkey. Thus, if Turkish is the most used language, the score is 0. This means that refugees who mostly speak Turkish have the highest commitment to Turkish society. Turkmen, Kyrgyz, and Uzbek are the languages that are linguistically closest to Turkish, so their score is 0.25. Kurdish is the second-most-common language spoken by people in Turkey, so its score is 0.50. The score for Arabic is 0.75, as it is the third-most-spoken language in Turkey. The refugees who have the least commitment mostly to speak their own languages, such as Urdu, Pashto, Farsi, and Georgian, which are not widely used in Turkey.

Table 2
Five Categories of Ethnic Identity in the Ethnosizer.

One-Dimensional Model	Two-Dimensional Model
(A) Commitment to Turkey	(B) Based on both countries
(1) Language	*(1) Language*
Use of written Turkish	Use of written Turkish
Use of spoken Turkish	Use of spoken Turkish
The language mostly spoken	Use of written language of origin
	Use of spoken language of origin
(2) Culture	*(2) Culture*
Preferred media	Preferred media
Preferred music	
Preferred meals	
(3) Ethnic Self-Identification	*(3) Ethnic Self-Identification*
Self-identity as Turkish	Self-identity as Turkish
	Self-identity as the ethnicity of origin
(4) Social Interaction	*(4) Social Interaction*
Ethnic identity of three closest friends and relatives	Ethnic identity of three closest friends and relatives
Visited Turkish friends during the prior year	
Ethnicity of employer	
Ethnicity of preferred tradesmen	
Turkish spouse	
(5) Migration History	*(5) Migration History*
Wish to stay in Turkey permanently	Intend to apply for Turkish citizenship
Take trips to the country of origin	Want to return to the country of origin

Source: Adapted from Constant et al. (2006).

Another one-dimensional ethnosizer is a cultural ethnosizer, which is also composed of three parameters: preferred media, preferred music, and preferred meals. All three parameters have five potential responses, with a score between 0 and 1, as in the previous scale: every day (0), a few times a week (0.25), a few times a month (0.50), rarely (0.75), and never (1). For example, with respect to the self-identification ethnosizer, we look at the response to "what is your ethnic origin?" Because the refugees do not define themselves as Turkish, the score for this parameter is 1 for all the variables.

For the social interaction ethnosizer, we pose five questions to determine the social environment of the refugees. The questions mainly aim to capture the degree of the refugees' mobility across countries, family life, and interactions with their friends. The ethnicity of their friends is scored based on the size of the ethnic populations in Turkey. The received and paid visiting frequency of the refugees are defined orderly and marked between 0–1 (every day (0), a few times a week (0.25), a few times a month (0.50), rarely (0.75), and never (1)). The refugees in Turkey have mostly fled war and instability in their home country and therefore still have family elsewhere. Instead of asking about those family members, we evaluate their interactions at work and in their daily lives, with two new variables, the ethnicity of their employer and of their preferred shopkeepers. These variables are scored in the same way as the previous question. In the last question, we ask whether they have a Turkish spouse, and the score is binary, 0 (for no) or 1 (for no).

The last one is the migration history ethnosizer, in which we ask two basic questions: (1) do you wish to stay in Turkey permanently? and (2) how many trips did you take to your home country in the past year?

The questions in these five dimensions are weighted equally. The answers by a respondent to the questions from each category of

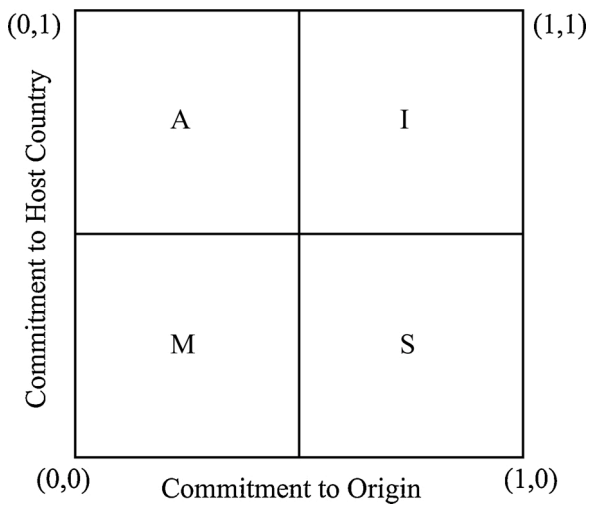

Fig. 1. Two-dimensional Ethnosizer.

factors generates ethnosizers for language, culture, social interaction, self-identification, and migration history. So, the one-dimensional ethnosizer is the mean assigned score of answers to the questions in all five categories. The closer the score of the measured ethnic identity is to 0, the less commitment to the origin it indicates, and the closer it is to 1, the less the refugee's devotion and commitment to the host society is.

To measure ethnic identity by the two-dimensional ethnosizer, we need information on commitments to both the host and home societies and cultures. The second column in Table 2 lists the variables used to measure ethnic identity in the two-dimensional model. We identified questions that compare a personal devotion to the culture and society in Turkey to the commitment to the culture and society of origin. In most cases, we paired each variable indicating commitment to Turkish culture with a variable measuring a similar type of commitment to the culture of origin. But the pairing is not required for the variable "culture," because the construction of the variable alone evaluates the strength of commitment to Turkish media and the media from the country of origin.

In the two-dimensional ethnosizer, the ethnosizer scale defines refugees in four respects: (1) integration, (2) assimilation, (3) separation, and (4) marginalization. In this scale, the closer the score of the measured ethnic identity is to 0, the more commitment to the host country it indicates, and the closer it is to 1, the lower the refugee's devotion and commitment to the host country is. Thus, assimilation, integration, separation, and marginalization are each bounded by the range $[0, 1]$. They are based simply on the balance of commitment between the home and the host societies.

