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WORKING WITHOUT BORDERS

The Promise and Peril of Online Gig Work

Short Notes Series #6: Spotlight on Gender Gaps in Online Hourly Rates

SOLUTIONS FOR YOUTH EMPLOYMENT

WORLD BANK GROUP Jobs

WORLD BANK GROUP Digital Development

Decoding Gender Disparities in Online Gig Work

Is the Gender Rate Gap a Confidence Gap?

2024

Executive Summary

The Opportunity

The global online gig workforce is expanding rapidly, now making up nearly 12% of the global labor force.* The flexibility of working hours and location associated with online gig work uniquely positions it as an avenue to boost female labor force participation, especially in regions with limited local job opportunities. About 42% of online gig workers are female, surpassing their 31.8% participation in the traditional labor market. However, challenges like internet disparities and unequal earnings persist, hindering the full realization of this potential. Further, in countries like India, Pakistan, and Mexico, their online gig representation falls short of their general workforce percentages.

The Research Question

This short note takes a deep dive into gender-based disparities in access to these new forms of work, especially asking whether there is a **gender gap in hourly rates that online gig workers "ask" for and earn from online tasks.** The analysis uses data from over 19,000 profiles on one of the largest English-language freelancing platforms.

Findings

Data from one of the largest global freelancing platforms shows that **women quote approximately 10% lower hourly rates than men, likely reflecting a difference in confidence**. While the gaps fluctuate across regions and task categories, the disparity remains, showing that online work patterns appear to mirror traditional labor market dynamics.

*This short note has been developed by **Karan Singhal** and **Natnael Simachew Nigatu**, S4YE, under the overall guidance of **Namita Datta**, S4YE Program Manager and Lead Author, Working Without Borders. The team is grateful to **Abigail Dalton**, Gender Group, for her valuable comments and to **Federica Saliola**, Manger Jobs Group, for her support.*

*Working without Borders: The Promise and Peril of Online Gig Work

Contents

Research Question

- While previous studies have explored gender differences in online marketplaces, limited evidence on the 'ask gap' and the gig economy's rapid evolution underscores the necessity for ongoing, detailed research to track emerging disparities. A few studies, such as in the online freelancing in the IT sector, where women earn 19% less than men (Liang et al. 2018), and on platforms like Upwork and Mturk, where US women bill 25% and earn 20% less than men, respectively, reveal factors unexplained by job type or experience (Foong et al. 2018, Adams-Prassl 2020)

- **In this note we asked the question: Is there a gender gap in quoted hourly rates for online gig work, and how do these variations differ across geographies and task categories?**

Data and Sampling

We gathered data on 19,000 online profiles of freelancers on one of the largest global online freelancing platforms.

Task categories:

- 10 distinct task categories as listed on the freelancing platform as of September 2023.
- These include tasks related to administrative support, artificial intelligence, information technology, finance, engineering, design, translation services and others.

Search Method: Utilized specific keywords matching each of the 10 task categories (e.g., "Artificial Intelligence Services").

Profile Availability: Each task-specific keyword displayed up to 10,000 top-ranked profiles, reflecting the platform's algorithmic results.

Sampling Methodology: From the available pool, we selected 200 random pages displaying information for 10 freelancer on each page (to target 2,000 profiles per task category, aiming for 20,000 profiles in total).

