Effects of Cultural Diversity on the Attrition Rates of International Students at US Doctoral Programs

by

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ABSTRACT

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Increasing demand for US graduate programs by the international students in the last few decades results in a more diverse set of students culturally in the graduate programs. We investigate the effect of cultural diversity of the international students at US doctoral programs on the likelihood of dropping out of the international students within the first four years of their studies. We use individual-level data for international Ph.D. students who study in the United States with F-1 visa at research and doctoral universities between the academic years 2004/05 and 2010/11. We measure cultural diversity by Hirschman–Herfindahl Index based on either country of citizenship of the students or language spoken by the students. Estimates show that increased level of cultural diversity among international students is associated with lower attrition rates of the students. On the other hand, students who have more peers from the same cultural background as themselves are also less likely to drop out of the programs. When we measure cultural diversity by country of citizenship, we conclude that the negative effect of diversity is much stronger in small-sized classes. However, the effect of diversity based on language spoken by the students does not vary considerably by the class size.

ÖZETÇE

Amerika'daki Doktora Programları İçerisindeki Kültürel Çeşitliliğin Yabancı Öğrencilerin Programı Bırakma Oranları Üzerindeki Etkileri

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Son yıllarda, yabancı öğrenciler tarafından Amerika'daki yüksek öğretim programlarına olan talebin önemli ölçüde artmasıyla akademik programlar içerisindeki kültürel çeşitlilik de artmaktadır. Bu çalışma ile Amerika'daki doktora programlarında öğrenim gören yabancı öğrenciler arasındaki kültürel çeşitliliğin, bu doktora öğrencilerinin kayıtlı oldukları programları tamamlamadan, ilk dört sene içerisinde programı bırakma oranları üzerindeki etkisini inceliyoruz. Bu çalışmada 2004/05 ve 2010/11 akademik yılları arasında, Amerika'da F-1 vizesi ile yabancı öğrenci statüsünde araştırma ve doktora üniversitelerinde eğitim gören doktora öğrencilerinin verisini kullanıyoruz. Kültürel çeşitliliği ölçmek için iki farklı indeks kullanıyoruz. Bu indekslerden ilkini öğrencilerin vatandaşı oldukları ülkelere göre, ikincisini ise öğrencilerin konuştukları ana dile göre oluşturuyoruz. Sonuçlar, yabancı öğrenciler arasındaki kültürel çeşitlilik arttıkça, bu öğrencilerin programı bırakma olasılıklarının azaldığını göstermektedir. Diğer taraftan, kendisi ile aynı kültürel zemine sahip öğrencilerle birlikte bulunan öğrencilerin de program bırakma oranlarının daha düşük olduğu gözlenmiştir. Son olarak, kültürel çeşitlilik indeksini vatandaşı olunan ülkeye göre hesapladığımız zaman öğrenci sayısına göre daha ufak sınıflarda kültürel çeşitliliğin negatif etkisinin daha güçlü olduğu sonucuna ulaşılmıştır. Fakat kültürel çeşitlilik indeksini öğrencilerin konuştuğu ana dile göre hesapladığımızda programlardaki öğrenci sayısının kültürel çeşitliliğin etkisi üzerinde pozitif ya da negatif bir etkisine rastlanmamıştır.

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ABBREVIATIONS

CGS	Council of Graduate Schools
CIP	Classification of Instructional Programs
FICE	Federal Interagency Committee on Education
NCES	National Center for Education Statistics
NSF	National Science Foundation
SEVIS	Student and Exchange Visitor Information System
SEVP	Student and Exchange Visitor Program
SEM	Science, Engineering and Mathematics
SSH	Social Sciences and Humanities
STEM	Science, Technology, Engineering, and Mathematics

1. INTRODUCTION

Number of doctoral degrees awarded in the United States has an upward trend since the end of the 1950s. According to the Survey of Earned Doctorates, conducted by the National Science Foundation (NSF), the number of graduates of US doctoral programs reached to 55,195 in 2018 with an average annual growth rate at 3.2%. As US doctoral programs are considered among the most prestigious and competitive graduate programs in the world, there is a considerable interest of international students to these programs. In 2018, the proportion of doctoral degrees awarded to international students who hold a temporary visa peaked at 31.9%. When international students are analyzed by their country of origin, students from top five countries made up 62.5% of all temporary visa holders who were graduated with a doctoral degree in 2018, and over the half of the international students at the doctoral level came from China, India, and South Korea. The internationalization of the graduate programs in the US universities and colleges brings a considerable amount of cultural and linguistic diversity to these institutions. However, it might also bring some obstacles in teaching and research environment. This research analyzes the effect of the cultural diversity of international students within a class on the likelihood of dropping out of the international Ph.D. students in the same class from the program during the first four years of their studies.

Cultural and ethnic diversity in schools and workplaces is an important and widely discussed topic in the literature (see the next section for a detailed discussion of these studies). The main question in this literature is whether the amount of diversity exposed by students or workers has a significant effect on the performance of individuals who belong the group of majority or minorities. Few studies have investigated the effect of cultural diversity on the academic performance of the students in the university settings. A very recent study conducted by Braakmann and McDonald (2018) show that the interaction with a more diverse set of students improves the academic performance of undergraduate students; however, the students also get benefit from being together with the other students from the same background as themselves. Chevalier, Isphording, and Lisauskaite (2020) also find that the diversity within a classroom in terms of language spoken by the students in that class has a positive impact on the academic performance of non-English-speaking undergraduate students. Similarly, in this research, we aim to show how cultural diversity in terms of country of citizenship or language spoken by the students as well as exposure to students from a similar background affect international students' academic performance at US doctoral programs. Unlike the earlier studies, this paper focuses on diversity at US doctoral programs. According to the Ph.D. Completion Project conducted by the Council of Graduate Schools (CGS), 30.6% of all Ph.D. students used to drop out of the graduate school without finishing their degrees in the first ten years in the 2000s, whereas this dropout rate was 23.6% for the first four years of the studies. It is also important to highlight that in this study we analyze four-year attrition rates of international students from doctoral programs of US research universities, specifically.

Obtaining data from the Student and Exchange Visitor Information System (SEVIS) of the US government, we analyze dropout rates of international students with more recent data in this paper. The SEVIS collects the records of each foreign-born student who is studying in US universities and colleges by holding a student visa. (See Demirci (2019) for the employment of the same data to understand the post-graduation placement choice of international students). The dataset provides information about some demographic and educational characteristics of international students, including their gender, country of origin, starting and ending year of the program, and the visa status from which we can infer whether the student obtained the pursued degree or not. Our variable of interest is dropping out of students from the doctoral programs within the first four years of their studies, which we refer as attrition throughout the paper. Our main explanatory variable is the cultural diversity in the classroom, which is measured as diversity by either country of origin of the international students or language spoken by the international students. To observe the impact of being together with the students coming from the similar backgrounds on the academic performance of the international students, we generate two variables: country composition and language composition. Country composition variable shows the share of international students who are coming from the same country in a class, keeping the current individual out of the computation. Similarly, language composition variable shows the percentage of international students who speak the same language in a class, excluding the current individual. We analyze the effect of the diversity on attrition rates of doctoral-level international students who started their education between the academic years 2004/05 and 2010/11. To control for time-varying, institution-specific, and field-specific tendencies in attrition rates, we also use the associated fixed effects in regressions. We also control for demographic variables, including sex, age, and country of birth.

We have used an instrumental variables (IV) approach to estimate the causal impact of the diversity on the attrition behavior. Since the total number of first-year doctoral students from each country changes by years in the whole US, this variation affects the cultural diversity in each Ph.D. program. We believe that universities make their admission decisions based on the applicant pool, so it is affected by the supply of students from each country. Thus, we generated instruments by apportioning the total number of international students for each country in a particular year to universities and academic programs according to the historical country compositions of universities and programs. The historical country composition of each department is measured by the distribution of students who started their programs before the academic year 2004/05 across US doctoral programs. Thus, to the degree that the historical country composition of each department is independent of US-level changes observed in the population of students from each origin country in later years, the instrument will satisfy the exogeneity condition.

Our first-stage estimation results show a statistically significant relationship between the observed diversity and its instrument. IV results show that a 10 percentage point increase in the diversity index based on country of citizenship (which is 39.5% of the standard deviation of the observed diversity in the data) is associated with 1.1 percentage point decrease in the attrition rates of international students (2.6% of the standard deviation of the observed attrition rates) in regressions where we control for field, university, country, and time fixed effects. This estimated effect becomes larger when we restrict our sample to the departments that accept at least one international student in each academic year throughout the analyzed period. In that case, we observe when the diversity index by country of citizenship increases by 10 percentage points (which is 49.9% of the standard deviation of the observed diversity in the data), the attrition rate decreases by 2.0 percentage points (4.7% of the standard deviation of the observed attrition rates). When we measure the diversity index in terms of language spoken by the students, the results stay very similar, but the magnitude of the effect of diversity gets slightly larger. These results show that diversity of international students improve the academic performance of international students at US doctoral programs.

Moreover, in small-sized classes, the decreasing effect of the diversity based on country of origin on attrition rates is much stronger. Estimates also show that the coefficients for both country composition and language composition variables are negative and statistically significant, which means that students who have more peers from the same cultural background as themselves are less likely to drop out of the program.