Fig. 1 represents the two-dimensional ethnosizer graphically and defines migrants in the positive quadrant. As mentioned above, the ethnosizer has four measures of ethnic identity differentiated by the strength of cultural and social commitment. The quadrants in Fig. 1 are as follows: assimilation (A), a strong identification with the host culture and society, coupled with weak identification with the country of origin; integration (I), in which an individual shows strong commitment to both the origin and the host societies; marginalization (M), weak dedication to both the host and origin countries; and separation (S), a strong commitment to the culture of origin paired with weak involvement in the host culture and country.

After defining the content of the two-dimensional ethnosizer, we construct it for each category. Starting with the language ethnosizer, we pose questions on the following: (1) writing skills in Turkish, (2) speaking skills in Turkish, (3) writing skills in the respondent's native language, (4) speaking skills in the respondent's native language. We use the same scoring system for the answers to these questions as explained earlier. Integration is defined as when a refugee's ability to speak Turkish is fair or more than fair (0.50) and so is the ability to speak the native language. Assimilation is defined as when the ability to speak Turkish is more than fair (0.50) and the ability to speak the native language is fair or less than fair. Separation is defined as when the ability to speak Turkish is less than fair (0.50) and the ability to speak the native language is fair or more than fair. Lastly, when the ability to speak Turkish and the ability to speak the native language are both less than fair (0.50), the respondent is defined as marginalized. As with the culture ethnosizer, as mentioned above, is the only variable that is not paired because it alone enables an evaluation of the strength of commitment to Turkish media and media in the country of origin.

In the two-dimensional self-identity ethnosizer, we consider self-identity categorization as Turkish and the person's original identity. In this sense, all the refugees in our sample define themselves in terms of their country of origin, which takes a value of 1. For the social interaction ethnosizer in two dimensions, we asked about the ethnic identity of the respondent's three closest friends and relatives. Finally, for the migration history ethnosizer, we posed different questions about respondents' future plans, such as (1) whether they intend to apply for citizenship and whether they want to return to their home country. The responses to question 1 are scored from high to low: very much (0), much (0.25), not much (0.5), neutral (0.75), and never (1); and the responses to question 2 are scored from low to high: never (0); neutral (0.25), not much (0.5), much (0.75), and very much (1).

In the two-dimensional ethnosizer, for each category that identifies identity, we define each respondent as integrated, assimilated, separated, or marginalized. The respondent can be classified as integrated in one category (e.g., for language) but marginalized or something else in another category (e.g., for migration history). Therefore, we count how many times the respondents are defined as integrated, assimilated, separated or marginalized in each category. In this way, each of these four variables can take a value between 0 and 5 for each category, and for each refugee they add up to five.

Using these definitions, we calculate statistics for the one- and two-dimensional ethnosizer to predict the degree of commitment (see Table 3), showing that the mean value of the one-dimensional ethnosizer (simply called ethnosizer in Table 3) is 0.78, which means lower commitment to the host society, Turkey, and thereby low integration with it. The scores for the ethnic group ethnosizers are: Pakistanis (0.637), Afghans (0.567), Arabs (0.563), Georgians (0.530), Kurds (0.505), Uzbeks (0.481), Turkmen (0.462),and Kyrgyzs (0.461) respectively (not in the table due to space limitations).

Table 3 shows some interesting patterns in the two-dimensional ethnosizers. The two-dimensional scale reveals integration, assimilation, separation, and marginalization, which are converted to the number of times in the five-commitment classifications defined above. The mean of separation is high, compared to other categories. The average refugee in our sample demonstrates stronger

Table 3
One-dimensional and two-dimensional ethnosizers.

Variable	N	Mean	Std. dev.	Min.	Max.
Ethnosizer	517	0.78	0.153	0.42	1.32
Integration	517	1.23	0.426	1	2
Assimilation	517	0.29	0.475	0	2
Separation	517	2.19	0.797	0	4
Marginalization	517	0.34	0.592	0	3

separation (2.19) than integration (1.23), marginalization (0.344), or assimilation (0.29). According to these measures (the two-dimensional ethnosizer), the refugees in Turkey have a stronger commitment to their culture and society of origin than to the host country (Turkey), which is also implied by the high level of the one-dimensional ethnosizer. The mean separation score of 2.19 means the refugees in the sample behave differently in more than two aspects of the five categories, such as language, culture, social interaction, self-identification, and migration history. Although the sample shows stronger separation than integration, the score for integration is positive, at 1.23. It means that the refugees in the sample reported more than one integration behavior among the five kinds of commitment. Moreover, the score for integration is much higher than that for marginalization.

We can also describe the distribution of integration processes such as integration, separation, assimilation, and separation in each category. For example, 76 *percent* of the refugees are integrated in only one field—predominantly that 60 *percent* of the refugees are integrated based on the migration history scale. They largely want to become citizens in Turkey. But we have to be cautious about this result because even if the refugees prefer to stay in Turkey in the future, as the migration history implies, the refugees in the sample do not have the opportunity to go back to their home countries because of war and political and social turbulence there. However,71 percent of the refugees are not marginalized in any of the five categories. This means that three out of four of the refugees have a commitment to either of the countries in each category. But the average residency of the refugees in the sample is not very long (nearly five years on average), their commitment to their culture of origin is greater. In line with this, our estimations show the depth of separation. Only four refugees are not defined as separated in each category. Nevertheless, this category. Meanwhile, our estimations show that the highest marginalization is among the Afghan-Pakistani refugees. Although 67 percent of the Afghan-Pakistani refugees are marginalized in two areas,23 percent of them are marginalized in three areas. Our objective in this study is not to elaborate further on the subject of the ethnosizer. This is why we did not proceed further on this subject. The ethnosizer parameter, whether one-dimensional or two-dimensional, allows us to evaluate its impact on the welfare of the refugees in Istanbul in the determination of their income and the wage gap between the refugees and native workers, which is analyzed below.