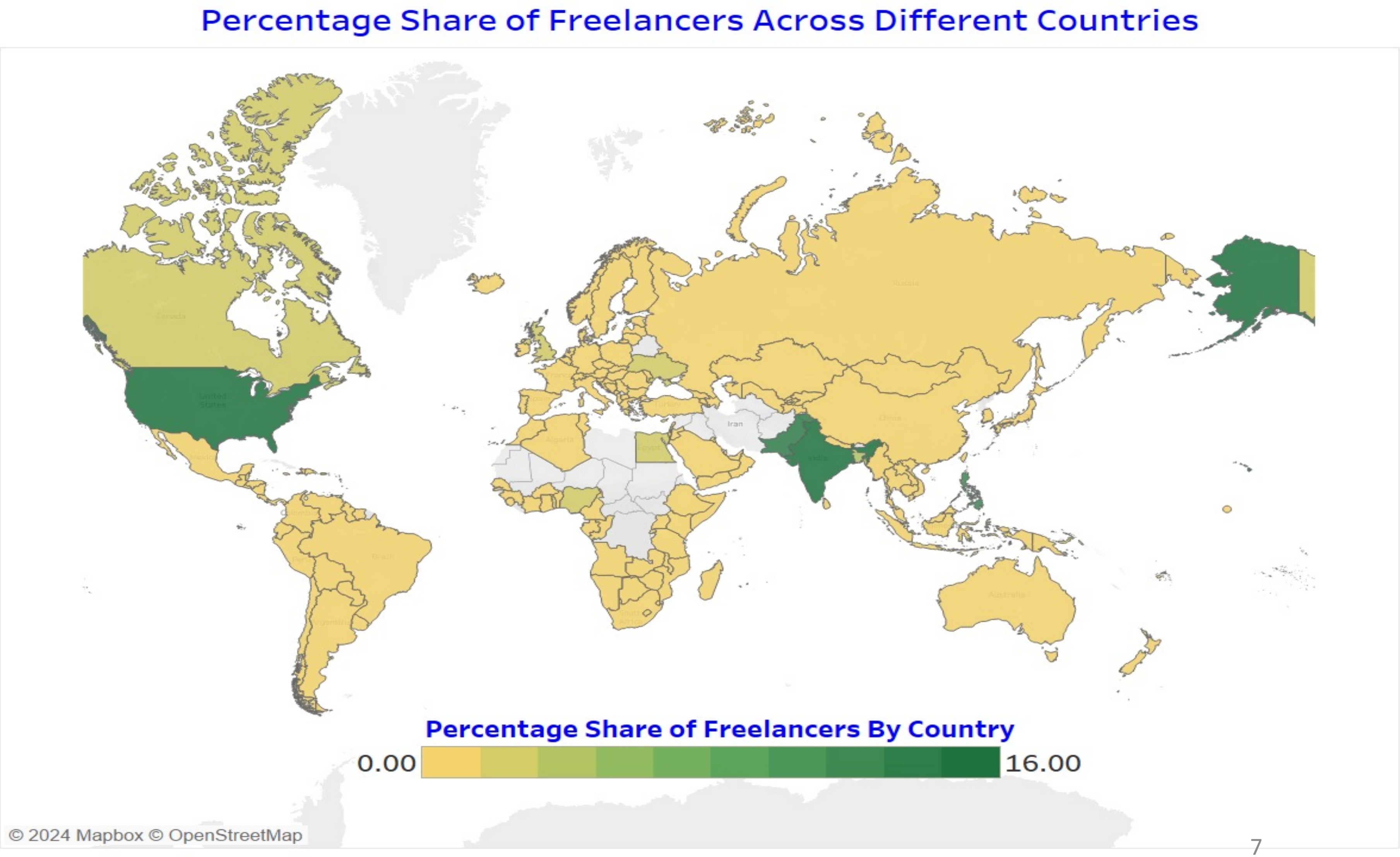
- Adopted an interval-based random sampling: Chose a starting number between 1 and 5, then sampled every 5th page thereafter.
- The data was collected in July 2023, and the final cleaning and data transformation process yielded a sample of 19,092 freelancers. No systematic bias was observed during the extraction and cleaning process.

Geographical Consistency: Profile consistency verified across different locations using VPN checks (e.g., USA, India).

More details about the sampling methodology, data extraction, description of variables and gender identification process is available in the Appendix

USA, India, Pakistan and Philippines have the largest share of online gig workers on the platform

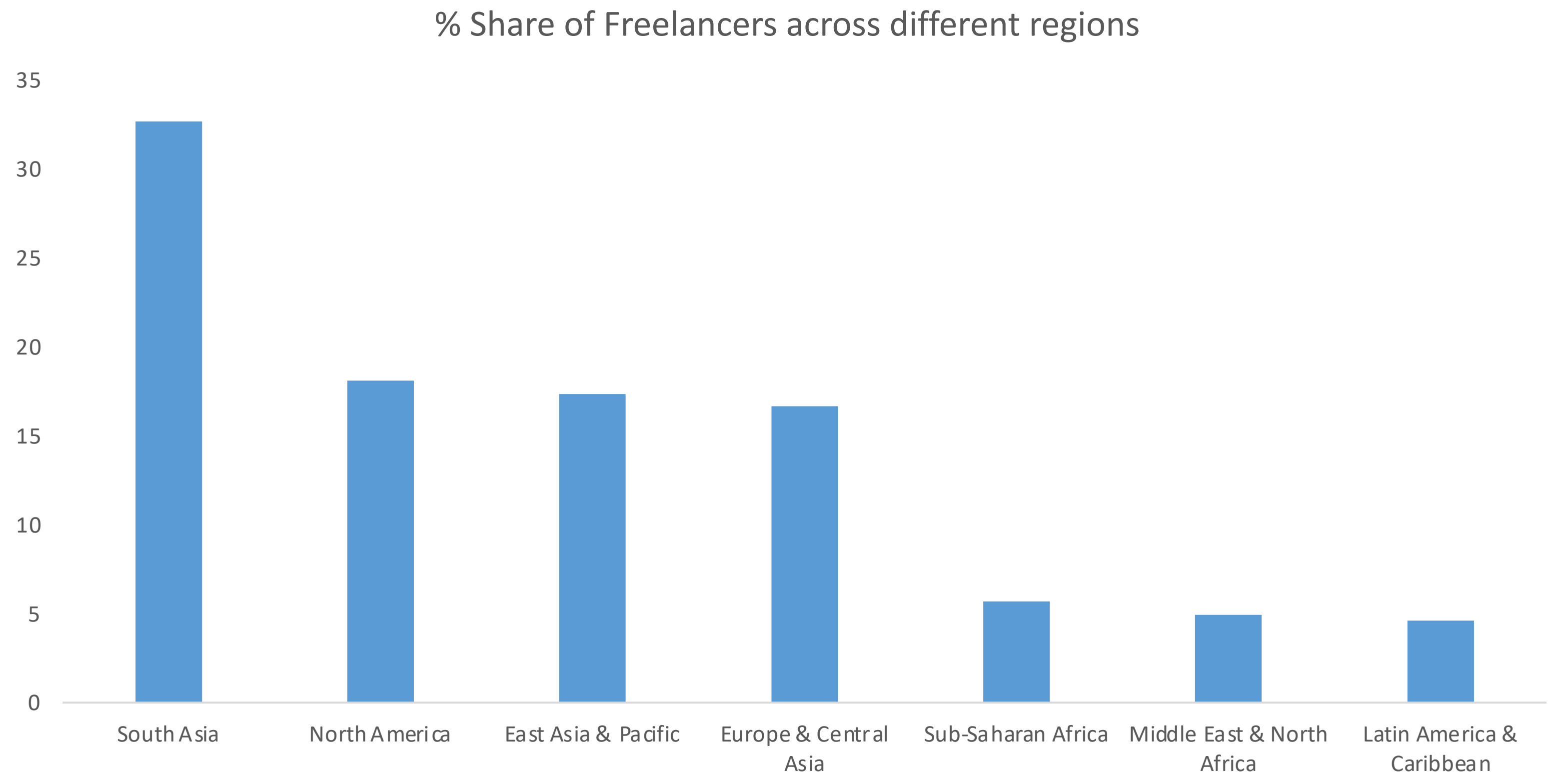
The platform has representation from over 150 countries. The list of countries and regional categorizations are available in the Appendix



