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**Abstract**

Existing evidence suggests that low-skilled refugee influx increases high school enrollment among native youth due to increased competition for jobs with low skill requirements. In this paper, I ask whether the refugee influx has also increased the intensity of human capital accumulation for those who are enrolled in school. Using the PISA database and implementing an empirical strategy designed to exploit the time variation in regional refugee intensity within a quasi-experimental setting, I show that the Math, Science, and Reading scores of Turkish native adolescents have notably increased following the Syrian refugee influx—conditional on parental education, which is used as a proxy for unobserved ability. The increase in PISA scores is more pronounced for males than females. Most importantly, the increase in test scores mostly comes from the lower half of the test score distribution. This suggests that the refugee influx has reduced the test score inequality among natives. I conclude that the labor market forces that emerged in the aftermath of the refugee crisis have led native adolescents, who would normally perform worse in school, to take their high school education more seriously.

**Keywords:** Syrian refugees; test scores; PISA; labor market channel.

**JEL Classifications:** I21; I25; I26; J61.

# 1 Introduction

There is a consensus in the literature investigating human capital investment that inequalities open up early in life and have persistent effects over the life cycle. Gaps in adolescent test scores reflect gaps in socio-economic outcomes later in life. Hence, measurement of inequalities in scholastic achievement—mainly in the form of test scores obtained during school education—is important for projecting future inequalities and designing appropriate policies or programs to close the early gaps. Different test scores (i.e., math, science, reading, etc.) measure different dimensions of human capital; therefore, focusing on multi-dimensional test scores would allow us to make judgments about different dimensions of socio-economic inequality in the society and to design more specific policies or programs addressing certain elements/dimensions of human capital inequality.

There is a vast empirical literature studying the impact of immigration on test scores of native youth in host countries [see Section 2 for a comprehensive literature review]. There are two main channels: (1) the labor market channel that improves the educational outcomes of natives due to increased competition in the low-skill labor market, and (2) the educational experience channel that worsens the educational outcomes of natives. The main insight behind the latter is that immigrant children interact with native children in school and/or classroom environments, and this interaction has some important implications for the quality of education. In particular, immigrant concentration in a region, school, or classroom is shown to be negatively correlated with scholastic achievement of native children in host countries. This paper focuses on the first channel, which highlights the labor market effects.

The main goal of this paper is to investigate the impact of Syrian refugees on the school performance (i.e., test scores) of adolescent children in Turkey. Massive refugee inflows may change natives' human capital investment decisions and educational outcomes. The sudden increase in the number of refugees in the aftermath of the Syrian crisis has brought this issue to the forefront in major host countries—such as Jordan, Lebanon, Iraq, and Turkey. In this paper, I investigate the impact of Syrian refugees on the PISA test scores of 15-year-old students Turkey. In a companion work (Tumen, 2018), I show that the high school enrollment rates among Turkish youth has increased

in response to increased refugee concentration. The main mechanism is that refugees displace low-skilled natives in the labor market and increased competition for jobs with low skill requirements generates a downward pressure on those jobs. The punchline is that reduced expected returns to staying low-skilled pushed young individuals toward school, which generated a notable increase in high school enrollment rates—especially among males with lower parental education, who are more likely to leave school and work in "bad" jobs. In this paper, I focus on the intensive margin of human capital accumulation. In particular, I ask whether the Syrian refugee influx has also increased the test scores of native adolescents.

To pin down the potential mechanisms driving this result, it would be important to understand the impact of Syrian refugees on host country labor market outcomes. There is an emerging literature investigating this issue. The main finding in this literature is that refugees in Turkey have, on average, lower skill levels than natives; they do not have easy access to work permit; so, they enter the labor market through informal manual jobs and displace natives informally employed in those jobs [see, e.g., Del Carpio and Wagner (2015), Tumen (2016), and Ceritoglu et al. (2017)]. Informally employed refugee workers provide important labor cost advantages and, accordingly, potential wages decline in the low-skill market (Balkan and Tumen, 2016). Informal refugee workers employed in manual tasks are complementary to formal native workers employed in more complex tasks (Akgunduz et al., 2018; Akgunduz and Torun, 2018). These results suggest that competition between refugees and natives for low-skill jobs imposes a downward pressure on employment probabilities and potential wages in the low-skill labor market. At the same time, increased availability of formal jobs with higher skill requirements encourages skill acquisition. As a result, the decline in the expected returns to staying low-skilled and the increase in the availability of jobs with high skill requirements may jointly increase the intensity of human capital accumulation among native youth.

To deal with the potential endogeneities due to the self-selection of refugees into locations, I use both the diff-in-diff specification proposed by Ceritoglu et al. (2017) and the IV-diff-in-diff specification developed by Del Carpio and Wagner (2015). The PISA micro-level data sets (waves 2009, 2012, and 2015) are used in the empirical analysis. I find that the Math, Science, and

Reading scores of Turkish native adolescents have notably increased following the Syrian refugee influx—conditional on parental education, which is used as a proxy for unobserved ability. The increase in PISA scores is more pronounced for males than females. Most importantly, the increase in test scores mostly comes from the lower half of the test score distribution. In other words, the estimates exhibit significant heterogeneity, which implies that the refugee influx has reduced the test score inequality among natives. I argue that the labor market forces that emerged in aftermath of the Syrian refugee crisis have led native adolescents, who would normally perform worse in school, to take their high school education more seriously.

The plan of the paper is as follows. Section 2 discusses the related literature. Section 3 describes the data set used in the empirical analysis, provides the details of the institutional setting, performs a basic analysis of the distributional consequences of the refugee influx, and describes the empirical methods used in the paper. Section 4 presents the results and discusses the heterogeneity implications. Section 5 concludes.

## 2 Related literature

There is a large literature investigating the impact of immigration on natives' educational outcomes. There are two main strands in the literature. The first strand focuses on the labor market channel, i.e., the increase in refugee concentration generates pressures in the low-skill labor market and those pressures provides incentives for increased school achievement. Denisova (2003), Smith (2012), McHenry (2015), Jackson (2016), Hunt (2017), and Tumen (2018) focus on the change in natives' school enrollment decisions as a response to increased competition in the low-skill labor market due to immigration.[1] These papers document that—despite the forces operating in the opposite direction—immigrants tend to crowd natives into higher education, since they drive the pay down in the low-skill market. The main reason is the increased competition in the low-skill labor market.