3. The integration and economic welfare of refugees

3.1. Determinants of income

In this section, we analyze the relationship between the economic welfare of refugees and their integration level (or commitment) and discrimination, defined by various concepts related to the ethnicity of refugees. To do so, we focus on how the income level of refugees is related to their ethnic status with other variables controlled. So, we conduct ordinary least squares (OLS) regressions on the refugees' income. In addition to measures of ethnic identity, the regressions include sociodemographic characteristics, household characteristics, educational and vocational attainment, and other variables.

First, we describe the variables derived from our data. The first one is what we call the solidarity parameter to capture another dimension of ethnicity. We derive it mainly from matching the ethnicities of employees and employers. If they match—that is, if an Arab employs an Arab—we define it as 1; otherwise, 0. In this way, we determine the ethnic solidarity and its impact on the income of refugees. This situation is also associated with a theoretical perspective of multistate hazard model defined as social capital theory in Palloni et al. (2001). Thus, the ties of friendship and kinship are transformed into a resource for gaining access to employment at the destination in the United States.

Another critical subject is the human capital level in the home countries of refugees. Although in the regression we use an education variable expressed in terms of the years of education as a separate indicator, it is apparently insufficient for grasping the quality of education. Given that almost all refugees in our sample completed their education in their home countries, an important question is whether the quality of schooling is comparable between the origin and host countries. To fill this gap, we add a supplementary variable. For this, we construct a variable called the "economic distance" between a home country and a host country as a cross-country proxy for the quality of foreign schooling. We assume that the more similar the level of development of a country is to that of Turkey, the more equal their educational standards are and the more likely it is that they have a common knowledge base with respect to the level of education. Empirical evidence shows that the returns to schooling and work experience are positively related to a country's gross domestic product (GDP) per capita (Coulombe et al., 2014; Lagakos et al., 2012).

For this purpose, we simply use the relative GDP per capita (Y) and calculate the logarithmic function of Turkey's GDP per capita (Y_{tur}) in terms of the home country's GDP per capita (Y_h):

$$hdist = log\frac{Y_{tur}}{Y_h}$$

The logarithm of GDP per capita is used to denote the marginal return of the level of economic performance on human capital endowment. As its value increases, the economic distance from the country of origin to Turkey increases, meaning that a decline is seen in its relative human capital. This variable of economic distance also helps us to diversify cultural or ethnic differences captured by the variables we construct called *ethnosizer and its components*.

Table 4 shows the regression results. They are based on the various specifications that we estimate, with additional controls. Model 1 relates income to the ethnosizer variable, and some control variables explained below. Then, to compare them, we estimate model 2, which includes discrimination, instead of the ethnosizer. In alternative model 3, we include the language ethnosizer together with other control variables in the first two models. In doing so, we focus on the effect of the linguistic distance of refugees to the local society. Finally, in model 4, we replace the ethnicity variable in model 1 with a variable that captures geographic ethnicity. All these explanatory variables are explained in detail below.

Table 4
Income Regression Results (log).

Income (log)	Model 1	Model 2	Model 3	Model 4
Age	0.016 (0.015)	0.016 (0015)	0.016 (0.015)	0.016 (0.015)
Age (squared)	−0.000 (0.000)	−0.000 (0.0001)	−0.000 (0.001)	−0.000 (0.001)
Gender (dummy; base: female)	−0.022 (0.058)	−0.004 (0.058)	−0.020 (0.058)	−0.020 (0.058)
Ethnicity (dummy; base: Kyrgyz and Turkmen				
Afghan	−0.302** (0.149)	−0.259* (0.149)	−0.321** (0.147)	
Arab	−0.136 (0.117)	−0.143 (0.116)	−0.127 (0.115)	
Georgian	−0.154 (0.127)	−0.097 (0.129)	−0.176 (0.126)	
Kurdish	−0.120 (0.139)	−0.097 (0.139)	−0.113 (0.138)	
Pakistani	−0.240 (0.153)	−0.181 (0.154)	−0.194 (0.154)	
Uzbek	−0.122 (0.129)	−0.092 (0.129)	−0.138 (0.129)	
Geographic identity				
Arab-Kurdish				0.142* (0.080)
Post-Soviet				0.176* (0.106)
Ethnosizer	−0.588** (0.276)			−0.605** (0.267)
Discrimination		−0.045** (0.019)		
Language ethnosizer			−0.337*** (0.114)	
Duration (years)	0.036** (0.016)	0.039** (0.016)	0.032** (0.016)	0.039** (0.016)
Education (years)	0.018*** (0.006)	0.017*** (0.006)	0.017*** (0.006)	0.018** (0.006)
Solidarity (dummy; base = 0)	0.227*** (0.059)	0.212*** (0.059)	0.208*** (0.058)	0.232*** (0.057)
Human capital distance	0.073* (0.044)	0.078* (0.044)	0.088** (0.044)	0.064* (0.037)
Constant	9.980*** (0.316)	10.003*** (0.315)	9.874*** (0.291)	9.718*** (0.326)
N	512	512	512	512
Adjusted R^2	0.111	0.119	0.118	0.114

Note: Standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The explained variable is mainly total income from all income components, such as salaries and wages. We have defined eight ethnic groups and three geographic identities based on the refugees' region of origin in terms of common cultural and social properties: Arab-Kurdish, post-Soviet (Turkic Republics; Turkmenistan, Kyrgyzstan, and Uzbekistan, and Georgia) and Afghan-Pakistani regions.