Source: Based on data extracted from the freelancing platform in July 2023

South Asia Region dominates representation on the platform

Patterns on this platform largely reflect the findings from the *Working without Borders* report, with South Asian countries such as India, Pakistan, and Bangladesh having a significant presence

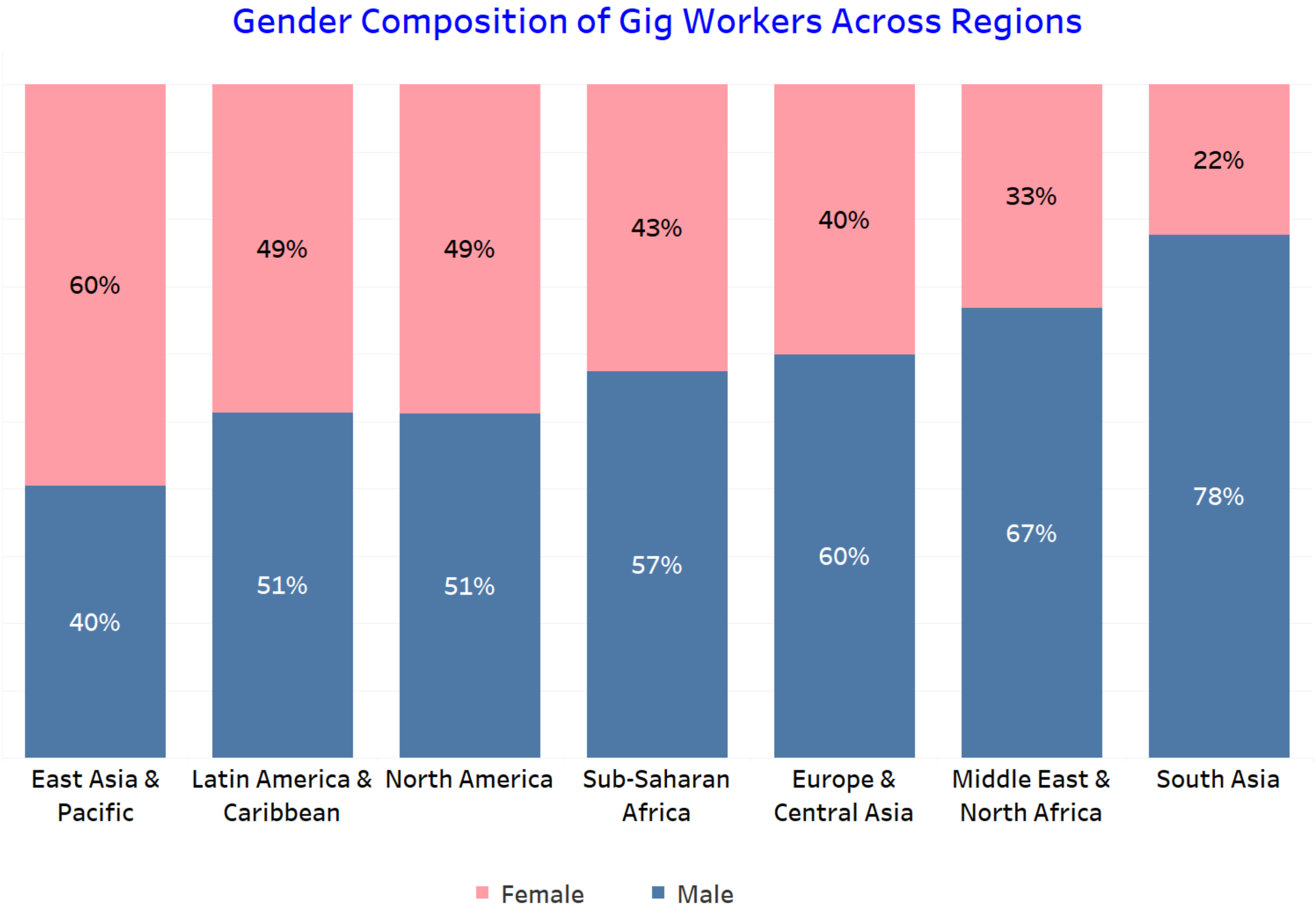


Source: Based on data extracted from the freelancing platform in July 2023

South Asia has the lowest percentage of female online gig workers on the platform