Several mechanisms can explain our findings. Firstly, being with a more diverse set of students might increase the exposure to a wider set of knowledge and perspectives. Students from different cultural backgrounds may demonstrate complementary skills and problem-solving abilities, which may also help students to improve their academic performance. Secondly, in programs with more diverse set of students, professors may adjust their teaching styles. For example, they may lower their speed of speaking or they may repeat more than usual to make the context clear. Therefore, these adjustments might also have significant impacts on the academic performance of the students. Lastly, in more diverse programs, competition among students might be higher and this may lead students to study more to be successful in the academic programs. This may also result in lower attrition rates on average in these programs. Yet, unfortunately, we cannot identify which mechanism drives the estimated result in this study because of the limitations in our data.

On the other hand, students coming from the same cultural background may more easily communicate with each other and share information, which also results in trust and cooperation among them. Therefore, being together with the students coming from the same cultural background is beneficial for the academic performance of the students. The effect of increasing diversity and having more peers from the same background can be seen as incompatible; however, in literature it is also discussed that there could be a tipping point after which increased homogeneity becomes unfavorable for students (e.g. Braakmann & McDonald, 2018). One possible mechanism is that students need to be together with other peers from the same cultural background as themselves to feel secure and confident to engage with a more diverse set of students. Thus, both increasing diversity and having more students from the same cultural background improve the academic performance of the students as empirically found in this study.

This paper is organized as follows. In Section 2, we review the existing literature on cultural diversity and discuss our contribution to the literature. In Section 3, we describe our data source, explain sample restrictions, and present trends in attrition rates as well as diversity. In Section 4, we explain our empirical approach and discuss the IV strategy. In Section 5, we present the regression estimates and summarize the results. Lastly, we conclude in Section 6.

2. LITERATURE REVIEW

The effects of cultural diversity on economic growth and social outcomes have been widely studied in the literature by researchers. The literature on cultural diversity implicitly assumes that: (1) people from different country of origin have different experiences, school and value systems, and (2) demographic differences are associated with different knowledge and skill sets. Consequently, in recent literature, the effects of cultural diversity on productivity and economic growth have been empirically explored in various studies. Most of the studies in existing literature on cultural diversity and economic performance uses the "diversity index" which is referred as the fractionalization index by Alesina et al. (2003). This fractionalization index reflects the probability that two randomly selected individuals within a group are from different demographic backgrounds, and it reaches to the maximum value of 1 asymptotically when each individual in the group comes from different backgrounds.

There are two very influential studies conducted by Ottaviano and Peri (2005, 2006), which investigate the effect of cultural diversity across US cities on the local productivity. They measure the cultural diversity in each city with the fractionalization index based on either the native languages spoken at home by residents of the city (Ottaviano and Peri, 2005) or the country of birth of the individuals in the city (Ottaviano and Peri, 2006). Both studies conclude that cultural diversity has a positive effect on the productivity of native people on average. As shown in Ottaviano and Peri (2006), US-born workers are paid higher wages on average if they live in culturally more diverse cities, than those people who live in cities with lower cultural diversity. Ager and Brückner (2013) also construct an index of cultural diversity based on the country of origin of the population at the county level and analyze the effect of cultural diversity on economic growth in the US economy. This paper focuses on the 1870-1920 period in the United States, while Ottoviano and Peri focus on the 1970-1990 period. The main finding of the paper is that an increase in the cultural diversity increases the output per capita considerably. Trax, Brunow and Suedekum (2015) aim to show the impact of cultural diversity on productivity at both macro and micro levels in the German economy. The key findings of their study indicate that: (1) the size of the group of foreign employees in a plant has no significant effect on productivity, but (2) higher diversity among foreign employees in terms of their nationalities is associated with higher total factor productivity in German manufacturing plants. Lastly, Alesina, Harnoss, and Rapoport (2016) present an cross-country comparison which examines the relationship between the birthplace diversity among individuals and economic welfare, and they conclude that birthplace diversity is positively correlated with the long-run income of the countries.

In school settings, there are very few studies have investigated the effects of diversity. Most of the studies have concentrated on the effects of immigrants or ethnic minorities in the schools on the academic performance of the students by using the share of minorities among all students. Commonly, these studies conclude that minority students have a negative impact on the other minority students. However, there are different results found about the effect of immigrant students on native students. For example, Jensen and Würtz Rasmussen (2011) illustrate that higher concentration of immigrants has a negative impact on both native and immigrant secondary education students in Denmark. On the other hand, according to Schneeweis (2015), immigrant concentration in primary schools in an Austrian city does not affect native students significantly but it can have negative effects on immigrant students by causing grade repetition and high track attendance. Hoogendoorn and van Praag (2012) present a similar study on the business graduate students in Netherlands, and they also use the share of students with a non-Dutch ethnicity to measure the ethnic diversity. In this paper, they assume that a larger share of minorities implies higher ethnical diversity. They measure the impact of the share of minorities on the team performance in terms of business outcomes, and they conclude that a moderate degree of ethnic diversity does not affect team performance, however positive effects are seen when the team is truly heterogeneous, i.e. when the majority of the team is ethnically diverse. Lastly, a study conducted by Anelli, Shih and Williams (2017) examines how foreign-born peers affect American college students' likelihood of graduating with a STEM major, and they find a significant negative impact of foreign-born peers on the natives. In this paper, they study the effect of foreign-born students within the two different groups: (1) international students who come to the US with a temporary visa for education purposes, and (2) the immigrant students who are US citizens or permanent residents. They conclude that international students have a positive impact on native students' likelihood of STEM completion, unlike immigrant students. Thus, the immigrant students are the group which brings about all negative effects on native students' STEM completion. In this paper, descriptive statistics show that international students have larger ability as proxied with SAT scores than not only immigrant students but also native students. Thus, they argue that international students are very highly selected. This distinction is important for this study, because in our research we are considering the effect of cultural diversity on the likelihood of dropping out of the international students, by generating a diversity index on only international students, excluding immigrant students. However, it is important to highlight that these studies mentioned above in school settings do not consider the diversity within the minority group and this is one of the main drawbacks of these studies.

Dronkers and van der Velden (2012) use an Hirschman–Herfindahl Index to measure the ethnic diversity based on country of origin and investigate the effects of diversity in the schools on the reading scores of both native and immigrant 15-year children in a large number of OECD member states. The results show that ethnic diversity in schools has a significant negative effect on the learning performance of both immigrant and native children. Moreover, Maestri (2017) also states that the share of non-native students may not be enough to measure the diversity and to explain educational outcomes. Therefore, she uses a Hirschman–Herfindahl Index based on country of origin of the mother or, if missing, that of the father, to measure the ethnic diversity. The results of the study on the primary school students in Netherlands show that ethnic diversity has a positive effect on the test scores of the minority students. There are few other recent studies that analyze the effect of diversity among college students on the students' performance. Braakmann and McDonald (2018) conduct a study in all (122) English universities for three cohorts and measure the effect of diversity on students' both academic performance and post-graduation outcomes, such as whether a student employed six months after graduation. However, they have information on the post-graduate outcomes only for the students who submit their answer to the Destination of Leavers of Higher Education survey (DLHE) which is officially administered by the UK government. They find that undergraduate level students get benefit both from an interaction with more diverse set of students and from being with students who come from the same background as themselves. Another study conducted by Chevalier, Isphording, and Lisauskaite (2020) also investigates how linguistic diversity in college affects the educational performance of undergraduate students at a British university. They use the nationality of a student to deduce the language spoken by the student in order to calculate linguistic diversity. The main results of the study show that: (1) both the share of non-English-speaking students and the diversity within the classroom have no effect on the performance of English speaking students, and (2) the diversity within the classroom has a positive impact on the academic performance of non-English-speaking students, especially for the low-achieving students.

Our paper adds to the literature on cultural diversity in various aspects. First, there are few studies on the effect of diversity in university settings; however, our research contributes to the literature as the first study conducted on the students in US higher education institutions. It is important because US higher education institutions have embraced internationalization with more than one million international students in each year since 2015. According to NSF, bachelor's degrees awarded to international students in 2018 made up 4.9% of all bachelor's degree recipients in the United States. However, the ratio of international students in the US graduate programs, both master's and doctoral programs, was 34.4% in the respective year. Since internationalization is higher in the graduate programs than the undergraduate programs, our research also contributes to the literature by analyzing the effect of diversity on international students in the Ph.D. level for the first time.

3. DATA

3.1. SEVIS Data

Our data comes from the Student and Exchange Visitor Information System (SEVIS) and this data source provides individual-level information on all international students enrolling in a Ph.D. program in one of the Student and Exchange Visitor Program (SEVP) certified universities in the United States with an F-1 visa between July 01, 2004 and July 01,2015. Only the SEVP-certified universities are allowed to sponsor international students and issue them F-1 visas. Thus, the data set allows us to capture a significant proportion of the international students who come to the United States temporarily. We divided data into cohorts according to academic year in which students start their training at a doctoral program. For example, students who start a doctoral program between July 01, 2004 and July 01,2005 represent the 2005 cohort. Each cohort in our data is comprised of approximately 25,000 students. The administrative data set covers demographic information about students including their country of origin, year of birth, and gender as well as the information about intended degree, including field of study, exact dates of the students' starting and ending time of the programs, and the status change date of the students.