Model 1 (column 1) is the base model, including basic demographic characteristics of refugees such as ethnicity, age, gender, and years of education. We wish to observe the effect of ethnicity in its preliminary form on the income of the refugees and the ethnosizer variable, controlling for other variables. Age and gender do not appear to have a critical effect on income, which is valid for all the models in Table 4. This indicates that compared to being Turkmen and Kyrgyz, which is the closest group to the host country in terms of level of ethnosizer, ethnicities of refugees mostly do not have a significant effect on their income.It is negatively affected by their ethnicity based on the closest group to the host country, which can be used as a proxy for residence. The only significant estimate is for Afghans, whose income is 30 percent below that of the native workers on average. This is also the case in models 2 and 3.

However, the ethnosizer parameter, which denotes commitment level to the host country, is highly effective regarding the earnings of refugees in Turkey, which is both significant and negative. As the ethnosizer increases, which implies lower commitment, the earnings of refugees decline. In line with this finding, refugees with a longer residence in Turkey on average earn more. With a longer duration, their integration rises and leads to higher income, which is around 1.8 *percent* for each additional year. This is robust across all the models. We show the impact of transferability of skills across countries using an indicator for the match in the occupations of the refugees between their home country and the host country: it is extremely low, around 1 percent of the refugees working in the same occupations in Istanbul as in their country of origin. Thus there is no strong connection between pre-migration and post-migration outcomes in the host country labor market. Their skills become more country specific with longer work experience in the country of origin. This may be one of the reasons for the positive impact of duration.

The solidarity variable, which depicts the ethnic connection between employers and employees, seems quite robust in all the models. Refugees whose ethnicity matches that of their employers earn approximately about 23 *percent* more. Education also seems to have be an important and positive factor in determining the income of the refugees. When their years of education increase by one year, their income increases approximately 1.8 *percent* on average. The number of years of schooling might not be sufficient for capturing the quality of education. For this reason, we employ *human capital distance*, which shows the potential difference in human capital between the origin and host countries. Its effect on the income level is negative and significant—that is, as this distance increases, the income of refugees declines significantly. The value of *human capital distance* is less than 1 for every country because all the source countries of refugees in the sample have less human capital than Turkey.

In model 2, we add a discrimination parameter, derived from the responses regarding whether the respondents face up discrimination in the workplace, scored across the interval $[0, 1]$. The correlation coefficient between discrimination and the ethnosizer is 0.138, which is negligible. However, because their coefficients have the same effect from different points of view, we do not use the two variables together in a single model. We want to see their separate contributions and compare them. Although the ethnosizer only takes into account the refugees, the discrimination variable reflects the local society's behavior as well. The discrimination variable reflects the perception of the refugees in terms of their acceptance by native residents, and it indicates that discrimination is negatively related to their income. In this model, the ethnosizer retains its effect on income in the same way, implying a robust effect. As in model 1, the coefficient of education has a positive impact on income, implying its robustness.

In model 3, by excluding the ethnosizer variable, we examine the specific impact of an important component of the ethnosizer, the language ethnosizer, which is a proxy for the language skills of refugees. It implies that refugees who have difficulty with the language of the host country earn less. In this model, the variables of solidarity, human capital distance, education, and duration have a significant impact on refugees' income. In model 4, unlike in the other estimations, we use geographic categories instead of ethnic identity to observe the effect of geographic identity. In the model, Afghan-Pakistani geography is arbitrarily chosen as the reference group to see whether any differences are due to geographic identity. Table 4, column 4, shows no change compared to the other three models, which consider only ethnicity. Geographic identity has a significant effect on income, unlike the model in which only ethnicity is incorporated into the regression model. The ethnosizer variable is still significant and negative, with a slightly larger magnitude. Education is again a critical variable with respect to income.

Consequently, all versions of the models we estimated show that ethnicity-related variables, such as the ethnosizer, discrimination, the language ethnosizer, and solidarity, have a significant impact on the welfare of refugees through different channels. However, these effects seem to be independent of the particular ethnicity or geography. Thus, being a refugee is more important than having a different ethnicity or geography. In this way, being a refugee cuts across all refugees, rather than their ethnicities. This shows that, in addition to the effects of being a refugee in Istanbul, human capital affects their income. In particular, education, the degree of education, and human capital distance parameters have robust effects on the income of refugees in Istanbul.

To analyze whether different income groups are affected differently, we also run quantile regressions at different quantiles of the distribution. In quantile regression, as seen in Fig. 2, almost all variables are within the confidence intervals of OLS coefficients. This implies that when refugees are sorted by income, for almost every income group, the independent variable has a similar effect, as shown by OLS. The absence of heteroskedasticity in the models confirms that quantile regression results do not significantly deviate from the OLS results.