The second strand, on the other hand, focuses on the crowding out effects. Studies including Betts (1998), Hoxby (1998), Betts and Lofstrom (2000), Borjas (2007), and Gould et al. (2009)

[1] See also Eberhard (2012) and Llull (2017).

document that immigrants either crowd natives out of education or reduce their test scores due to a combination of factors such as limited command of English and within-class negative externalities.[2] Neymotin (2009), Geay et al. (2013), Ohinata and van Ours (2013), Shih (2017), Assaad et al. (2018), and Figlio and Ozek (2019), on the other hand, report zero or positive impact of increased immigrant concentration within the class/school on natives' educational outcomes. The mechanism that this strand focuses on is the "education experience" channel. According to this channel, increased refugee concentration may reduce the quality of instruction due to various factors such as lower-quality peer interactions, language barriers, and easier teaching standards imposed by the instructors.

This paper can be placed into the literature focusing on the mechanism operating through labor market opportunities. The papers in this literature generally focuses on the impact of immigration on school enrollment rates—see, e.g., Hunt (2017) and Tumen (2018). Different from those papers, I focus on the test scores rather than enrollment rates. I find that the increase in refugee concentration in Turkey generates an improvement in Math, Science, and Reading scores of the PISA test. This is the first paper estimating the impact of Syrian refugees on test scores of native youth in Turkey.

# 3 Empirical setting

## 3.1 Data description

I use the Programme for International Student Assessment (PISA) data produced by the OECD.[3] PISA is a triennial international survey which aims to evaluate education systems worldwide by testing the skills and knowledge of 15-year-old students. As of 2015, around 500,000 students, representing 28 million 15-year-olds in 72 countries, took the internationally agreed two-hour test. Students were assessed in science, mathematics, reading, collaborative problem solving, and financial literacy. Micro data from the 2000, 2003, 2006, 2009, 2012, and 2015 waves are publicly available from the OECD website. The PISA dataset includes regional variation in test scores for

[2] See also Jensen and Rasmussen (2011), Foster (2012), Brunello and Rocco (2013), Roed and Schone (2016), Frattini and Meschi (2019), Tumen (2019), and Bossavie (2019).

[3] See http://www.oecd.org/pisa/aboutpisa/ for more detailed information on the PISA database.

Turkish youth. It also includes information on gender, mother's and father's education, grade, month of birth, and other characteristics. The standardized nature of test scores provides a strong basis for comparison across students exposed and non-exposed to refugees. I focus on three waves of the PISA micro data: 2009, 2012, and 2015. 2009 and 2012 are the years with no refugee intensity and they are set as the pre-influx period.[4] 2015 is defined as the post-influx period. The PISA data set uses NUTS1-level regional categorization for Turkey. To match the change in refugee intensity with this categorization, the Ministry of Interior data is used to construct the refugee-to-population ratios at NUTS1 level.

### 3.2 Institutional details

After the onset of the Syrian crisis, the number of Syrian refugees in Turkey has increased steadily over time. Around 50% of the refugees in Turkey are of age 17 and below—i.e., they are at school age. Over time, it became clear that the Syrian crisis will not be resolved soon and a majority of the Syrian refugees will stay in Turkey permanently. Accordingly, the Ministry of National Education has started a project funded by the European Union, called PICTES, to facilitate the integration of Syrian refugees into the public education system in Turkey. The project was launched in mid 2016.

Although the project has been very successful in increasing the school enrollment rates of Syrian children, the improvement in the rate of school enrollment has been limited among children of age 14 and above due to various reasons—the main reason is that male adolescent Syrians above age 14 strictly prefers work to school. The final PISA wave used in the analysis is 2015. As of 2015, the school enrollment rates among refugees of age 14 and above were extremely low—as the PICTES project started in 2016. These observations rule out the validity of the second channel—i.e., the school experience channel—described in Sections 1 and 2. In other words, any impact of the Syrian refugee influx on the test scores of native adolescents should operate through the labor market channel.

[4] In fact, the refugees started to enter the country in 2012, but the number of refugees as of 2012 was very low to have an impact on the test scores of natives. Removing 2012 from the analysis does not change the results.

### 3.3 Econometric model and identification

The empirical setup is a basic diff-in-diff analysis. Following Tumen (2018), I use two versions of the diff-in-diff setup. The first one is a simple before-after comparison of the regions exposed and not exposed to the refugee influx, which is similar to Ceritoglu et al. (2017). The second is an IV-diff-in-diff approach exploiting the variation in refugee concentration over time/across regions and using the weighted distance from the source governorates in Syria to destination provinces in Turkey as an IV—similar to Del Carpio and Wagner (2015). The Syrian refugee inflows started in 2012 and accelerated over time [see Figure (1)]. Until late 2012, the number of Syrians was almost zero in the entire country. From late 2012 to mid-2014, the refugees were mostly located close to the Turkey-Syria border. After mid-2014, part of the refugees moved toward the western regions of the country. Figure (3) shows the distribution of refugees across NUTS1 regions as of the end of 2015.[5]

The baseline diff-in-diff specification performs a basic before-after comparison across regions with high refugee concentration versus those with almost no refugees in the spirit of Card and Krueger (1994). The IV specification, on the other hand, addresses the potential selection problem due to the endogeneity of location choice.