The data provides five different categories for students' status of F-visa. These are 1) "Completed": Students who have already completed their program, 2) "Active": Students who are actively attending a program, 3) "Deactivated": Students who have transferred to another program, 4) "Terminated": Students whose status have been terminated due to non-compliance with visa regulations, and 5) "Cancelled": Students who has not attended the program or not entered the country within 60 days after the program start date. However, the ratio of students who have "Canceled" status is very low, which is only 0.16% in all data. Then, according to our interests, we have regrouped the students into three categories as "Continuing", "Completion", and "Attrition" to infer their graduation status. Although, direct information about the students who drop their programs is not provided, we have deduced it from the students' reported status. In our new classification, we count the students whose status are "Deactivated", "Terminated" or "Cancelled" as "Attrition" since neither they are actively following a program, nor they have completed it. For instruments, we again use administrative data from the SEVIS for the students who started their doctoral programs before the academic year 2004/05 and graduated from the programs in between the academic years 2004/05 and 2010/11. This data set allows us to observe the total number of graduated students from each country of origin for each department during the time period. Additionally, we create an alternative diversity index in terms of the language spoken by the students. However, we have no direct information in data on the language spoken by the students. Therefore, we used the CIA World Factbook to create a data set in order to match every country in our sample with the most commonly spoken language in that country, then we assigned the language to the students coming from that country.[1] Table A.1 in the appendix summarizes the languages, related nationalities, and the share of speakers in our sample.

3.2. Sample Restrictions

We have data on international students who started a doctoral program between the academic years 2004/05 and 2014/15. Our aim is to observe four-year attrition rates of the international Ph.D. students; thus, we restrict the analysis with the students entering a doctoral program from 2004/05 to 2010/11 only, which consists of 179,570 students. We used the 1994 edition of the Carnegie Classification of Institutions of Higher Education to restrict our data by the institution types. According to this classification, doctorate-granting universities are divided into four categories as Research Universities 1, Research Universities 2, Doctoral Universities 1, and Doctoral Universities 2. [2]

[1] CIA World Factbook is publicly available at https://www.cia.gov/library/publications/the-world-factbook/fields/402.html

[2] **Research Universities I:** These institutions give high priority to research and award 50 or more doctoral degrees each year. In addition, they receive annually $40 million or more in federal support.
Research Universities II: These institutions give high priority to research and award 50 or more doctoral degrees each year. In addition, they receive annually between $15.5 million and $40 million in federal support.
Doctoral Universities I: These institutions award at least 40 doctoral degrees annually in five or more disciplines.
Doctoral Universities II: These institutions award annually at least ten doctoral degrees in three or more disciplines or 20 or more doctoral degrees in one or more disciplines.
More information is available at http://carnegieclassifications.iu.edu/downloads/1994_edition_data.xls

Therefore, we divided universities in our data into five categories: “Pub Res1”: Public universities belong to the group Research Universities 1, “Priv Res1”: Private universities belong to the group Research Universities 1, “Pub Doct”: Public universities classified in either Research Universities 2 or Doctoral Universities 1 or 2, “Priv Doct”: Private universities classified in either Research Universities 2 or Doctoral Universities 1 or 2, and the “Other” universities which do not belong to these groups. Consequently, as the first four categories contain 87% of all students in our data set, we excluded the “Other” universities for further analysis. After we eliminated the cohorts to ones who started between academic year 2004/05 and 2010/11 and restricted our data according to the institution types, the remaining data includes 157,570 students. Lastly, to apply IV estimation, we restricted our sample with the departments that have historical data on graduated students who started their programs before the academic year 2004/05 and graduated from the doctoral program between the academic years 2004/05 and 2010/11. This allows us to eliminate the departments with very few observations throughout time, which allows us to make a reasonable estimation on the effect of diversity. As a result, the restricted sample consists of 141,704 students, distributed across 7 cohorts, 242 universities, and 7,317 departments.

We have information on the field of study for each individual, and we used a detailed version of the Classification of Instructional Programs (CIP) for each field of study provided by the National Center for Education Statistics (NCES). [3] We generated a unique code for each cohort per each university and department by using the CIP codes which is different for each field of study as well as the FICE code which is an identification code for the institutions of higher education in the United States. For example, 20091426140701 is a unique code to identify the students who belong to cohort 2009 and registered a Ph.D. program in Chemical Engineering (which has the CIP code 140701) at Yale University (which has the institutional FICE code 1426). For further analysis, we excluded the students from our sample if we could not generate this code due to the lack of information. However, we excluded only 10 observations because of the missing information.

[3] Detailed information about the Classification of Instructional Programs (CIP) is available at https://nces.ed.gov/ipeds/cipcode/Default.aspx?y=55

Table 3. 1: Summary Statistics of PhD Students of 2005-2011 class

	Total	Male	Female
Number of Observations (N)	179,537	110,186	69,351
Distribution by University Type			
Pub Res1	80,384	49,447	30,937
Priv Res1	30,987	18,887	12,100
Pub Doct	33,612	20,899	12,713
Priv Doct	12,551	7,699	4,852
Other	22,003	13,254	8,749
Demographic Characteristics of Students at Research & Doctoral Universities (i.e., excluding "Other")			
Number of Observations (N)	157,534	96,932	60,602
Mean Starting Age	27.1	27.2	27.0
% SEM	59.7%	66.6%	48.6%
% SSH	14.0%	11.2%	18.3%
% OTH	26.4%	22.2%	33.1%
Top-5 Countries			
% China	29.3%	28.1%	31.2%
% India	15.0%	16.4%	12.7%
% South Korea	10.2%	10.0%	10.5%
% Taiwan	4.9%	4.3%	5.7%
% Canada	4.1%	3.6%	4.8%
Demographic Characteristics of Students in the Sample (i.e., excluding department with no historical data)			
Number of Observations (N)	141,683	88,647	53,036
Mean Starting Age	27.0	27.1	26.8
% SEM	61.6%	68.2%	50.8%
% SSH	13.8%	11.1%	18.3%
% OTH	24.6%	20.8%	30.9%
Top-5 Countries			
% China	30.0%	28.7%	32.2%
% India	15.0%	16.5%	12.6%
% South Korea	10.3%	10.1%	10.6%
% Taiwan	4.9%	4.4%	5.7%
% Canada	3.9%	3.5%	4.5%

Note: We used SEVIS data to calculate the number of students, and we categorized universities in terms of the 1994 edition of the Carnegie Classification of Institutions of Higher Education. In our sample, we exclude the students from the departments which we have no historical data on the graduated students between 2004/05 and 2010/11. In data we have 33 students who identify themselves as neither female nor male. Thus, we exclude these students in Table 3.1.

Table 3.1 presents the summary statistics of all international Ph.D. students entering a doctoral program between the academic years 2004/05 and 2010/11 at one of the research or doctoral universities and also the summary statistics of the students consist of our sample for the same period of time. We distributed students across three main categories by broad fields as Science, Engineering and Mathematics (SEM), Social Sciences and Humanities (SSH), and the Others (OTH). Almost 61.6% of all students in our sample attend a Ph.D. program in the SEM fields, while the ratio reaches at 68.2% among male students and decreases to 50.8% among female students. This is consistent with one of the biggest concerns about the under-representation of women, especially in the SEM fields, since the ratio of female students in the SEM fields is only 30.8% in our sample. Overall, female students' ratio in our sample is 37.4%. On the other hand, 18.3% of female students in the sample attends a Ph.D. program in one of the SSH fields, while the ratio decreases to 11.1% for male students. The largest group among all students in our sample regarding to country of origin is students from China, at 30.0%, and the ratio reaches to 32.2% among female students. The second largest group is students from India, at 15.0%, which is followed by South Korea, at 10.3%. As you can see in the Table 3.1, our sample is a good representative of all international Ph.D. students at research and doctoral universities in the US in terms of the distributions based on country of origin, gender, and broad fields.

3.3. Analysis of Attrition Rates

We generated a dummy variable for the attrition to see the percentage of students who drop out of the Ph.D. program within the first four years of their study. In order to make this distinction, we calculated the duration each student spent in a program by using the intended degree information provided by the SEVIS data. For the students who did not complete their studies, we used the status change date as the final date of study and calculated the program duration as the difference between the status change date and the program start date. We also used the CIP codes to generate average completion and attrition rates presented by disciplines and broad fields later.