3.2. *Working probability*

Using information from our sample data on migration in Istanbul, this section focuses on refugees' employment status. The richness of the information in the survey enables us to search for the main explanatory factors with respect to refugees' participation in the labor market. To do so, we use probit models to analyze the impact of ethnic identity, controlling for the main determinants of the

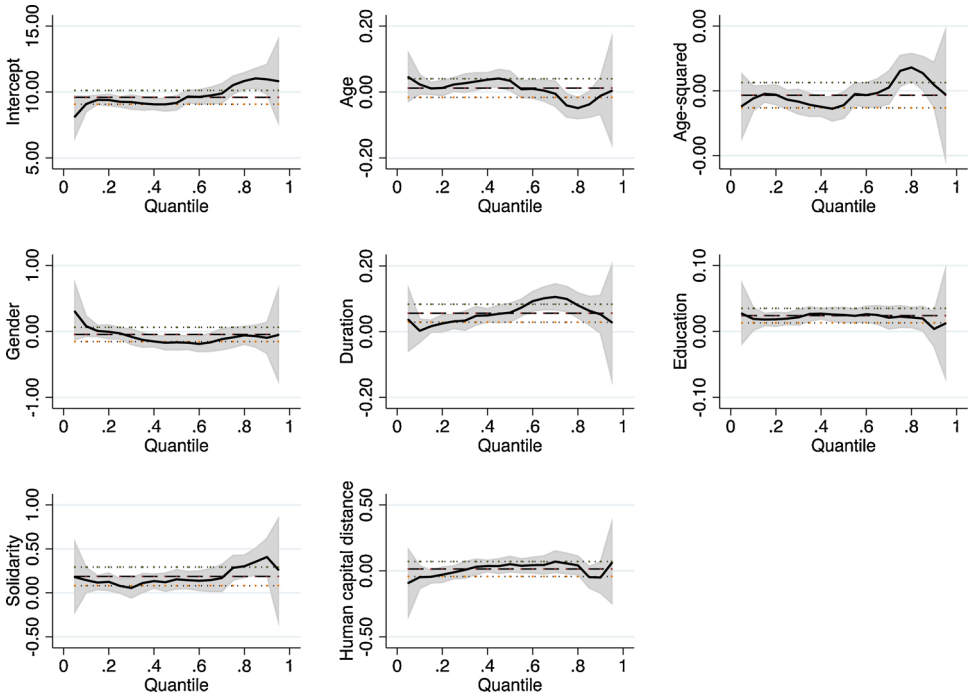

Fig. 2. Explanatory Variables Across Different Quantiles.
Note: Solid lines: quantile regression estimates. Dotted lines: quantile regression estimate 5% and 95 % confidence bounds (the gray band, based on bootstrapping). Dashed lines: OLS estimate along with same confidence bounds.

employment status of refugees in Istanbul. The models show the likelihood of employment.

Because the probit model is nonlinear, the effect of an independent variable on the dependent variable changes from one individual to another, so, we use marginal effects.[3] Table 5 shows average partial effects (APE), which are obtained by calculating the marginal effects for every observation and then taking their average. It measures the percentage-point increase in the probability of employment as the independent variable changes by one percentage point. The models are validated in terms of sensitivity (positive probability is predicted with a 93.7 percent success rate) and the pseudo R-squared is above 0.45. The specificity rate, which is the rate of correctly specified or predicted negative probabilities, is 67 percent, which is also high enough.

The probability of employment increases with age until age thirty-three, and then the effect of aging turns negative. The average effect of age is 0.002 at its mean, which is slightly below thirty. Being a male, however, increases the probability of employment by thirty-two percentage points, and it is significant at the 1 percent level. This is likely to arise from the fact that the employment prospects of women are more religiously determined (religious restrictions due to Islamic perceptions) and their lower integration into the labor market. The likelihood of employment of refugees is positively correlated with the number of years of schooling. It raises their likelihood of employment but at a low rate. One more year of education increases the probability of employment by only by 1.1 percentage points. Refugees' probability of employment decreases as their human capital increases, meaning that as the human capital of the refugees' countries of origin declines compared to Turkey, the probability of finding a job drops, which implies the validity of human capital. However, the duration of refugees' residence in Turkey seems to reduce the probability of employment. Living longer in the host country does not have a significant effect on the probability of employment. The coefficient is negative but still insignificant only in models 2 and 4, probably due to the characteristics of their occupations, which are precarious and insecure jobs that do not guarantee them long-term employment. In line with our findings, Borjas (1985) finds that, even when these migrants have long residence, their earnings might not reach the level of that of local workers. The empirical results by Constant and Massey (2003) also show that this fact does not change even in a long-term analysis on Germany. They found strong evidence that earnings assimilation (catching up to wages earned by local workers) takes more than a decade. The earning gap with respect to human capital endowments made a negligible difference.

Concerning the effect of ethnic identity on the probability of employment, the ethnosizer has a positive but an insignificant effect on the refugees' likelihood of employment. That is, being more committed to the host society lowers the probability of working, but it is not significant. The discrimination variable has results that are consistent with those of the ethnosizer variable, but they are significant. This implies that even though refugees observe the discrimination directed against them or have less commitment to the host country, they still keep working. Hence factors other than ethnic-related ones, such as education and human capital, are crucial for participation in the labor market. They are found to be important in predicting whether a migrant is unemployed.

3.3. Wage gap

The wage discrimination or gap between refugees and local workers is another important way to observe the difference in the welfare of refugees relative to native workers. In the sense of wage discrimination, in particular, we seek the determinants of the wage gap. In labor economics, the conventional definition of wage discrimination is linked to productivity. According to Heckman et al. (1998), wage discrimination means that an employer pays a different wage to two individuals who are identical except with respect to a characteristic such as gender or race—with the crucial qualification that these characteristics have no direct effect on productivity.

We obtained information regarding the wage gap by asking employed refugees in our survey how much they are paid compared with local workers in the same workplace doing the same job. During the data collection, we observed native workers as well, although our sample does not include them. Therefore, their statements about their wage gap mirror their perception of the wage gap via their observations. We see that on average the wage gap is TL 800–900, about 20–25 percent less than the wage received by native workers. The distribution of the wage gap (in log) found in our survey is shown in Fig. 3. The distribution depicts two models, with an M-shape. They are clustered at the low and high levels of the wage gap. In between are a number of refugees, for whom there is a serious wage gap. It also shows that the wage gap can rise to extreme values, for example, in some sectors refugees receive 50–80 percent less than native workers. The highest wage gap is seen among Afghans, who earn around 30–35 percent less than native workers on average. In descending order, Georgians, Kyrgyz, Kurds, and Arabs are other ethnic groups with high wage gaps.