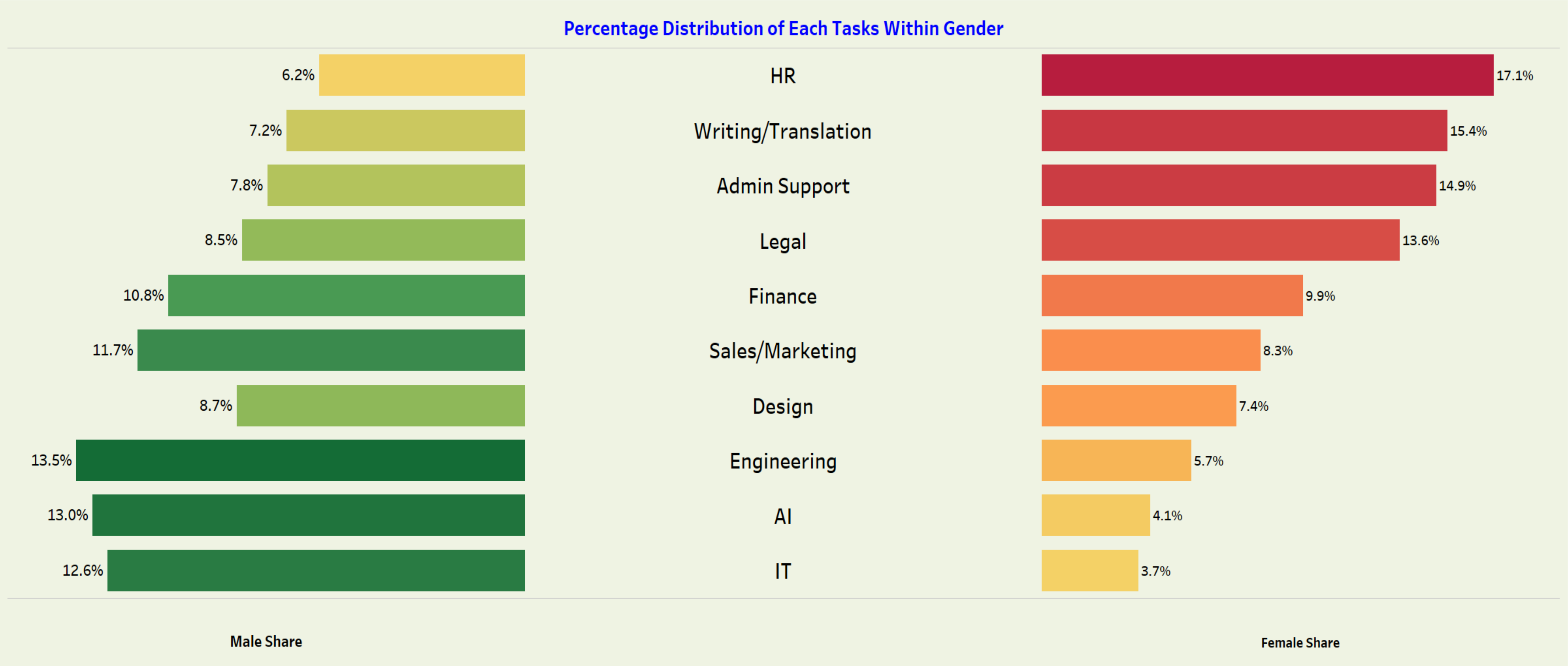
- Overall, 39.5% of the freelancers on this platform are female

- In the EAP, the higher share of females is mainly influenced by a significant presence of female freelancers from the Philippines. These freelancers are primarily engaged in the administrative support tasks on the platform



Source: Based on data extracted from the freelancing platform in July 2023

Women participate more in tasks like HR, but less in IT and AI services…reflecting similar patterns in occupational segregation in the offline labor market