Table 3.2 provides the average attrition rates conditional on the institution types and the broad fields. According to our data, the average four-year attrition rate at research and doctoral universities is 24.6% on average for all international Ph.D. students who started their program between 2004/05 and 2010/11. The average attrition rate does not change sharply in terms of the broad fields. Students in the SSH fields have the highest attrition ratio at 25.9%, whereas the students in the SEM fields have the lowest attrition rate at 24.2%. According to institution types, the average attrition rate is the lowest for

Table 3.2: Four-Year Attrition Rates of the PhD Students

Panel A: For All Students at Research and Doctoral Universities

By Institution Types/Broad Fields	ALL	SEM	SSH	OTH
All Universities				
Attrition Rate (%)	24.6%	24.2%	25.9%	24.8%
Number of Observations (N)	157,560	93,994	22,011	41,555
Pub Res1				
Attrition Rate (%)	23.8%	22.7%	28.1%	24.4%
Number of Observations (N)	80,388	49,757	10,274	20,357
Priv Res1				
Attrition Rate (%)	16.9%	16.3%	16.7%	18.1%
Number of Observations (N)	30,994	16,257	5,899	8,838
Pub Doct				
Attrition Rate (%)	31.9%	32.1%	33.3%	31.0%
Number of Observations (N)	33,626	21,573	3,409	8,644
Priv Doct				
Attrition Rate (%)	28.8%	28.8%	28.5%	29.1%
Number of Observations (N)	12,552	6,407	2,429	3,716

Panel B: For All Students in the Sample

By Institution Types/Broad Fields	ALL	SEM	SSH	OTH
All Universities				
Attrition Rate (%)	24.3%	24.0%	25.3%	24.4%
Number of Observations (N)	141,704	87,361	19,545	34,798
Pub Res1				
Attrition Rate (%)	23.8%	22.7%	28.0%	24.5%
Number of Observations (N)	74,114	47,368	9,218	17,528
Priv Res1				
Attrition Rate (%)	16.8%	16.3%	16.4%	17.9%
Number of Observations (N)	28,722	15,356	5,517	7,849
Pub Doct				
Attrition Rate (%)	32.0%	32.1%	32.9%	31.1%
Number of Observations (N)	28,087	18,881	2,777	6,429
Priv Doct				
Attrition Rate (%)	27.7%	28.0%	27.2%	27.4%
Number of Observations (N)	10,781	5,756	2,033	2,992

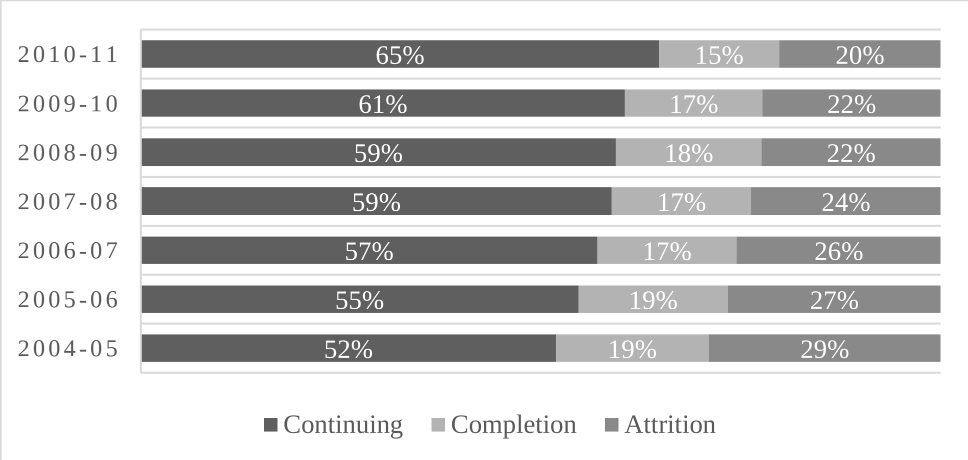
Notes: Each cell represents the average attrition rate of international students conditional on the university type and the broad field. Panel A gives the statistics for all students who attend a PhD program at a research or doctoral university, whereas Panel B gives the average rates for the students in our sample.

the private research universities (Priv Res1) at 16.9%, whereas the public doctoral universities (Pub Doct) have the highest attrition rate on average at 31.9%. Panel B in the Table 3.2 summarizes the four-year attrition rates in our sample (i.e., excluding students in departments that do not have historical data), which is 24.3%, on average. Also, the attrition rates by university types and fields are very similar between Panel A and Panel B. Thus, we can conclude that the average four-year attrition rates of Ph.D. students are lower for the research universities than the doctoral universities. Similarly, the average attrition rates do not vary considerably according to the broad fields in our sample. If we look at the disciplines in the SEM & SSH fields, then the highest average attrition rate in our sample is seen in the Social Sciences (26.3%), which is followed by the Physical Sciences (26.1%), and the lowest average attrition rate is seen in the Mathematics and Statistics (22.9%), which is followed by the Life Sciences (23.4%).

There is very limited information about the attrition rates from Ph.D. programs in the literature. The main reference source for comparison purpose is the "Ph.D. Completion and Attrition Report" which was published by the Council of Graduate Students (CGS) in 2008. However, there is a major difference between our data and the data used by CGS. In the CGS report, not only international students, but also domestic students registered at US doctoral programs are taken into account. However, in our sample, we only have international students. Despite this difference between the data sets, the cumulative four-year attrition rates reported by the CGS report and the rate we found in this study do not differ much. According to the CGS, the average four-year attrition rate is 23.6% for the combined sample of domestic and international students entering 1992/93 through 1994/95, 24.2% for students entering 1995/96 through 1997/98, and 20.2% for students entering 1998/99 through 2000/01. According to our data, the average attrition rate is 24.6% for all international students entering 2004/05 through 2010/11. However, there is a decreasing trend in the attrition rates throughout the years, which is presented in Figure 3.1.

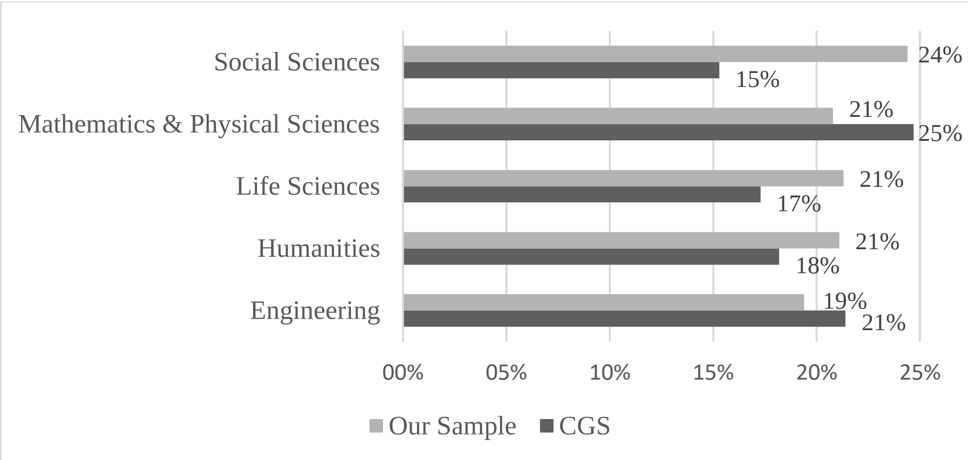
On the other hand, we also made a comparison between the cumulative four-year attrition rates of international students in our sample and the attrition rates published by the CGS for the cohorts entering 1998/99 through 2000/01 according to fields of study in Figure 3.2. For this purpose, we restricted our data only by the 29 universities in the US which have submitted data for the CGS project. The cumulative four-year attrition rates in our sample and the attrition rates published by the CGS are very close to each other in engineering. The similarity may be explained by the fact that international students' ratio is the highest in the SEM fields in the US, and engineering consists of almost 50% of all students in the SEM fields. In our sample, the ratio of students in engineering programs among the SEM fields is 50.3%. Moreover, as you can see in Figure 3.2, the average attrition rates in our sample are lower than the attrition rates presented in the CGS report not only for Engineering, but also for mathematics and physical Sciences. This is also consistent with the facts that international students' ratio is the highest in the SEM fields and the completion ratio is higher among the international students than the domestic students, which is also presented in the CGS report.

Figure 3. 1: **Overall Four-Year Cumulative Continuing, Completion, and Attrition Rates by Cohorts**



Notes: The sample includes international students who started a doctoral program in between the academic years 2004/05 and 2010/11 at research and doctoral universities in the US. These ratios are generated by the status of the students at the end of the fourth year of the academic programs.

Figure 3. 2: Comparison of Four-Year Cumulative Attrition Rates by Disciplines



Notes: In this figure we compare the four-year attrition rates presented in the CGS report for the cohorts entering 1998/99 through 2000/01 and the attrition rates of the students entering 2004/05 through 2010/11 in our sample in terms of disciplines. The main difference is that in our sample we have only international students; however, in the CGS report on completion and attrition rates at US doctoral programs, the sample consists of both native and international students.

4. EMPIRICAL STRATEGY

In this section, we aim at demonstrating how cultural and linguistic diversity of international students in a particular Ph.D. class (i.e., the group of international students who started their Ph.D. studies in a particular year at a particular program of a US university) affect the attrition behavior of international students in that class. In empirical model, we used either diversity by country of citizenship or diversity by language spoken by the students since these two variables of interest are significantly correlated with each other (i.e., the correlation is 0.9389 between these two variables in the sample). We used different combinations of independent variables in our model to illustrate the effects that are not subject to the omitted variable bias. However, before talking more about the empirical model, first we need to explain how the diversity indices and some other explanatory variables are generated.

4.1. Diversity Measures

Diversity Indices: We generated two different diversity indices: the first is based on the country of citizenship of the students, and the second is based on the language spoken by the students. First, we defined the diversity index according to the country of citizenship by the Herfindahl-Hirschmann concentration index as

$$D_{tp}(c) = 1 - \sum_{c=1}^{C} (s_{ctp})^2$$

where s_{ctp} represents the share of students from the country *c* with *c* = 1, …, C in the program *p* and year *t* (i.e., in a particular class that is identified as a combination of *p* and *t*) among all international students within that class. That share variable, s_{ctp}, is calculated as

$$s_{ctp} = \frac{N_{ctp}}{N_{tp}}$$

where N_{ctp} represents the number of students from country *c* in program *p* at time *t*, and N_{tp} represents the number of all international students in the same program *p* at time *t*.