Even though the wage gap information is critical in several respects, we cannot use various decomposition methods because we do not know the characteristics of the native workers in the same workplace as the refugees in our survey. Despite this shortcoming, we can still determine the dynamics of the wage gap using appropriate econometric modeling. To do this, we run the regression estimation on various models to explain the wage gap with variables such as sociodemographic characteristics, education, and other explanatory variables. We also include various measures of ethnic identity that recognize typically unobservable labor market influences. See Table 6.

Because the tests indicate the existence of heteroskedasticity, we used heteroskedasticity-consistent standard errors, yielding an unbiased estimator of coefficients. The coefficients are mostly compatible with the insights of the theoretical debate in the literature. Except in model 1, the age of refugees does not have any significant effect on the wage gap. This is also the case for gender in all models, which does not have an important effect. In fact, this might be because the number of women in our survey is insufficient, and migrant husbands often do not allow their wives to work outside the home because most of the refugees are religiously conservative.

[3] We also estimated a linear probability model, however, results show that a probit model fits the data better because a large percentage of predicted probabilities are outside the interval 0,1, and the relation is not linear.

Table 5
Probit models for employment of refugees in Istanbul.

Working probability	Average partial effects			
	Model 1	Model 2	Model 3	Model 4
Age	0.024** (0.009)	0.023** (0.009)	0.024** (0.009)	0.019*** (0.007)
Age (squared)	−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)	−0.000*** (0.000)
Gender (dummy; base = female)	0.324*** (0.019)	0.319*** (0.019)	0.324*** (0.019)	0.257*** (0.016)
Ethnicity				
Afghan	0.006 (0.066)	0.004 (0.071)	0.008 (0.063)	
Arab	−0.237*** (0.058)	−0.220*** (0.059)	−0.220*** (0.059)	
Georgian	all working			
Kurdish	−0.363*** (0.095)	−0.380*** (0.097)	−0.371*** (0.095)	
Pakistani	all working			
Uzbek	all working			
Geographic identity				
Arab-Kurdish				−0.243*** (0.042)
Post-Soviet				0.032 (0.035)
Ethnosizer	0.161 (0.159)			0.153 (0.125)
Discrimination		0.021* (0.012)		
Language ethnosizer			0.113 (0.072)	
Duration (years)	0.000 (0.010)	−0.003 (0.010)	0.002 (0.010)	−0.001 (0.008)
Education (years)	0.011*** (0.003)	0.011*** (0.003)	0.011*** (0.003)	0.009*** (0.003)
Solidarity (dummy; base = 0)	−0.021 (0.032)	−0.011 (0.033)	−0.015 (0.033)	−0.014 (0.025)
Human capital distance	−0.051* (0.028)	−0.054* (0.027)	−0.057** (0.028)	−0.028 (0.020)
N	406	406	406	517
Pseudo R^2	0.455	0.460	0.458	0.503

Note: Standard errors are in parenthesis: *** $p < 0.01$, ** $p<0.05$, * $p < 0.1$.

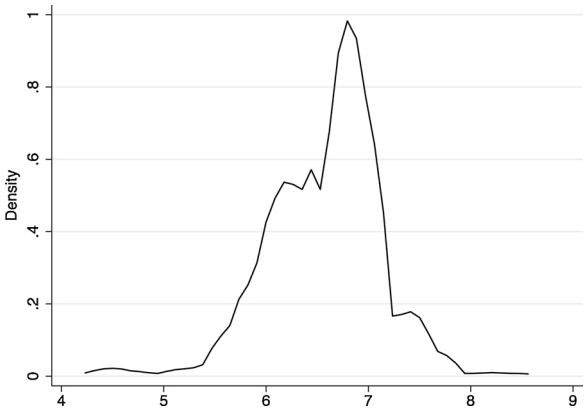

Fig. 3. Distribution of The Wage Gap.

In model 1, other than among Georgians, the wage difference between ethnic groups is not significant though it is positive (higher wage gap) for some ethnic groups, such as Afghans, and negative (lower wage gap) for others. Georgian refugee workers earn significantly less than the base group of Turkmen and Kyrgyz refugees. This finding is in line with the fact that the discrimination in the labor market is determined by their responses. Afghan, Pakistani, and Georgian refugees are mostly exposed to more discrimination than Arab and Kurdish refugees in Istanbul.[4] As mentioned earlier, our reference group is the Kyrgyz-Turkmen ethnic group, which has the lowest ethnosizer value, meaning a higher commitment to the country. This is also true from the geographical perspective. Thus, the wages of refugees are not significantly affected based on coming from diverse regions, compared with native workers, as seen in model 4. This is probably consistent with their refugee identity, rather than their ethnic identity, because we see this in the significance of discrimination variables in other models.

Education has a significant effect on the wage gap in most of the models in Table 6. The education level of refugees is a significant parameter in the wage gap, especially in models 1, 3, and 4, which implies a narrower wage gap for educated refugees. An increase in education of one additional year by the refugees reduces the wage gap by $6-7$ *percent*. To capture the effect of education or

[4] Afghans and Pakistanis are mostly exposed to discrimination at work. The rate of Afghan-Pakistanis who are exposed to discrimination at work "sometimes" or "generally" is 52%. The second and third mostly discriminated identities ar Kurdish and Georgian refugees. But only 19% of Turkmen and Uzbek refugees responded to the discrimination question saying "sometimes" or "generally."