#### 3.3.1 The diff-in-diff model

The first specification is based on the difference-in-differences strategy implemented by Balkan and Tumen (2016), Ceritoglu et al. (2017), and Tumen (2018). The post-influx period is defined by the dummy variable $A_{iy}$ as:

$$A_{iy} = \begin{cases} 1 & \text{if year} \geq 2012; \\ 0 & \text{if year} < 2012, \end{cases}$$

where $i$ and $y$ indexes individuals and years, respectively. The pre-influx years are 2009 and 2012, while the post-influx period is 2015. Similarly, two groups of regions are defined as treatment and

[5] Table (1) and Figure (2) provide a detailed description of NUTS1-level regional categorization in Turkey.

control groups by the dummy variable $T_{ir}$ as:

$$T_{ir} = \begin{cases} 1 & \text{for the treatment group;} \\ 0 & \text{for the control group,} \end{cases}$$

where $r$ indexes regions. There are three main specifications for the treatment and control regions. Figure (4) visually characterizes those specifications. In the first specification, the treatment group consists of region 12, while the control group includes regions 10 and 11. The second specification extends the treatment and control regions as follows: the treatment group consists of regions 6 and 12, while the control group includes regions 8, 9, 10, and 11. Finally, the third specification uses the entire country and defines the treatment and control groups as follows: the treatment group consists of regions 1, 6, and 12, while the control group includes regions 2, 3, 4, 5, 7, 8, 9, 10, and 11.

The choice of regions is not arbitrary. The treatment and control regions in the first specification consist of neighboring regions with similar economic, social, ethnic, cultural, religious, and historical characteristics. They are the least developed regions in the country and they have immediate comparability. Refugee intensity is among the major distinguishing factors between those regions—as Tumen (2016) and Ceritoglu et al. (2017) argue. The difference in refugee intensity can easily be observed from Table (2). The first specification is the narrowest definition of treatment and control regions. The second specification slightly extends the first specification by including region 6—the region with the second highest refugee intensity—into the treatment regions, and regions 8 and 9—regions neighboring the narrowest control regions and also with almost zero refugee intensity—into the control regions. The third and final specification includes the Istanbul region (the region 1), which has the third highest refugee intensity, into the treatment regions, while the rest of the regions are placed into the control regions. As we move from the first to the third specification, the immediate comparability between the treatment and control regions becomes less and less obvious, and self selection starts becoming a more serious issue—which I address in Section 3.3.2 using an appropriately designed IV strategy.

The diff-in-diff regression model can be formally specified as follows:

$$S_{irt} = \beta_0 + \beta_1(T_{ir} \times A_{it}) + \boldsymbol{\beta_3'} \boldsymbol{X}_{irt} + f_r + f_t + \epsilon_{irt}, \tag{1}$$

where $S_{irt}$ is variable characterizing the PISA test score of individual $i$ of age 15 in region $r$ and in year $t$, $\boldsymbol{X}_{irt}$ is a vector of individual-level characteristics, $f_r$ and $f_t$ are region and year fixed effects, respectively, and $\epsilon_{irt}$ is an error term. The coefficient ($\beta_1$) of the interaction between $T_{ir}$ and $A_{it}$ gives the causal effect of interest.

The vector of individual-level covariates, $\boldsymbol{X}_{irt}$, include gender, father's education, mother's education, grade fixed effects, and month-of-birth fixed effects. Parental education variables control for the intensity of parental investment in human capital and can also be used as a proxy for unobserved ability. The grade and month-of-birth fixed effects are included to control for the maturity and education level factors.

### 3.3.2 The IV model

To address the endogenous location choices of refugees, I use the IV specification developed by Del Carpio and Wagner (2015). This specification exploits the time-region variation in refugee-to-population ratio across Turkey and uses data from the entire Turkey. The main estimating equation can be formulated as follows:

$$S_{irt} = \alpha_0 + \alpha_1 R_{rt} + \alpha_2 \ln(D_{rt}) + \boldsymbol{\alpha_3'} \boldsymbol{X}_{irt} + f_r + f_t + \epsilon_{irt}, \tag{2}$$

where $R_{rt}$ is the region-level refugee-to-population ratio and $D_{rt}$ is the year-specific shortest distance between the most populated province of the region and the nearest border-crossing. The variable characterizing the shortest distance between the most populated province of the region and the nearest border-crossing is defined such that $D_{rt} = 0$ before (and including) 2012 and $D_{rt} = D_t$ after 2012. Following Del Carpio and Wagner (2015), I put the distance variable into the estimating equation in natural logarithms. The motivation comes from the empirical gravity models in the international trade literature. The inclusion of the year-specific distance variable ensures

that the estimates are not contaminated by the omission of variables correlated with distance to border and affecting the outcome variable of interest.

To address the potential endogeneity of the refugees' location decisions within Turkey, I follow Del Carpio and Wagner (2015) and Akgunduz et al. (2018) to construct an IV strategy as follows. The variable $R_{rt}$ is potentially correlated with $\epsilon_{irt}$ in Equation (2), which can bias the estimates. The reason is that the refugee concentration may be disproportionately high in regions offering better labor-market options and other socio-economic opportunities. In other words, $R_{rt}$ and $S_{irt}$ may be indirectly correlated through an unobserved factor in $\epsilon_{irt}$. To address this concern, the following IV is constructed:

$$\text{IV}_{rt} = N_t \sum_j \pi_j \frac{1}{L_{jr}}, \tag{3}$$

where $N_t$ is the total number of refugees in Turkey in year $t$, $\pi_j$ is the fraction of Syrian population living in each Syrian governorate $j$ in the pre-conflict period (I use 2010), and $L_{jr}$ is the shortest travel distance between each Syrian governorate $j$ and the most populated city of each region $r$ in Turkey.[6] One possibility is that the outcomes may be correlated with distance to border as the Syrian crisis directly hits the border regions and its impact diminishes as distance to border goes up. However, I directly control for the distance to nearest border-crossing by including the log of year-specific distance to nearest border crossing, $D_{rt}$, into the estimating equation. Since there are multiple—exactly 6—border-crossings between Syria and Turkey, it is possible to separate the distance effect from the location choice decision using this IV strategy. There is a single instrument and I use the 2SLS estimator in instrumenting $R_{rt}$ with the distance-based variable/metric $\text{IV}_{rt}$ specified in Equation (3).