C represents the total number of countries represented in program *p* and year *t*. Then, we repeated the same method to calculate the diversity index according to the language spoken by the students as

$$D_{tp}(l) = 1 - \sum_{l=1}^{L} (s_{ltp})^2$$

where s_{ltp} shows the share of students who speak the language *l* with *l* = 1, …, L among all international students within a class (i.e., $s_{ltp} = \frac{N_{ltp}}{N_{tp}}$). L represents the total number of languages spoken in that class. Thus, D_{tp} indicates the diversity of the program p for the cohort t, and this diversity index measures the probability that two randomly drawn individuals within a class have different country of citizenship or language background. Intuitively, when all individuals belong to the same group, this index reaches its minimum value 0, and when there are no individuals belong to the same group, it converges to its maximum value 1. According to Ottaviano and Peri (2006), this index accounts for two main dimensions of the diversity: "richness" of the program (i.e., the number of groups within a program) and "evenness" of the groups' sizes (i.e., balanced distribution of students across groups). Empirically, diversity is commonly measured by this Herfindahl-Hirschmann concentration index based on country of birth of individuals (Ottaviano and Peri, 2006; Alesina, Harnoss, and Rapoport, 2016) and the language spoken by individuals (Ottaviano and Peri, 2005). Chevalier, Isphording and Lisauskaite (2020) also use the same index to measure diversity within the classroom by using language spoken by the students, but they use leave-me-out measures when calculating the diversity index. (i.e., keeping the individual *i* out of the computation.)

Country composition of students: In the data, we have information on the students' country of citizenship and by using this information, we calculated the share of students from the same country for each class in our sample. In this calculation, we used leave-me-out measures of share, where the current individual observation is kept out of the computation. Thus, we define the country composition variable for a student from country c in a particular program p at time t as the percentage of students from country c among all international students in the same program, excluding the student (i.e., $C_{ctp} = \frac{N_{ctp}-1}{N_{tp}-1}$).

The variable C_{ctp} takes its minimum value 0 if there is only one student from country c within a class (i.e., $N_{ctp} = 1$). In addition, if the total number of international students (N_{tp}) in a class is 1, then we accepted C_{ctp} as 0.

Language composition of student: As we mentioned before, we have no direct information in data on the native languages spoken by students, but we deduced this information from the country of origin of the students. If a country has more than one official language, we accepted the most commonly spoken language only. However, if there are more than 10 languages spoken in a country, and if English is one of the official languages, then we accepted English as the language of students from that country. This occurred in Ghana, Zambia, and Zimbabwe for example. Also, we accepted English as the most commonly spoken language in India and Pakistan, but we used Mandarin for Singapore, Hong Kong, and Taiwan. Again, by using leave-me-out measures, we calculated the share of students who speak the same language within a class for every program in our sample.

Table 4.1 presents the average diversity indices in our sample, conditional on the institution types and the broad fields. For all universities in the sample, the average diversity in a Ph.D. class according to country of citizenship is 0.58, whereas the number declines to 0.53 for the linguistic diversity. The average diversity indices in the SEM and SSH fields are higher than the other disciplines for all institution types. On the other hand, we see higher diversity ratios in the research universities than the doctoral universities on average. In addition, Figure 4.1 shows how the average diversity indices change by time for the students in our sample, conditional on the broad fields. Generally, we observe that diversity indices are higher in the SEM fields than the SSH fields. Overall, the average diversity indices do not change by time considerably but there is a notable decrease in both diversity indices from 2006/07 to 2007/08 for the SSH fields, then it changes very slightly by time.

Table 4. 1: Diversity Indices for the Ph.D. Students in the Sample

Panel A: Diversity Index by Country of Citizenship

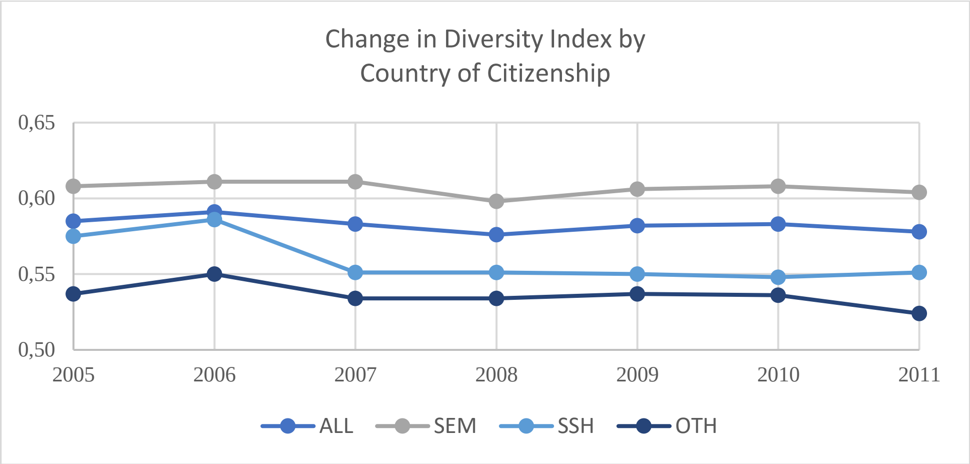
By University Types\Fields	ALL	SEM	SSH	OTH
All Universities				
Mean	0.58	0.61	0.56	0.54
Standard Deviation	0.25	0.23	0.29	0.27
Pub Res1				
Mean	0.60	0.63	0.55	0.53
Standard Deviation	0.24	0.22	0.29	0.27
Priv Res1				
Mean	0.62	0.63	0.60	0.60
Standard Deviation	0.26	0.24	0.29	0.26
Pub Doct				
Mean	0.54	0.56	0.51	0.49
Standard Deviation	0.26	0.24	0.29	0.28
Priv Doct				
Mean	0.52	0.53	0.56	0.49
Standard Deviation	0.27	0.25	0.31	0.28

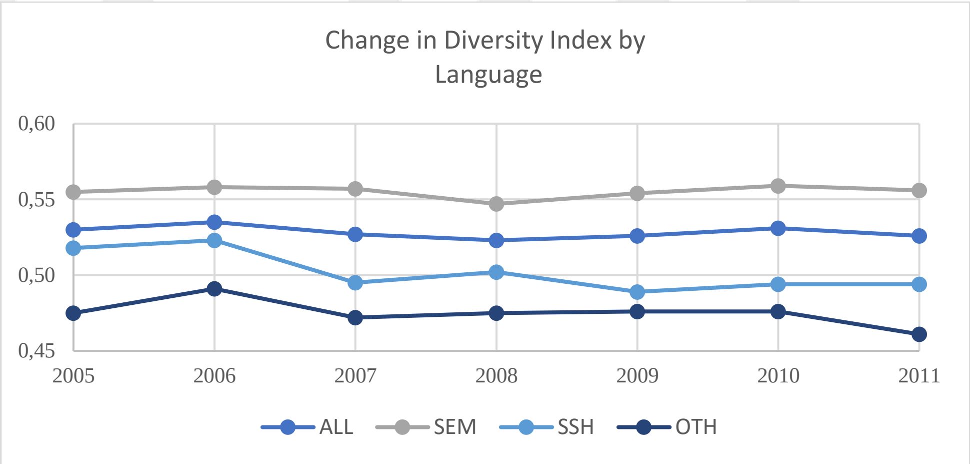
Panel B: Diversity Index by Language

By University Types\Fields	ALL	SEM	SSH	OTH
All Universities				
Mean	0.53	0.56	0.50	0.48
Standard Deviation	0.25	0.23	0.29	0.26
Pub Res1				
Mean	0.55	0.58	0.49	0.49
Standard Deviation	0.24	0.22	0.29	0.26
Priv Res1				
Mean	0.54	0.57	0.54	0.49
Standard Deviation	0.26	0.24	0.30	0.27
Pub Doct				
Mean	0.49	0.51	0.46	0.44
Standard Deviation	0.25	0.24	0.29	0.27
Priv Doct				
Mean	0.47	0.49	0.50	0.44
Standard Deviation	0.26	0.25	0.29	0.27

Notes: In this table, each cell shows the average diversity index conditional on the university types and broad fields in our sample. While Panel A gives the statistics based on the diversity index by country of citizenship, Panel B gives the statistics based on the diversity index by language spoken by the students.

Figure 4. 1: Change in the Average Diversity Indices by Time, Conditional on the Broad Fields, in the Sample





Notes: In these figures, we presented how the diversity indices change by years in our sample conditional on the broad fields. Year 2005 represents the cohort 2005 who start a PhD program in the academic year 2004/05 for example.

4.2. Regression Specifications

We begin our analysis by studying the relationship between the diversity index and the attrition behavior of students within the first four years of the program, using the Ordinary Least Squares (OLS) regression analysis, in which we estimate the following equation

$$(1) \qquad Y_{itp} = \beta_0 + \beta_1 D_{tp} + \beta_2 X_{itp} + \delta_t + \delta_c + \delta_u + \delta_f + \varepsilon_{itp}$$

where i indexes individuals, p indexes degree programs, and t indexes entry cohorts. Y_{itp}, our dependent variable, represents the attrition behavior of student i within the first four year of the program, and it is 1 if the student drops out the program, 0 otherwise. The variable X_{itp} denotes a vector of demographic variables for individual i, including gender and age. δ_t illustrates the set of year fixed effects. Additionally, we control for country fixed effects, field fixed effects, and university fixed effects where c indexes country of origin of the students, f indexes field of the studies, and u indexes universities in our sample. Our main explanatory variable D_{tp} represents the diversity index of the program p for the cohort t, as we explained before. It can be calculated according to students' country of origin (c) or the language spoken by the students (l). We used these two indices separately and reported results for both in the later part.