Table 6
Wage gap regression results.

Wage gap (log)	Model 1	Model 2	Model 3	Model 4
Age	−0.136 (0.104)	−0.132 (0.105)	−0.135 (0.104)	−0.149 (0.107)
Age (squared)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.0012 (0.002)
Gender (dummy; base = female)	0.365 (0.417)	0.016 (0.414)	0.329 (0.417)	0.329 (0.431)
Ethnicity				
Afghan	0.201 (0.794)	0.197 (0.822)	0.322 (0.790)	
Arab	−1.050 (0.649)	−0.968 (0.653)	−1.078*(0.642)	
Georgian	1.101* (0.608)	0.267 (0.614)	1.090* (0.596)	
Kurdish	−0.131 (0.783)	−0.048 (0.752)	−0.214 (0.781)	
Pakistani	−0.081 (0.844)	−0.166 (0.855)	−0.171 (0.847)	
Uzbek	−0.428 (0.705)	−0.430 (0.716)	−0.378 (0.706)	
Geographic identity				
Arab-Kurdish				−1.254*** (0.443)
Post-Soviet				−0.058 (0.544)
Ethnosizer	1.476 (1.582)			1.869 (1.641)
Discrimination		0.398*** (0.099)		
Language ethnosizer			0.628 (0.606)	
Duration (years)	−0.168* (0.096)	−0.196** (0.090)	−0.168* (0.095)	−0.122 (0.095)
Education (years)	−0.071* (0.039)	−0.007 (0.032)	−0.072* (0.039)	−0.067* (0.040)
Solidarity (dummy; base: none)	−2.484*** (0.377)	−2.172*** (0.376)	−2.305*** (0.372)	−2.446*** (0.367)
Human capital distance	0.145 (0.256)	0.097 (0.255)	0.087 (0.258)	0.024 (0.206)
Constant	7.758*** (2.101)	7.377*** (1.968)	8.224*** (1.994)	8.042*** (2.208)
N	414	414	414	414
Adjusted R^2	0.265	0.261	0.265	0.213

Note: Standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

experience on the wage gap, we incorporate the parameter human capital distance. As the human capital distance of refugees rises, their wage gap increases, but it is not significant. All these variables related to skill and experience are relevant in the context of the wage gap, such as income and the probability of employment. These findings are partially in line with the theory explaining wages or wage differences by differences in human capital endowments among workers. However, as see below, although refugees in Istanbul are suffering a wage gap, part of the wage gap depends on the measurement of productivity used.

Refugees with a longer duration in Turkey have a narrower wage gap. This effect is insignificant in three models. The effect of duration is likely to originate in being accustomed to working conditions in the host country and the ability to find better jobs in accordance with their ability and jobs in their home country. This implies that with more years of residence, the initial wage differential decreases steadily over time.

Examining the effects on the wage gap of the commitment of refugees and the ethnic discrimination they experience, we see that, as integration by the refugees declines (captured by a rise in the ethnosizer), the wage gap increases, as seen in the positive sign of the coefficient of the ethnosizer in models 1 and 4, but it is not significant. As with discrimination, as seen in Table 6, all the parameters that capture the discrimination level of the refugees indicate that discrimination increases the wage gap. The variable of discrimination in the labor market in Table 6 is used to observe only the effect of the treatment of the refugees in the workplace by their native co-workers, which is highly and negatively correlated to the wage gap; in model 2, this effect significantly increases the wage gap.

Another ethnicity-related parameter in the wage gap is the variable solidarity, which shows the ethnic match between employers and employees. On average, when they match, the wage gap significantly narrows, implying solidarity between ethnic groups. In fact, Arab refugees form a large group and have more years of residence, which might be an advantage for them in matching with employers. However, we think that this matching reduces their level of integration, denoted by the parameter ethnosizer, because even without integrating into the society where they live, they can find jobs and be less adversely affected by the wage gap because of the solidarity between employers and employees who have the same ethnicity. In this sense, integration slows. The result might reflect the fact that the refugees' co-workers might mostly have the same ethnicity, so they do not need to use the Turkish language, which implies that integration in the labor market is also related to the network channels and language skills of workers.

Further analysis concerning the wage gap requires a quantile analysis. The existence of heteroskedasticity is consistent with this fact. We wonder whether wage gaps have some trends with respect to various quantiles of the wage gap between refugees and native workers. Overall wage differences between refugees and native workers in Istanbul take a steady upward pattern, starting at 0 at the bottom and reaching about 60–80 percent at the top. That is, we find a sharp increase in the quantile wage gap: the wage gap is negligible at low percentiles, then it jumps sharply between the 40th and 50th percentile and keeps rising at high wages. These differences reach a maximum gap at around the 8th-9th decile, which implies a markedly wider wage gap against foreign professionals than against foreign blue-collar workers.

The coefficient of solidarity, as seen in Fig. 4, is a striking example of the potential benefit of quantile regressions. The OLS coefficient (the solid, horizontal line) indicates that the coefficient of solidarity is positive at low and middle quantiles, meaning that solidarity increases the wage gap, but at higher quantiles it reduces the wage gap of the refugees, and its coefficient is negative and much lower than the OLS coefficient.