## 4 Results and discussion

In this section, I report the results of the diff-in-diff and IV regressions using alternative specifications. There are three main outcome variables: Math, Science, and Reading test scores obtained

[6] Google maps is used to calculate the shortest travel distances. There are 14 Syrian governorates and 12 NUTS-level regions in Turkey, which means that the distance is calculated between 168 distinct routes.

from the PISA data base. Following the convention in the literature, the test scores are used in two different forms: (1) natural logarithm and (2) standardized values. The standard errors are clustered at region level in all regressions. The results are reported separately for the entire sample, males, and females.

Table (3) reports the results of the baseline diff-in-diff analysis. Test scores are used in natural logarithm form—so, the coefficients are interpreted as percentage point changes in test scores. The results from all three diff-in-diff specifications reveal that the Math scores increased by 2.1-4 percentage points in response to increased refugee concentration, and the estimated increase comes almost entirely from males. The estimates are stronger for narrowly-defined treatment and control groups, while they get smaller as extended treatment and control groups are introduced. The increase in the Reading scores is slightly larger—in the range of 2.7-5.1 percentage points. Again, the increase comes from males. For the Science scores, the estimated increase is in the interval of 2.4-3.2. Different from the Math and Reading scores, the Science scores of females also increased in addition to the increase in males' scores.

Table (4) also reports the results of the diff-in-diff estimation; the difference from the results reported in Table (3) is that the dependent variable is defined in standardized form rather than natural logarithm. This suggests that the estimates can be interpreted in terms of standard deviations rather than percentage points. The estimates suggest that the refugee influx increased the PISA test scores in the rage of 0.1-0.25 standard deviation and, similar to the results reported in Table (3), the increase mostly comes from males.

Table (5) documents the baseline IV estimates. The results of the IV analysis also confirm that the refugee influx has generated an increase in the test scores of native youth in Turkey. Similar to the results of the diff-in-diff analysis, the IV analysis also indicates that Math, Science, and Reading scores increased as a consequence of the massive refugee influx. However, different from the diff-in-diff results, the increase comes from both males and females. Whether the dependent variable is defined in natural logarithms or standardized values does not affect the qualitative nature of the estimates in a significant way.

Overall, the baseline results suggest that the intensity of human capital accumulation (as it is measured by the Math, Science, and Reading scores of the PISA test) has increased among 15-year-old natives in response to the increased Syrian refugee concentration in Turkey. The increase in test scores can be attributed to the labor market forces. The influx of low-skilled Syrian refugees increased the competition for jobs with low skill requirements in Turkey. The increase in competition for those jobs has reduced the employment opportunities and also the starting wages. Tumen (2018) shows that the increase in low-skilled refugee concentration increased the high school enrollment rates among Turkish native youth. The findings of the current study complements Tumen (2018) as follows: the main finding is that the increase in low-skilled refugee concentration also increased the intensity of human capital accumulation in the intensive margin. Labor market is an alternative for young males in Turkey. Consistent with this observation, the majority of the regression specifications suggests that the increase in test scores mostly come from males. There are some specifications in which females' test scores have also been estimated to increase in a statistically significant way. Those specifications include the entire country. The western regions in Turkey also offer employment opportunities for young females; so, in the regressions for the entire country, it is not unexpected to see some increase in females' test scores.

It should also be noted that the period of analysis does not cover the periods with increased refugee concentration in the Turkish education system. The PISA sample includes 15-year-old students. As of 2015, the school enrollment rates of 15-year-old Syrians were almost zero. Moreover, the Ministry of National Education started the PICTES project—which aims to heavily invest in the integration of Syrian refugees into the Turkish public education system. Therefore, the negative education experience impact of increased refugee concentration—mostly due to potential communication barriers, lack of high-quality peer effects, and decrease in the quality of instruction—is not observed for the period of analysis. The remaining impact can be purely attributed to the labor market mechanism.

**Heterogeneous effects.** To understand the distributional consequences of the refugee influx, I re-perform the econometric analysis focusing on different portions of the test score distribution. Specifically, I focus on the upper and lower halves of the distribution, i.e., above and below the

median score. I use the IV-2SLS specification, which is more general than the diff-in-diff specifications. Different from the baseline analysis and without loss of generality, I pool the three test scores and include test subject dummies into the regression. Standard errors are clustered at region (NUTS1) level.

Table (6) presents the results. Panel A and B reports the estimates for below-median and above-median samples, respectively. The results suggest that the increase in test scores following the refugee influx comes almost entirely from the bottom half of the test-score distribution, while the estimates for the upper half are statistically insignificant. This result holds for both males and females, while the difference is starker for males than females. The heterogeneity in the estimates supports the validity of the proposed mechanism. The increase in the low-skilled labor supply following the refugee influx reduced the employment opportunities and wages for low-skilled natives. Tumen (2018) argues that the decline in the labor market opportunities for natives has increased high school enrollment rates among natives. This paper documents that the test scores of natives have also increased following the influx and the increase mostly comes from the lower portion of the skill distribution. The increase in the intensity of human capital investment among low-skilled natives suggests that the refugee influx has provided incentives for educational upgrading.

## 5 Concluding remarks

In this paper, I aim to come up with a rich set of estimates pertaining to the impact of refugees on early inequalities among natives in Turkey. Differences in test scores proxy differences in human capital development. Therefore, immigration may affect the inequality dynamics in a society through its impact on the quantity and quality of early human capital acquisition. The type of immigration and the skill composition of immigrants are important determinants of the nature of this impact. This is the first paper estimating the impact of Syrian refugees on the standardized test scores of natives in host countries.

I show that the Math, Science, and Reading scores of Turkish native adolescents have notably

increased following the Syrian refugee influx—conditional on parental education, which is used as a proxy for unobserved ability. The increase in PISA scores is more pronounced for males than females. Most importantly, the increase in test scores mostly comes from the lower half of the test score distribution and from adolescent with lower parental education. This suggests that refugee influx has reduced the test score inequality among natives. The results survive a variety of placebo tests and other robustness checks. I argue that the labor market forces that emerged in aftermath of the refugee crisis have led native adolescents, who would normally perform worse in school, to take their high school education more seriously. Although the labor market channel arising in response to the refugee influx reduces the gap between low and high achieving natives, the school achievement gap between natives and refugees likely increase. The PICTES program jointly implemented by the Turkish government and the European Union should invest further in reducing those gaps.