Further, we add students' composition within a class into the regressions since the diversity indices measure the overall diversity in the class and take the same value for all students. However, the country composition or the language composition of the students in a class takes different values for the students who come from different backgrounds. Thus, our new regression specification can be written as

$$(2) \qquad Y_{itp} = \beta_0 + \beta_1 D_{tp} + \beta_2 X_{itp} + \beta_3 C_{ctp} + \delta_t + \delta_c + \delta_u + \delta_f + \varepsilon_{itp}$$

where C_{ctp} represents the country composition of students from country c in degree program p at time t. However, we replaced the country composition variable C_{ctp} with another variable which shows the language composition of the students in the same class when we use the language spoken by the students to create the diversity index. Like the diversity indices, we do not use these two variables at the same time since there is a strong correlation between them (0.8527). We further estimated the regressions by dividing our sample into smaller samples according to broad fields and class size. Since the average class size fluctuates according to disciplines and broad fields, we preferred to use median class size for each broad field, and divided samples by two groups as below median class size and above median class size.

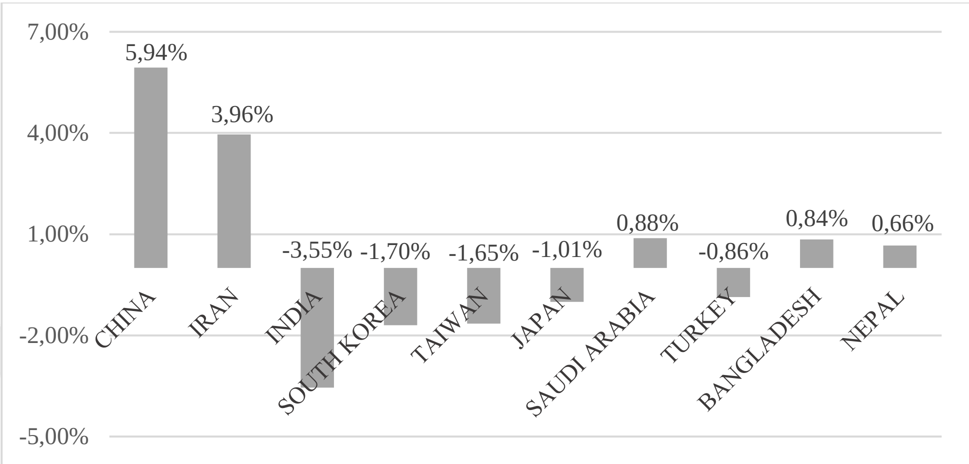
4.3. Instrumental Variable (IV) Strategy

One potential problem about our model is that students are not randomly admitted by the schools, but very likely some schools consider the gender and cultural diversity in classes when admitting students while some others do not. However, when the students apply to graduate programs, they do not have enough information about the other candidates and also when they are admitted by a university, they still do not know the composition of the students who also get an offer from that university. Therefore, we can say that for students, the admission process is exogenous. However, for universities, the admission process can be affected by diversity measures, which would cause an endogeneity issue.

Since the supply of graduate students from different countries may fluctuate from time to time significantly, this can affect the diversity of the international students in the graduate programs. Figure 4.2 illustrates the top-10 countries in terms of the variation in the share of students from these countries between the 2005 and the 2011 cohorts in our sample. We see a large dominance of Chinese students in each cohort, but also as you can see in Figure 4.2, the ratio of Chinese students in the Ph.D. programs increased from 2005 to 2011 considerably. On the other hand, we see a significant decrease in the ratio of Ph.D. students from India in 2011 in comparison with the share in 2005. Therefore, we generated an instrument for diversity index by apportioning total number of international students for each country to universities and academic programs according to the universities' and programs' historical country compositions.

Each department's historical country composition was measured by the students who have started their programs before the academic year 2004/05 and graduated from the doctoral program in between the academic years 2004/05 and 2010/11. The historical data is also coming from the SEVIS, and it is individual-level data for F-visa students (see Demirci 2019 for details of this data set). Our recent data allows us to observe the total number of international students who come to the US with F-visa for doctoral studies any time between July 01, 2004 and July 01,2015. Thus, we calculated the total supply of international students for each country by years from the recent data. Then, by multiplying the total supply of students from country c at time t with the historical composition of country c for the academic program p, we generated estimated number of students from country c in program p at time t. Then, by using these estimations, we generated instruments for the diversity indices as well as the country and language composition variables for all academic programs and cohorts in our sample.

Figure 4. 2: **Top-10 countries according to the variation in the ratio of students from these countries between the 2005 and 2011 cohorts in the sample**



Notes: We generated this figure according to the percentage of students from each country in our data set for the cohorts 2005 and 2011. Then, we reported top-10 countries according to the percentage point change in the share of students in these countries between 2005 and 2011.

More specifically, let's assume the total number of students from country c who are graduated from the academic program p throughout 2004 and 2010 is represented by H_{cp}, and the total number of graduated students from country c is represented by $\mathrm{H}_{c} = \sum_{p}(\mathrm{H}_{cp})$. Then, for each department in the data set, we calculated the share of the department among all Ph.D. students coming from the country c, which is $\mathrm{s}_{cp} = \mathrm{H}_{cp}/\mathrm{H}_{c}$. Further, we used the exact supply of the Ph.D. students from country c in year t for the 2004/05 to 2010/11 entry classes, which is represented by N_{ct}. We generated an estimation for the number of students in each department from country c at time t which is shown as $\tilde{\mathrm{N}}_{ctp} = \mathrm{s}_{cp} \times \mathrm{N}_{ct}$. Then, we calculated estimated class size for each program p at time t as $\tilde{\mathrm{N}}_{tp} = \sum_{c}(\tilde{\mathrm{N}}_{ctp})$. Lastly, according to the estimated number of students from each country and the estimated class sizes, we calculated estimated diversity indices and estimated country composition and language composition variables by using the same formulas we explained before. The diversity indices that are calculated based on $\tilde{\mathrm{N}}_{ctp}$ are used as the instrument for D_{tp} in the IV regressions.

5. RESULTS

5.1. Main Regression Results

We first present OLS results for the effect of cultural diversity on the attrition behavior of international Ph.D. students in Table 5.1. In Panel A, diversity index by country of citizenship is used as an explanatory variable, whereas in Panel B, we used diversity index by language spoken by the students. Each column in Table 5.1 reports the coefficient estimates for the diversity indices along with the robust standard errors clustered at the field level. Column (1) reports the regression results with just the diversity index without any control variable, and the coefficient is negative and significant at 1% significance level. However, we believe that students' country of origin may influence the students' performance at graduate schools since education systems differ from country to country. Also, students coming from some countries may have more difficulties in adaptation than others. Therefore, we control for demographics (age and gender) as well as country fixed effects and time fixed effects in further regressions. As we expected, both gender and age have a significant impact on the attrition decision of the students. According to the OLS results, students who start a Ph.D. program at a higher age are more likely to drop out of the program. Also, we can conclude that female students have a higher likelihood to drop out of the program. However, as it can be seen in Column (2), controlling country and time fixed effects as well as the demographics did not change the coefficient of diversity index considerably, just decreased it slightly. Estimates show that increasing diversity index by one percentage point decreases the likelihood of attrition by 0.0526 and 0.0445 percentage points by country of citizenship and by language, respectively.

In Column (3) university fixed effects and field fixed effects are also included to control for the differences in difficulty levels among academic programs. We have already known that the average attrition rate of the students changes by the institution type. The lowest rate is observed for the private research universities at 16.8%, while the public doctoral universities have the highest attrition rate at 32.0% in our sample (see Table 3.2). Therefore, we believe university specific effects may have an important impact on the attrition behavior of the students. As you can see in Column (3), the coefficient of the diversity index decreases considerably as we control this variability resulting from universities and fields, but it is still negative and significant at 1% significance level. Then, we restricted our sample by the departments which accept at least one international student in each year from 2004/05 and 2010/11 to have a balanced panel and our sample size decreased to 103,302 students who are distributed across 2,315 departments. As a result, the estimated coefficient for the diversity index became insignificant even at 10% significance level with the new sample.

Table 5. 1: Effects of Cultural Diversity on Attrition Rates of International Students, OLS Estimations

	(1)	(2)	(3)	(4)
Panel A: By Country of Citizenship				
Diversity index	-0.0629***	-0.0526***	-0.0265***	-0.0119
	(0.0071)	(0.0068)	(0.0064)	(0.0092)
Female		0.0248***	0.0262***	0.0300***
		(0.0027)	(0.0026)	(0.0031)
Age		0.0057***	0.0030***	0.0041***
		(0.0005)	(0.0004)	(0.0005)
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X
R2	0.00138	0.0158	0.0518	0.0501
N	141,704	141,704	141,704	103,302
Panel B: By Language				
Diversity index	-0.0533***	-0.0445***	-0.0245***	-0.0101
	(0.0071)	(0.0067)	(0.0064)	(0.0090)
Female		0.0253***	0.0262***	0.0300***
		(0.0027)	(0.0026)	(0.0031)
Age		0.0058***	0.0030***	0.0041***
		(0.0005)	(0.0004)	(0.0005)
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X
R2	0.00096	0.0155	0.0518	0.0501
N	141,704	141,704	141,704	103,302

Notes: Robust standard errors clustered at field level are reported in parenthesis.
***Significant at 1%, **significant at 5%, *significant at 10%.