In other variables, we see no big difference between the quantile and OLS coefficients. Fig. 4 shows examples of the ethnosizer and

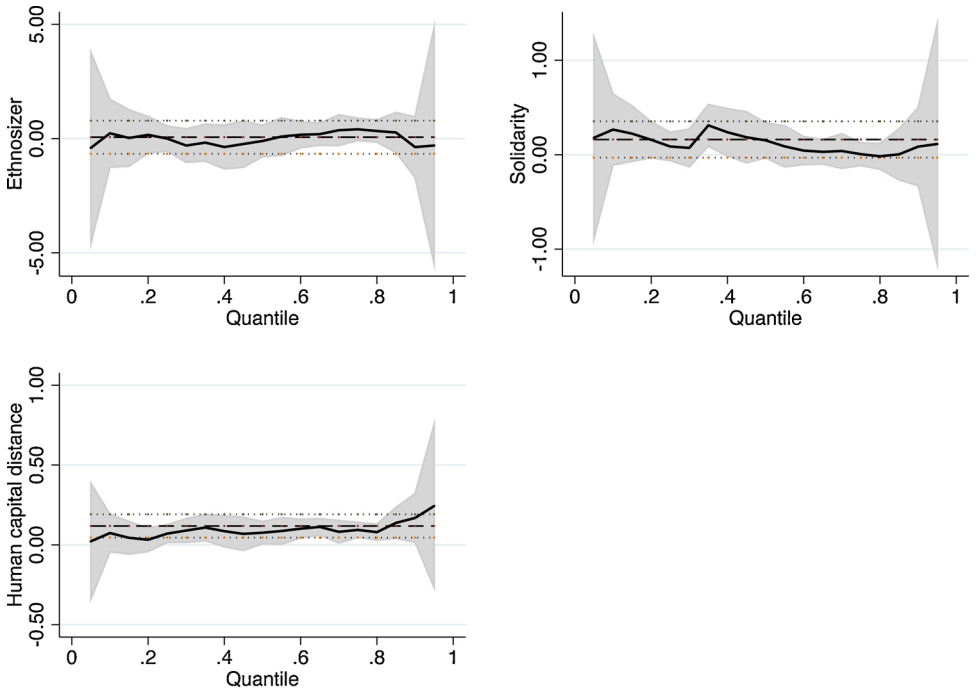

Fig. 4. Distribution of Quantiles by Ethnosizer, Solidarity and Human Capital Distance.
Note: Solid lines: quantile regression estimates. Dotted lines: quantile regression estimate 5% and 95 % confidence bounds (the gray band, based on bootstrapping). Dashed lines: OLS estimate along with same confidence bounds.

human capital distance for other variables. Their value is the same across all quantiles. Education and duration do not have a larger effect on the wage gap of refugees, which implies that the contribution to the wage gap of additional experience vanishes almost completely in the highest income brackets.

4. Conclusion

In this study, our survey data include a rich set of household and labor-related characteristics relevant for understanding the determinants of labor market success across refugees of different ethnicities in Istanbul. We consider a rich set of control variables that recognize typically unobservable labor market influences. In particular, we examine individual personality traits and integration barriers by taking into account the metrics of refugees' proximity to Turkey based on their home countries' level of cultural distance. Using microdata, we construct a complex and refined index called the ethnosizer scale to determine the distance from minority ethnic identities in Istanbul to the majority identity. Using this parameter, we analyze the impact on their economic welfare of the refugees of their degree of commitment in Istanbul, in terms of their earnings, participation in labor markets, and wage gap with native workers.

To empirically measure the ethnic identity of refugees and analyze its impact on their economic welfare, we benefit from the ethnosizer, which is an index used to measure the intensity of an ethnic identity with respect to society in the host and home countries. This measurement uses information on language, culture, social interactions, history of migration, and ethnic self-identification. According to these measures, the refugees in Turkey demonstrate a stronger commitment to the culture and society of their country of origin than to Turkey's.

The ethnosizer and other concepts used to depict the level of discrimination are crucial because although the weak market position of the refugees is observable with their qualifications, there are also unobservable parameters that show the relationship between economic outcomes and ethnicity, which is captured by the identity-related concepts we introduce in the study. Even though we use additional control variables, specifically demographic and personal characteristics, we demonstrate that ethnic identity and discrimination are still crucial explanations for the outcomes in labor markets. Incorporating dimensional ethnosizers and discrimination parameters into standard regressions to examine the particular contribution of ethnic identity, we find that ethnic identity and discrimination matter significantly, and our findings are very robust to the model specifications.

We also analyze whether wage differentials are due to observable differences in, for example, human capital endowments or unobservable influences, such as identity and discrimination. Our findings support the fact that both ethnic identity–related variables and human capital variables affect the wage gap between refugees and native workers in Istanbul. This result is more comprehensive than that in the literature that focuses predominantly on ethnic background. We also employ quantile regression approaches to examine this effect at different quantiles of the wage gap.

In this study, our findings from various regression models show that the identity of being a refugee, rather than any specific ethnic

identity or geographic identity, is more crucial in the economic outcomes of refugees in Istanbul. Their common characteristics, which are related to being a refugee, the ethnosizer, education, and human capital, have a greater effect on their income level, probability of employment, and wage gap. Therefore, to improve the employment and labor market prospects of refugees, the Turkish government should be more dedicated to improving their common identity, which can be accomplished by offering more education, occupational training, and social policies to increase their integration.

Although the study helps enhance understanding of the economic status of refugees, it has some limitations. First, the refugees examined in this study have resided in Turkey for a short period, a median of five years. Longitudinal panel data on individuals over a longer period would provide a more accurate understanding of their adjustment process. Second, to decompose the wage gap in a more refined way, we need to collect personal characteristics of Turkish co-workers of the refugees, however, this data is unavailable.

Acknowledgements

We collected the data for this research (SDK-2018-3369) with support from the Yıdız Technical University Scientific Research Fund (BAP) between 2018-2020.

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