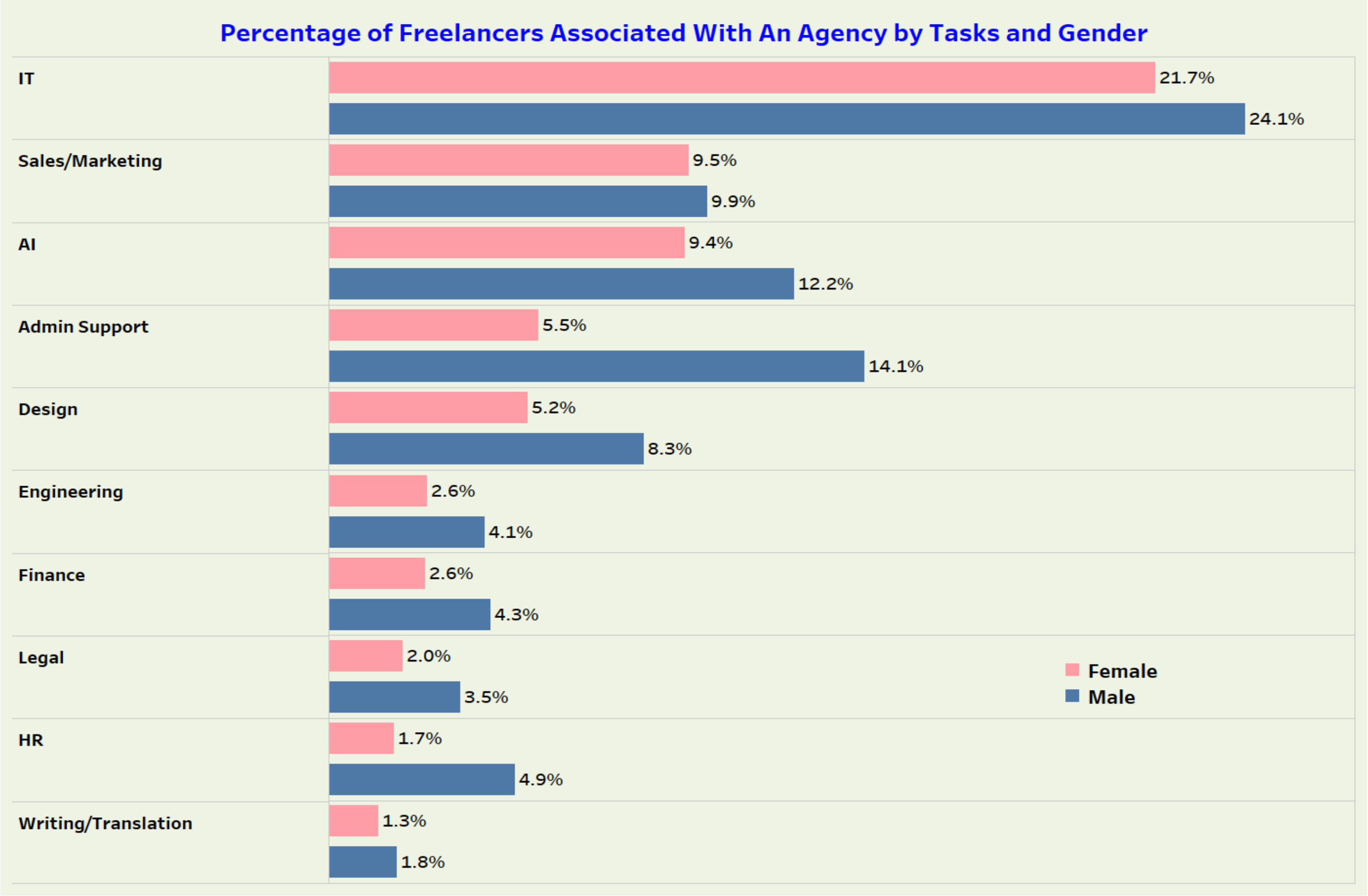
Source: Based on data extracted from the freelancing platform in July 2023

Men are over twice as likely to associate with an agency* on the platform, even in some female-dominated tasks

- Overall, 7% of freelancers on the platform are associated or work with a formal agency, with 9% among males and 4.3% among females

- Geographical differences are evident, with agency association as high as 20% among Indian freelancers and a low 4% among freelancers from the US

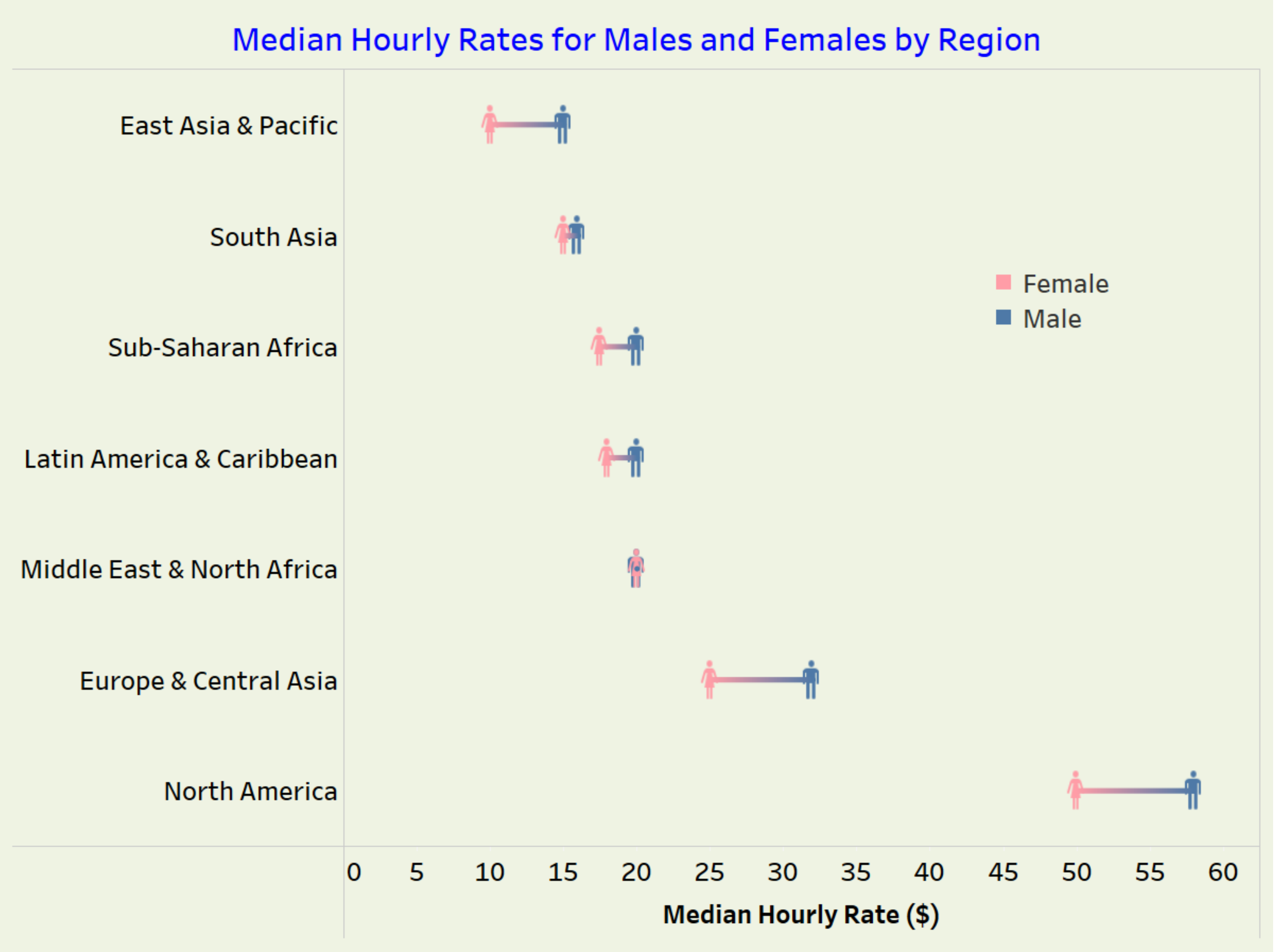
** Agencies on the platform offer specialized services and maintain a pool of affiliated freelancers. Although freelancers associated with agencies may experience reduced flexibility and control over projects compared to when they are independent, they gain experience for future work, build a credible reputation and profile for more opportunities to be involved in larger projects..*