On the other hand, as we discussed before, there is a potential endogeneity issue in the OLS estimation. Thus, as a second step, we proceed using an IV approach to estimate the casual impact of diversity. In all specifications presented in Table 5.2, the first-stage regression results confirm that the estimated diversity index ($\tilde{D}_{tp}$) is strongly and positively correlated with the actual diversity index at 1% significance level. Also, we can conclude that first-stage F statistics in the IV estimations are sufficiently large to avoid weak instrument bias. (See Table 5.3 for the first-stage F statistics.)

Table 5. 2: First Stage Estimation Results by Using Estimated Diversity Indices as Instruments for Actual Diversity Indices

	(1)	(2)	(3)	(4)
Panel A: By Country of Citizenship				
Estimated diversity index	0.4494***	0.4284***	0.2532***	0.2668***
	(0.0120)	(0.0115)	(0.0088)	(0.0143)
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X
R2	0.185	0.214	0.378	0.360
N	141,704	141,704	141,704	103,302
Panel B: By Language				
Estimated diversity index	0.4509***	0.4248***	0.2362***	0.2556***
	(0.0117)	(0.0110)	(0.0087)	(0.0140)
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X
R2	0.183	0.217	0.376	0.371
N	141,704	141,704	141,704	103,302

Notes: Robust standard errors clustered at field level are reported in parenthesis. In each regression we also control for demographics (age and gender) in addition to fixed effects specified on the table.
***Significant at 1%, **significant at 5%, *significant at 10%.

In Table 5.3, IV estimation results show statistically significant estimations in each specification with various combinations of fixed effects. As the OLS estimates, when we control for country fixed effects and time fixed effects only, the coefficient of the diversity index is negative and significant, which is consistent with our OLS results. When we also control for university and field fixed effects, the effect of diversity gets smaller slightly, but it is still significant at 1% significance level. The results show that one standard deviation increase in the diversity index according to students' country of citizenship (sd=0.2535) decreases the likelihood of dropping out of the students in that class by 2.16 percentage points (which is 5.04% of the standard deviation in the observed attrition rates). Similarly, one standard deviation increase in the diversity index based on language spoken by the students (sd=0.2491) is associated with 2.73 percentage points decrease in the likelihood of dropping out of the students (which is 6.36% of the standard deviation in the observed attrition rates), as shown in Column (3). On the other hand, when we use balanced panel, increasing diversity by one standard deviation (0.2003 and 0.2035 respectively by country of citizenship and by language) reduces the likelihood of attrition by 2.66 and by 3.12 percentage points, respectively.

Table 5. 3: Effects of Cultural Diversity on Attrition Rates of International Students, IV Estimations

	(1)	(2)	(3)	(4)
Panel A: By Country of Citizenship				
Diversity index	-0.1620***	-0.1399***	-0.0854***	-0.1330***
	(0.0182)	(0.0183)	(0.0268)	(0.0454)
N	141,704	141,704	141,704	103,302
First-Stage F-statistics	1410.5	1385.9	464.1	188.2
Panel B: By Language				
Diversity index	-0.1442***	-0.1229***	-0.1094***	-0.1533***
	(0.0186)	(0.0188)	(0.0304)	(0.0479)
N	141,704	141,704	141,704	103,302
First-Stage F-statistics	1489.1	1501.4	517.5	276.7
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X

Notes: Robust standard errors clustered at field level are reported in parenthesis. In each regression we also control for demographics (age and gender) in addition to fixed effects specified on the table.
***Significant at 1%, **significant at 5%, *significant at 10%.

The estimated effects of diversity on the attrition behavior of students are much stronger in magnitude when we use IV estimation rather than OLS estimation. This may result from some omitted variables in the OLS estimation that have a significant impact on the attrition likelihood of the students and that are also correlated with the diversity of the students. One potential omitted variable might be the diversity among faculty members in the departments. However, in our data, we are unable to observe the information on the faculty members. Therefore, our OLS estimations for the effect of diversity on the attrition likelihood of the students are biased and inconsistent. We can consider that in the departments with a more diverse set of faculty members, the language barriers between professors and students might be much stronger and this might also impact the communication between professors and students negatively. Therefore, if the departments with diverse faculty have also diverse international student body, then the decreasing role of diversity among students on attrition rates might be underestimated in the OLS estimation. The observed difference between the OLS and IV estimates supports this hypothesis.

Table 5. 4: Effects of Cultural Diversity on Attrition Rates of International Students, IV Estimations, Including Student Composition within the Class

	(1)	(2)	(3)	(4)
Panel A: By Country of Citizenship				
Diversity index	-0.1842***	-0.1635***	-0.1103***	-0.1998***
	(0.0185)	(0.0183)	(0.0292)	(0.0556)
Country composition	-0.1128***	-0.1358***	-0.1445***	-0.1279***
	(0.0133)	(0.0245)	(0.0247)	(0.0314)
N	141,704	141,704	141,704	103,302
First-Stage F-statistics	964.39	367.94	207.29	102.92
Panel B: By Language				
Diversity index	-0.1713***	-0.1497***	-0.1258***	-0.2283***
	(0.0190)	(0.0189)	(0.0325)	(0.0613)
Language composition	-0.1142***	-0.1248***	-0.1087***	-0.1312***
	(0.0125)	(0.0208)	(0.0218)	(0.0300)
N	141,704	141,704	141,704	103,302
First-Stage F-statistics	820.05	399.67	278.61	150.76
Time fixed effects		X	X	X
Country fixed effects		X	X	X
University fixed effects			X	X
Field fixed effects			X	X
Balanced Panel				X

Notes: Robust standard errors clustered at field level are reported in parenthesis. In each regression we also control for demographics (age and gender) in addition to fixed effects specified on the table. ***Significant at 1%, **significant at 5%, *significant at 10%.

In the next regressions we also included either country composition or language composition of the students as an explanatory variable to explain the relationship between the likelihood of attrition and the diversity better. We used instruments for both diversity indices and students' composition variables. According to the IV estimations presented in Table 5.4, the effect of diversity in both Panel A and Panel B gets bigger in magnitude. We also conclude that the coefficients for country composition and language composition variables are negative and significant at 1% significance level. This means that when students are together with the other students from the same background as themselves, this decreases their likelihood of attrition. As you can see in Column (3), one percentage point increase in the country composition is associated with 0.1445 percentage points decrease in the attrition rate. When, we restricted our sample with the departments which accept at least one international student in each year, we observe that one percentage point increase in the country composition is associated with 0.1279 percentage points decrease in the attrition rate. As you can see in Panel B, the coefficients of language composition are also very similar.

Table 5. 5: Effects of Cultural Diversity by Country of Citizenship on Attrition Rates of International Students, IV Estimations, Conditional on Class Size and Broad Fields

		All Classes	Small Classes	Large Classes
ALL	Diversity Index	-0.1998***	-0.2454**	-0.1845**
		(0.0556)	(0.1044)	(0.0821)
	F-statistics	102.92	48.81	32.18
	N	103,302	35,507	67,795
SEM	Diversity Index	-0.1955***	-0.3084**	-0.0751
		(0.0756)	(0.1333)	(0.1011)
	F-statistics	72.76	33.72	23.94
	N	69,549	26,459	43,090
SSH	Diversity Index	-0.072	0.0728	-0.9138***
		(0.0880)	(0.3727)	(0.2702)
	F-statistics	13.82	2.01	10.31
	N	11,873	2,940	8,933
OTH	Diversity Index	-0.2367**	-0.2055	-0.4735
		(0.1009)	(0.2327)	(0.3881)
	F-statistics	33.67	9.36	4.48
	N	21,880	6,108	15,772

Notes: Robust standard errors clustered at field level are reported in parenthesis. In each regression we control for age and gender as well as time, country, field, and university fixed effects. We also use country composition of the students as an explanatory variable in these regressions in addition to diversity index.
***Significant at 1%, **significant at 5%, *significant at 10%.

Lastly, Table 5.5 and Table 5.6 consider the effects of diversity on subgroups in terms of broad fields and class size, by country of citizenship and by language, respectively. For each broad field, we calculated median class size according to all (141,704) students in our sample. Then, we repeated the regressions with balanced panel (Column (4)) for two categories: small classes which have less students than the median class size, and large classes which have more students than the median class size. Estimates show that diversity based on country of citizenship has a much stronger effect on the attrition rate in small classes than the large classes. According to broad fields, SEM is the only group that we have a significant estimate on the effect of diversity in small classes. Therefore, we can conclude that SEM is the group driving the overall decreasing effect of diversity on the attrition rates in small classes, but this is also because the SEM students consist of 74.5% of all students in that group. On the other hand, the effect of diversity based on languages spoken by students does not vary considerably by the class size as you can see in Table 5.6.