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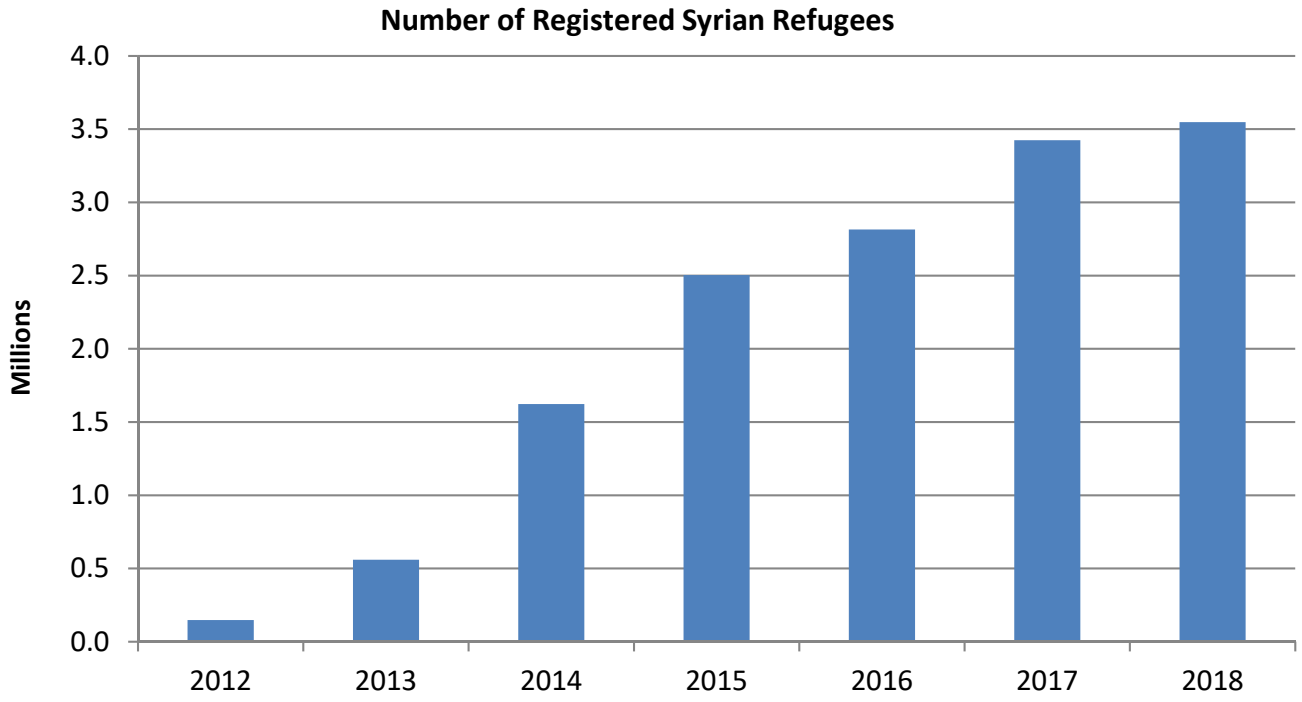


**Figure 1: Number of registered Syrian refugees in Turkey.** This figure plots the number of registered Syrian refugees in Turkey from 2012 to 2018—as of August 2018. The data sources are the UNHCR and the Government of Turkey. See: https://data2.unhcr.org/en/situations/syria/location/113.

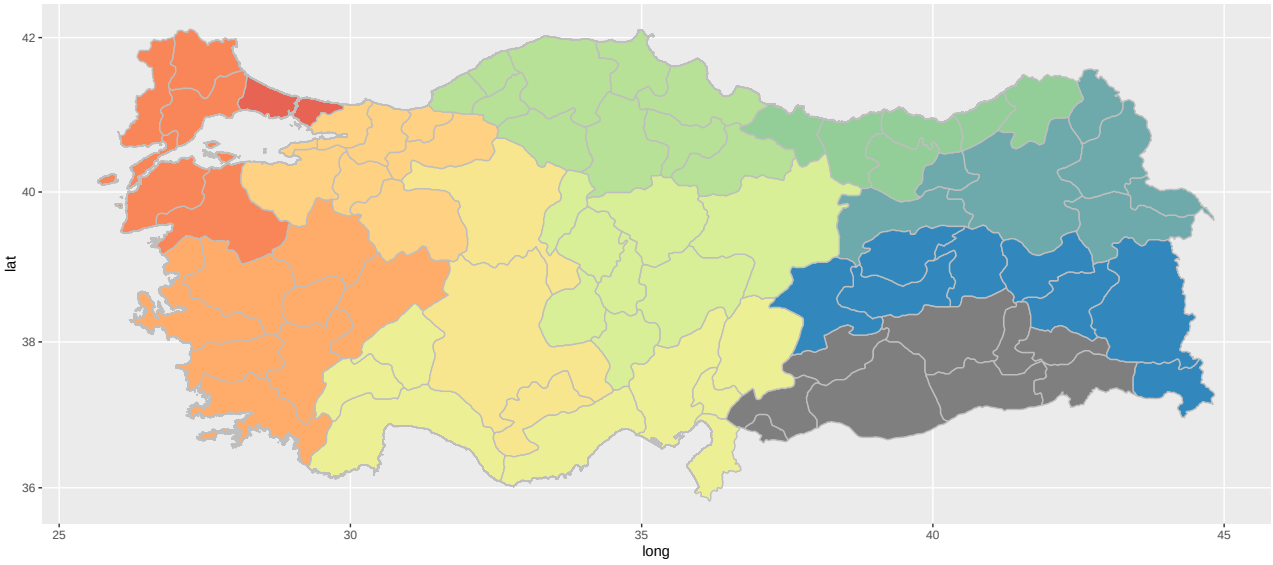


**Figure 2: Regional map (Turkey).** This figure displays the NUTS1-level regional classification for Turkey. Table (1) below lists the provinces included into each NUTS1 region.