Source: Based on data extracted from the freelancing platform in July 2023

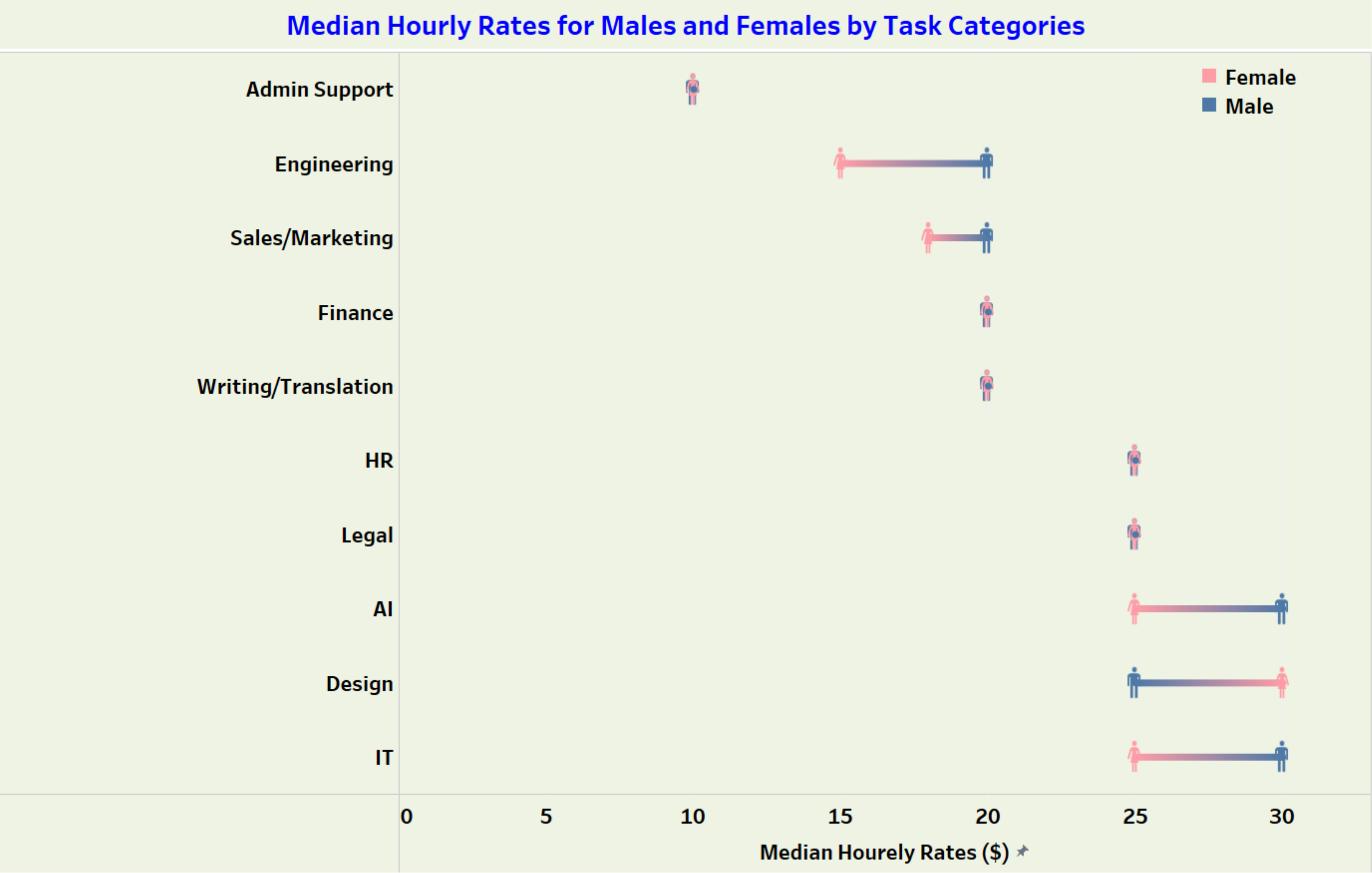
Women consistently have lower hourly rates than men across regions

- Overall, the median rate quoted on the platform is $25 for males and $20 for females
- Significant differences among females as well - the median EAP female quotes $10, while a North American counterpart quotes five times higher at $50 for work on the platform
- Gender gaps are higher in North America and Europe, at least partly due to a greater gender gap in higher-paying tasks like AI and IT. For instance, in South Asia, 8% of females work in AI services compared to 12% of males, while in North America, it's 3% females versus 17% males.