Table 5. 6: Effects of Cultural Diversity by Language on Attrition Rates of International Students, IV Estimations, Conditional on Class Size and Broad Fields

		All Classes	Small Classes	Large Classes
ALL	Diversity Index	-0.2283***	-0.2489**	-0.2364***
		(0.0613)	(0.1167)	(0.0893)
	F-statistics	150.76	52.92	46.33
	N	103,302	35,507	67,795
SEM	Diversity Index	-0.2334***	-0.3795***	-0.0935
		(0.0858)	(0.1442)	(0.1087)
	F-statistics	123.16	30.42	27.08
	N	69,549	26,459	43,090
SSH	Diversity Index	-0.1104	-0.0434	-0.8231**
		(0.1491)	(0.6230)	(0.3471)
	F-statistics	27.23	3.11	6.74
	N	11,873	2,940	8,933
OTH	Diversity Index	-0.2463**	0.0259	-0.4874**
		(0.1039)	(0.2255)	(0.2309)
	F-statistics	35.58	12.84	11.51
	N	21,880	6,108	15,772

Notes: Robust standard errors clustered at field level are reported in parenthesis. In each regression we control for age and gender as well as time, country, field, and university fixed effects. We also use language composition of the students as an explanatory variable in these regressions in addition to diversity index.
***Significant at 1%, **significant at 5%, *significant at 10%.

5.2. Robustness

In our main estimations, we control for both university and field fixed effects. The purpose of this is to capture the common attrition rates among students in each university or each field on the academic performance of the students since we have already known that in some universities and in some fields, we observe lower average attrition rates than others. However, more specifically, each department (i.e., a pair of university and field) may have different impacts on the students' performance. Therefore, controlling university and field fixed effects cannot be sufficient to control the variability in some cases. To address the robustness of our main results, we re-estimated our regressions by controlling department fixed effects instead of university and field fixed effects. Table A.2 in the appendix reports result from both OLS and first-stage estimations. As you can see, OLS estimations for the diversity indices in both balanced panel and whole sample are insignificant even at 10% significance level. On the other hand, we present the IV estimation results with department fixed effects in Table A.3. However, we interpret these results with caution since the first-stage F-statistics are below the critical level (i.e., less than 10); thus, the estimations suffer from the weak instrument bias. This can be resulted from that we do not have a sufficiently long panel data. We can only observe the departments for seven years and also the number of students in the Ph.D. departments are very limited, which is 5.27 for the SSH fields and 11.22 for the SEM fields in our sample, on average.

6. CONCLUSION

The number of international students has been increasing in US doctoral programs for the last few decades and there is a growing demand of international students to these programs. Colleges consider diversity measures when admitting students and publish the diversity parameters like female students' ratio and international students' ratio as well as the information about ethnic minorities in their webpages. This gives us an idea that diversity in graduate programs has been used as a good signal to attract international students. Thus, our interest in this paper lies in estimating the effect of cultural diversity on the attrition behavior of the international Ph.D. students.

In the existing literature, studies which investigate the effect of cultural diversity on the academic performance of the students in university settings find that cultural diversity is beneficial for the students (e.g. Braakmann and McDonald (2018) and Chevalier et al. (2020)). The estimated effect of cultural diversity in this paper is consistent with the recent findings. We find that cultural diversity within the classroom is significantly and negatively correlated with the attrition rates of the international Ph.D. students. Thus, students being together with a more diverse set of students are less likely to drop out of the graduate program. Estimates also show that diversity based on country of citizenship has a much stronger effect in small classes than the large classes. In addition, we find that the coefficients of both country composition and language composition are significantly negative, which means that students also get benefit from being together with the students from the same background as themselves. This can be explained by the idea that students with the same cultural background may find it easier to communicate and build a cooperation among themselves. On the other hand, being with a more diverse set of students increase the exposure to a wider set of knowledge and perspectives which may also help students to improve their academic performance.

Since there is not a similar study which investigates the effect of cultural diversity in the US graduate programs, this paper contributes to the literature to understand the impact of the increasing internationalization of the graduate programs in the US in terms of the cultural diversity on the academic performance of graduate students. However, it is important to highlight that the estimated effects reported in this paper only consider the international students who attend a doctoral program in the US with a temporary visa (or specifically F-1 visa). Therefore, in this study we have no estimation of how cultural diversity impact the academic performance of native students. Future research on the internationalization and the increased diversity at US graduate programs may hopefully consider the effect of cultural diversity on native students.

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APPENDIX

Table A. 1: Sample Composition by Language Background

Language	Associated Nationalities	Number of Speakers	Share in Sample (%)
MANDARIN	China, Hong Kong, Macau, Singapore, Taiwan	50,862	35.89%
ENGLISH	Anguilla, Antigua and Barbuda, Australia, The Bahamas, Barbados, Belize, Bermuda, British Virgin Islands, Cameroon, Canada, Cayman Islands, Dominica Eritrea, Fiji, Gambia, Ghana, Grenada, Guyana, India, Ireland, Jamaica, Kenya, Liberia, Malawi, Malta, Montserrat, New Zealand, Nigeria, Pakistan, Papua New Guinea, Philippines, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and The Grenadines, Sierra Leone, Sint Maarten, South Africa, Sri Lanka, Swaziland, Tanzania, Tonga, Trinidad and Tobago, Turks And Caicos Islands, Uganda, United Kingdom, Zambia, Zimbabwe	35,064	24.74%
KOREAN	North Korea, South Korea	14,570	10.28%
SPANISH	Argentina, Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Spain, Uruguay, Venezuela	6,477	4.57%
ARABIC	Algeria, Bahrain, Egypt, Gaza Strip, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates, West Bank, Western Sahara, Yemen	4,291	3.03%
PERSIAN	Afghanistan,Iran	4,149	2.93%
TURKISH	Turkey	4,032	2.85%
GERMAN	Austria,Germany,Switzerland	2,153	1.52%
JAPANESE	Japan	1,946	1.37%
FRENCH	Benin, Burkina Faso, Central African Republic, Congo (Brazzaville), Congo (Kinshasa), Cote D'Ivoire, France, French Polynesia, Gabon, Guinea, Haiti, Luxembourg, Madagascar, Mali, Martinique, Monaco, Niger, Rwanda, Senegal, Togo	1,477	1.04%
PORTUGUESE	Angola, Brazil, Cape Verde, Mozambique, Portugal	1,410	1.00%
RUSSIAN	Belarus, Russia	1,325	0.94%
GREEK	Cyprus, Greece	969	0.68%
ROMANIAN	Moldova, Romania	941	0.66%
DUTCH	Belgium, Netherlands, Netherlands Antilles, Suriname	409	0.29%
ALL OTHER (49)		11,629	8.20%
TOTAL SAMPLE		**141,704**	**100%**

Notes: All languages either have share in sample larger than 1.00% or spoken more than one country have listed in the table. Other languages have regrouped as "All Other".

Table A. 2: Effects of Cultural Diversity on Attrition Rates of International Students, OLS Estimations and First Stage Estimations with Department FEs

Panel A: By Country of Citizenship

OLS Estimates			First Stage Estimates		
Diversity index	0.0032	0.0144	Estimated diversity index	0.1688***	0.1910***
	(0.0075)	(0.0102)		(0.0551)	(0.0678)
Time fixed effects	X	X	Time fixed effects	X	X
Country fixed effects	X	X	Country fixed effects	X	X
Department fixed effects	X	X	Department fixed effects	X	X
Balanced Panel		X	Balanced Panel		X
R^2	0.117	0.081	R^2	0.582	0.515
N	141,027	103,302	N	141,027	103,302

Panel B: By Language

Diversity index	0.0049	0.0133	Estimated diversity index	0.1865***	0.2166***
	(0.0074)	(0.0099)		(0.0552)	(0.0683)
Time fixed effects	X	X	Time fixed effects	X	X
Country fixed effects	X	X	Country fixed effects	X	X
Department fixed effects	X	X	Department fixed effects	X	X
Balanced Panel		X	Balanced Panel		X
R^2	0.117	0.081	R^2	0.574	0.514
N	141,027	103,302	N	141,027	103,302

Notes: Robust standard errors clustered at department level are reported in parenthesis. In each regression we also control for demographics (age and gender) in addition to fixed effects specified on the table.
***Significant at 1%, **significant at 5%, *significant at 10%.

Table A. 3: Effects of Cultural Diversity on Attrition Rates of International Students, IV Estimations with Department FEs

	(1)	(2)	(3)	(4)
Panel A: By Country of Citizenship				
Diversity index	1.6957***	1.5119**	1.9506**	1.7343**
	(0.6383)	(0.6527)	(0.8212)	(0.8127)
Country composition			0.2709	0.2335
			(0.1817)	(0.1657)
N	141,027	103,302	141,027	103,302
First-Stage F-statistics	9.87	8.13	4.36	3.82
Panel B: By Language				
Diversity index	1.1966**	1.0060**	1.3306**	1.1137*
	(0.4760)	(0.4689)	(0.5817)	(0.5728)
Language composition			0.1438	0.1122
			(0.1113)	(0.1109)
N	141,027	103,302	141,027	103,302
First-Stage F-statistics	11.98	10.30	5.51	4.88
Time fixed effects	X	X	X	X
Country fixed effects	X	X	X	X
Department fixed effects	X	X	X	X
Balanced Panel		X		X

Notes: Robust standard errors clustered at department level are reported in parenthesis. In each regression we also control for demographics (age and gender) in addition to fixed effects specified on the table. In Column (1) and (2), country/language composition variables are not included in the regressions.

***Significant at 1%, **significant at 5%, *significant at 10%.