| Region # | Provinces |
|---|---|
| Region 1 | Istanbul |
| Region 2 | Tekirdag, Edirne, Kirklareli, Balikesir, Canakkale |
| Region 3 | Izmir, Aydin, Denizli, Mugla, Manisa, Afyonkarahisar, Kutahya, Usak |
| Region 4 | Bursa, Eskisehir, Bilecik, Kocaeli, Sakarya, Bolu, Duzce, Yalova |
| Region 5 | Ankara, Konya, Karaman |
| Region 6 | Antalya, Isparta, Burdur, Adana, Mersin, Hatay, Kahramanmaras, Osmaniye |
| Region 7 | Kirikkale, Aksaray, Nigde, Nevsehir, Kirsehir, Kayseri, Sivas, Yozgat |
| Region 8 | Zonguldak, Karabuk, Bartin, Kastamonu, Cankiri, Sinop, Samsun, Tokat, Corum, Amasya |
| Region 9 | Trabzon, Ordu, Giresun, Rize, Artvin, Gumushane |
| Region 10 | Erzurum, Erzincan, Bayburt, Agri, Kars, Igdir, Ardahan |
| Region 11 | Malatya, Elazig, Bingol, Tunceli, Van, Mus, Bitlis, Hakkari |
| Region 12 | Gaziantep, Adiyaman, Kilis, Sanliurfa, Diyarbakir, Mardin, Batman, Sirnak, Siirt |

**Table 1: Provinces in NUTS1 regions in Turkey.** There are 81 provinces in 12 NUTS1-level regions in Turkey. This table shows the provinces included in each NUTS1 region.

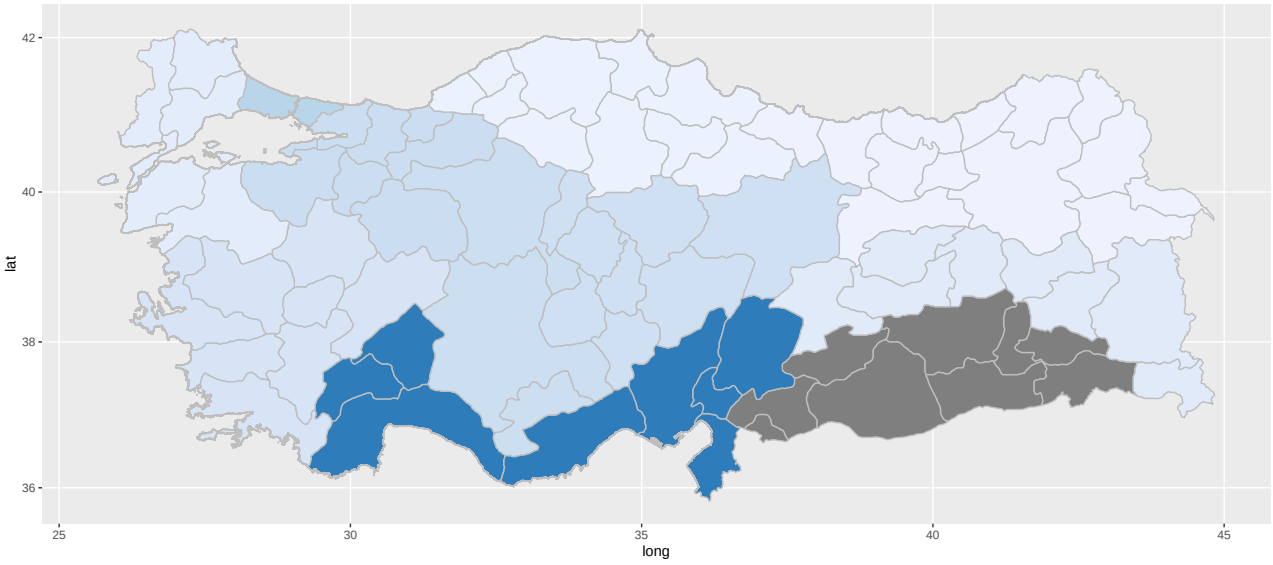


**Figure 3: Refugee shares as of 2015.** This figure displays the refugee shares in Turkey at NUTS1-level as of the end of 2015. Table (2) below documents the numerical refugee share values in each region—calculated as the ratio of the number of registered Syrian refugees to the native population in each NUTS1 region as of the end of 2015. Darker areas represent the regions with higher refugee-to-population ratios.

| **Region #** | **Refugee share (%)** |
|---|---|
| Region 1 | 2.45 |
| Region 2 | 0.51 |
| Region 3 | 1.09 |
| Region 4 | 1.59 |
| Region 5 | 1.52 |
| Region 6 | 7.37 |
| Region 7 | 1.46 |
| Region 8 | 0.14 |
| Region 9 | 0.10 |
| Region 10 | 0.07 |
| Region 11 | 0.65 |
| Region 12 | 11.32 |

**Table 2: Refugee shares in NUTS1 regions in Turkey.** This table shows the refugee shares in each of the NUTS1-level region as of the end of 2015 in Turkey. The regions with highest refugee concentration are Region #12 (11.32%) represented with black color in Figure (2), Region #6 (7.37%) represented in dark blue color in Figure (2), and Region #1 (2.45%), which is the Istanbul region.