Source: Based on data extracted from the freelancing platform in July 2023

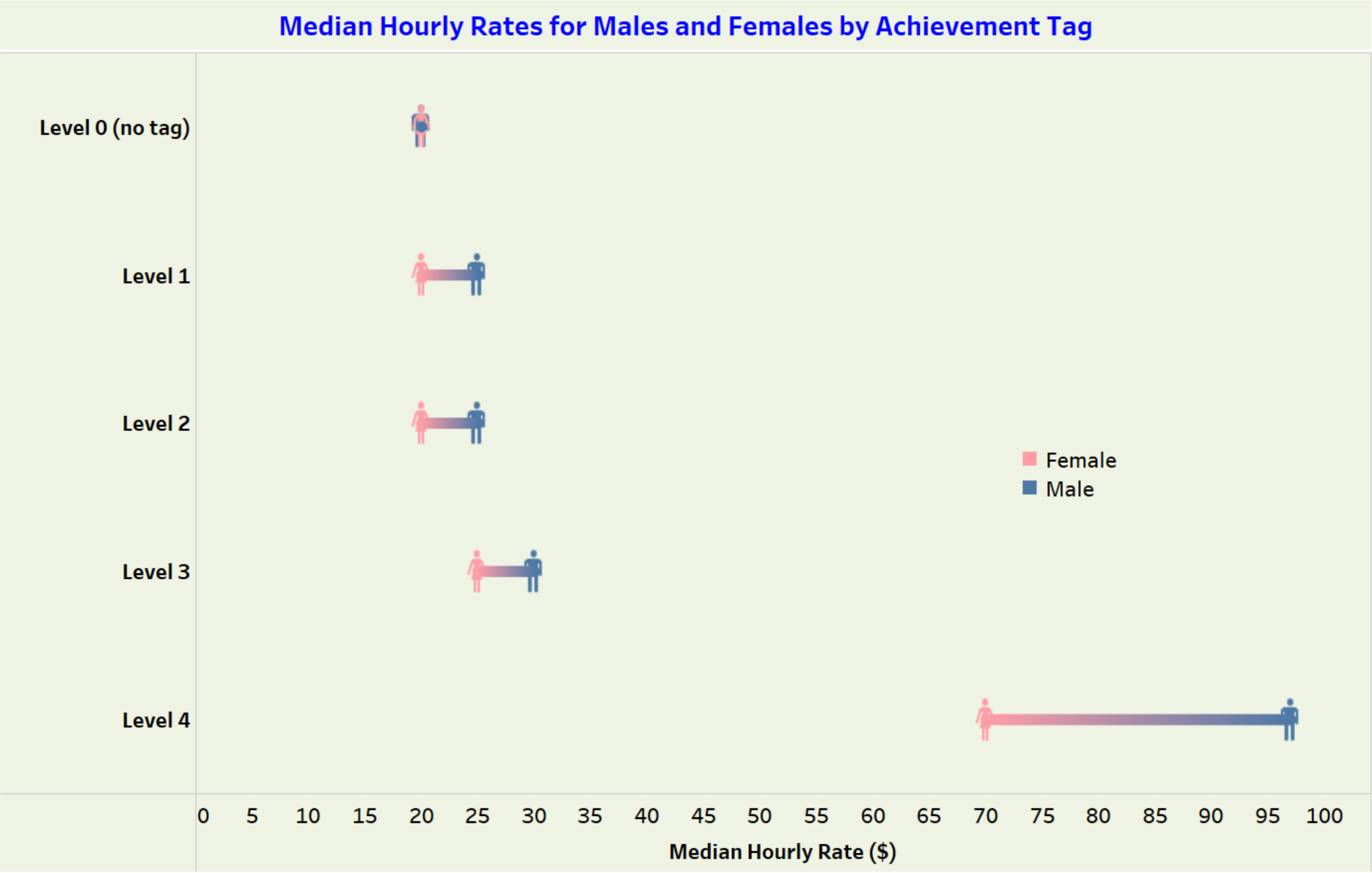
Men quote higher rates than women on most tasks, but design tasks are an exception



Source: Based on data extracted from the freelancing platform in July 2023

Even among those with high achievement tags on the platform, women consistently exhibit lower median hourly rates