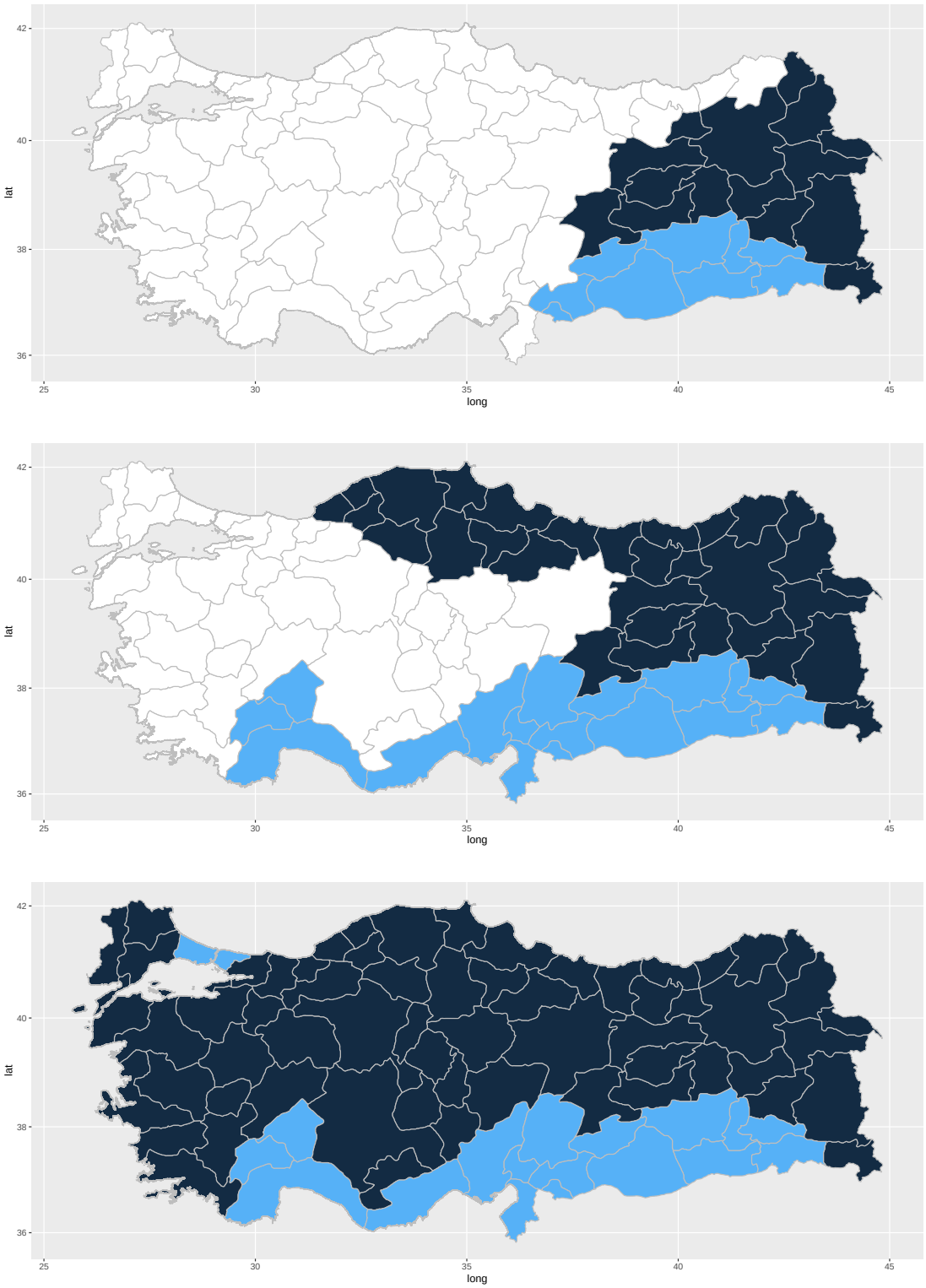


**Figure 4: DID specifications.** This figure displays the three different regional specifications used in the DID estimations. Dark blue color represents the control regions, while the light blue color represents the treatment regions.

**DID ESTIMATION**

**Dependent variable: Natural logarithm of the corresponding test score**

| | **Math** | | | **Science** | | | **Reading** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **All** | **Male** | **Female** | **All** | **Male** | **Female** | **All** | **Male** | **Female** |
| | **Specification I** | | | | | | | | |
| Refugee effect | 0.040* | 0.042*** | 0.034 | 0.024* | 0.002 | 0.047* | 0.038 | 0.024 | 0.045 |
| | (0.015) | (0.003) | (0.026) | (0.008) | (0.003) | (0.014) | (0.027) | (0.016) | (0.033) |
| # of obs. | 2,580 | 1,317 | 1,263 | 2,580 | 1,317 | 1,263 | 2,580 | 1,317 | 1,263 |
| | **Specification II** | | | | | | | | |
| Refugee effect | 0.033* | 0.041** | 0.024 | 0.032* | 0.026 | 0.038* | 0.051* | 0.058* | 0.040 |
| | (0.016) | (0.014) | (0.021) | (0.015) | (0.015) | (0.017) | (0.021) | (0.023) | (0.021) |
| # of obs. | 6,079 | 3,123 | 2,956 | 6,079 | 3,123 | 2,956 | 6,079 | 3,123 | 2,956 |
| | **Specification III** | | | | | | | | |
| Refugee effect | 0.021** | 0.021* | 0.023 | 0.027** | 0.025* | 0.029* | 0.027* | 0.030* | 0.023 |
| | (0.009) | (0.011) | (0.014) | (0.012) | (0.013) | (0.015) | (0.013) | (0.016) | (0.016) |
| # of obs. | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 |

**Table 3:** ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors are clustered at region level. Year fixed effects, region fixed effects, month-of-birth fixed effects, grade fixed effects, mother's education, and father's education are included as control variables into all regressions. A gender dummy is also included in regressions for all sample (i.e., columns 1, 4, and 7).

**DID ESTIMATION**

**Dependent variable: Standardized value of the corresponding test score**

| | Math | | | Science | | | Reading | | |
|---|---|---|---|---|---|---|---|---|---|
| | **All** | **Male** | **Female** | **All** | **Male** | **Female** | **All** | **Male** | **Female** |
| | **Specification I** | | | | | | | | |
| Refugee effect | 0.181* | 0.193*** | 0.152 | 0.133* | 0.019 | 0.255** | 0.168 | 0.095 | 0.217 |
| | (0.052) | (0.014) | (0.091) | (0.033) | (0.008) | (0.055) | (0.112) | (0.071) | (0.134) |
| # of obs. | 2,580 | 1,317 | 1,263 | 2,580 | 1,317 | 1,263 | 2,580 | 1,317 | 1,263 |
| | **Specification II** | | | | | | | | |
| Refugee effect | 0.149 | 0.190** | 0.101 | 0.179* | 0.150* | 0.209* | 0.238** | 0.272** | 0.187 |
| | (0.079) | (0.065) | (0.098) | (0.070) | (0.071) | (0.082) | (0.089) | (0.102) | (0.095) |
| # of obs. | 6,079 | 3,123 | 2,956 | 6,079 | 3,123 | 2,956 | 6,079 | 3,123 | 2,956 |
| | **Specification III** | | | | | | | | |
| Refugee effect | 0.106** | 0.107* | 0.106 | 0.162** | 0.155** | 0.170* | 0.136** | 0.153* | 0.119 |
| | (0.045) | (0.053) | (0.071) | (0.062) | (0.069) | (0.086) | (0.060) | (0.073) | (0.080) |
| # of obs. | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 |

**Table 4:** ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors are clustered at region level. Year fixed effects, region fixed effects, month-of-birth fixed effects, grade fixed effects, mother's education, and father's education are included as control variables into all regressions. A gender dummy is also included in regressions for all sample (i.e., columns 1, 4, and 7).

**IV-2SLS ESTIMATION**

| | Math | | | Science | | | Reading | | |
|---|---|---|---|---|---|---|---|---|---|
| | **All** | **Male** | **Female** | **All** | **Male** | **Female** | **All** | **Male** | **Female** |
| **Panel A** | **Dependent variable: Natural logarithm of the corresponding test score** | | | | | | | | |
| OLS | 0.006*** | 0.006*** | 0.006* | 0.007*** | 0.007*** | 0.008*** | 0.009*** | 0.010*** | 0.008** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) |
| Red. form | 0.020** | 0.018*** | 0.023* | 0.020*** | 0.012** | 0.028*** | 0.025** | 0.020** | 0.030** |
| | (0.007) | (0.006) | (0.012) | (0.006) | (0.006) | (0.008) | (0.010) | (0.008) | (0.012) |
| 1st stage | 2.164*** | 2.159*** | 2.165*** | 2.164*** | 2.159*** | 2.165*** | 2.164*** | 2.159*** | 2.165*** |
| | (0.321) | (0.326) | (0.318) | (0.321) | (0.326) | (0.318) | (0.321) | (0.326) | (0.318) |
| IV-2SLS | 0.009*** | 0.008*** | 0.011** | 0.009*** | 0.006*** | 0.013*** | 0.012*** | 0.009*** | 0.014*** |
| | (0.002) | (0.002) | (0.005) | (0.002) | (0.002) | (0.003) | (0.004) | (0.003) | (0.005) |
| $F$-stat | 45.50 | 43.79 | 46.40 | 45.50 | 43.79 | 46.40 | 45.50 | 43.79 | 46.40 |
| # of obs. | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 |
| **Panel B** | **Dependent variable: Standardized value of the corresponding test score** | | | | | | | | |
| OLS | 0.029** | 0.030*** | 0.029 | 0.042*** | 0.038*** | 0.046*** | 0.042*** | 0.046*** | 0.036** |
| | (0.011) | (0.009) | (0.016) | (0.010) | (0.011) | (0.013) | (0.009) | (0.008) | (0.015) |
| Red. form | 0.094** | 0.082** | 0.107* | 0.106** | 0.068* | 0.148*** | 0.119** | 0.090** | 0.147** |
| | (0.038) | (0.030) | (0.058) | (0.037) | (0.035) | (0.048) | (0.050) | (0.041) | (0.062) |
| 1st stage | 2.164*** | 2.159*** | 2.165*** | 2.164*** | 2.159*** | 2.165*** | 2.164*** | 2.159*** | 2.165*** |
| | (0.321) | (0.326) | (0.318) | (0.321) | (0.326) | (0.318) | (0.321) | (0.326) | (0.318) |
| IV-2SLS | 0.044*** | 0.038*** | 0.049** | 0.049*** | 0.031** | 0.069*** | 0.055*** | 0.042*** | 0.068*** |
| | (0.014) | (0.010) | (0.023) | (0.013) | (0.012) | (0.018) | (0.018) | (0.014) | (0.024) |
| $F$-stat | 45.50 | 43.79 | 46.40 | 45.50 | 43.79 | 46.40 | 45.50 | 43.79 | 46.40 |
| # of obs. | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 | 14,876 | 7,464 | 7,412 |

**Table 5:** ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors are clustered at region level. Year fixed effects, region fixed effects, month-of-birth fixed effects, grade fixed effects, natural logarithm of the year-specific distance to nearest border crossing, mother's education, and father's education are included as control variables into all regressions. A gender dummy is also included in regressions for all sample (i.e., columns 1, 4, and 7). The OLS model regresses the test score on refugee share and other controls; the reduced form model regresses the test score on the distance-based IV and other controls; and the IV-2SLS model uses the distance-based variable as an IV for the refugee share to regress the test score on refugee share and other controls.

**IV-2SLS ESTIMATION: HETEROGENEITY**

| | **All** | **Male** | **Female** |
|---|---|---|---|
| **Panel A** | | **Below median** | |
| 1st stage | 2.155*** | 2.122*** | 2.182*** |
| | (0.179) | (0.179) | (0.180) |
| IV-2SLS | 0.008** | 0.009*** | 0.006* |
| | (0.003) | (0.003) | (0.003) |
| $F$-stat | 146.86 | 139.93 | 147.19 |
| # of obs. | 21,800 | 11,618 | 10,182 |
| **Panel B** | | **Above median** | |
| 1st stage | 2.182*** | 2.225*** | 2.150*** |
| | (0.328) | (0.331) | (0.328) |
| IV-2SLS | 0.006 | 0.007 | 0.005 |
| | (0.004) | (0.004) | (0.004) |
| $F$-stat | 44.21 | 45.19 | 43.02 |
| # of obs. | 22,828 | 10,774 | 12,054 |

**Table 6:** ***, **, and * refer to 1%, 5%, and 10% significance levels, respectively. Standard errors are clustered at region level. Year fixed effects, region fixed effects, month-of-birth fixed effects, grade fixed effects, test subject fixed effects, natural logarithm of the year-specific distance to nearest border crossing, mother's education, father's education, and gender are included as control variables into all regressions. The upper (lower) panel restricts the sample to test scores below (above) the 50th percentile.