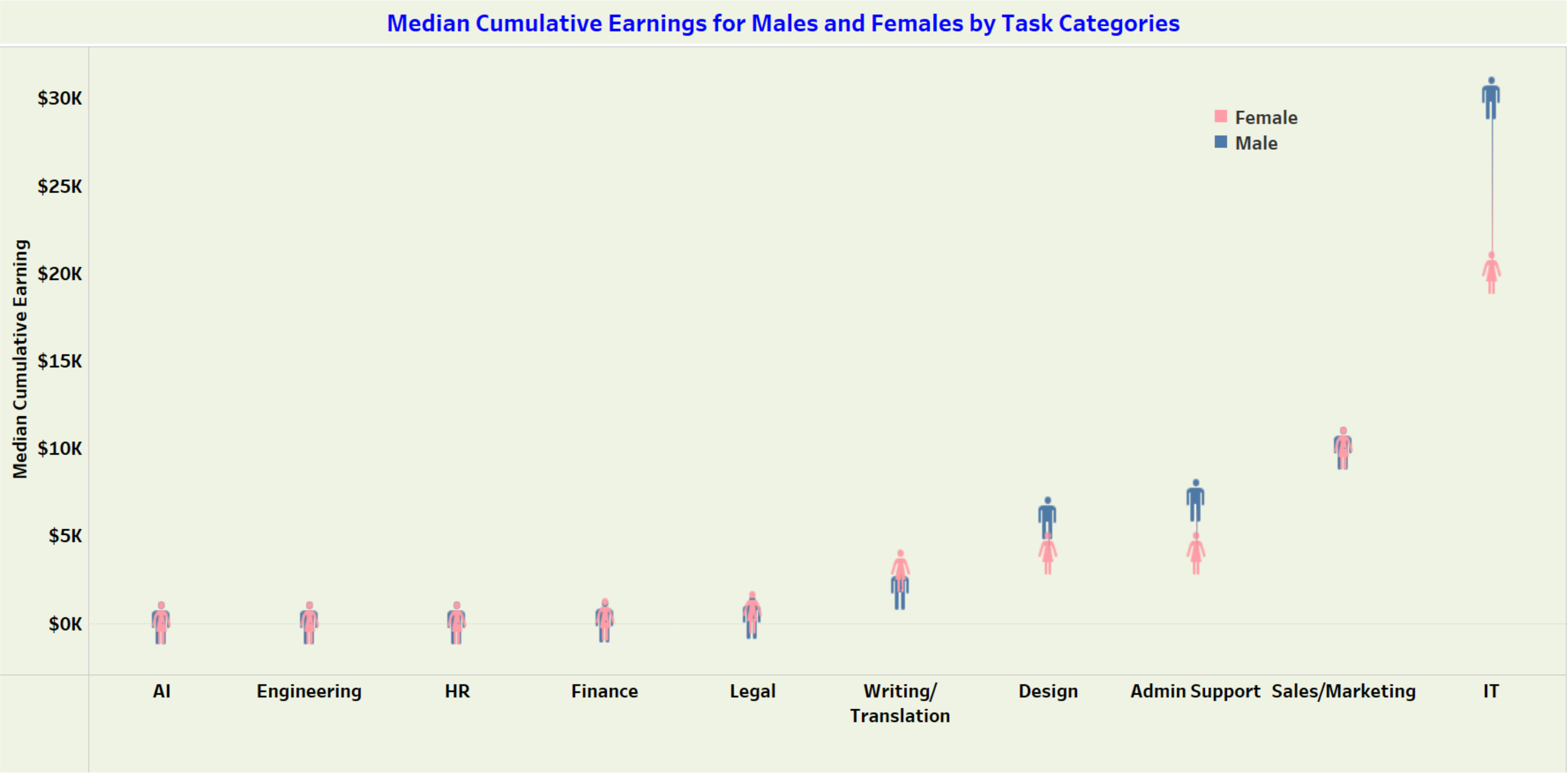
The platform assigns achievement tags based on freelancers' job completion rate, success rate, and recent earnings. Acquiring the highest tag (Level 4) requires an interview.



Source: Based on data extracted from the freelancing platform in July 2023

Men dominate in many task categories, particularly in IT, with higher median cumulative earnings; median earnings are zero for both males and females in several tasks

Note: This analysis is derived from approximately 16,500 (86%) of the sample, as cumulative earnings data is unavailable for all freelancers. Exceptions include those associated with agencies and individuals with premium accounts who opt not to disclose their earnings



Source: Based on data extracted from the freelancing platform in July 2023

Women quote ~10% lower hourly rates than men - even after controlling for observable factors

	(1)	(2)	(3)	(4)	(5)	(6)
	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr
Female	-0.0902***	-0.118***	-0.115***	-0.106***	-0.103***	-0.105***
	(0.0134)	(0.0118)	(0.0118)	(0.0115)	(0.0124)	(0.0122)
Controls						
Region	No	Yes	Yes	Yes	Yes	No
Task category	No	Yes	Yes	Yes	Yes	Yes
Agency Association	No	No	Yes	Yes	Yes	Yes
Achievement tags	No	No	No	Yes	Yes	Yes
Cumulative earnings	No	No	No	No	Yes	No
Country Fixed Effects	No	No	No	No	No	Yes
Constant	3.132***	3.605***	3.588***	3.473***	3.412***	2.702***
	(0.00842)	(0.0222)	(0.0222)	(0.0223)	(0.0243)	(0.0188)
N	19063	19063	19063	19063	16469	16501

Standard errors in parentheses. *p<0.10, ** p<0.05, *** p<0.01

Note: These results are from a linear regression using logarithmic hourly rates as the outcome variable. Columns 1 to 5 present stepwise estimates with the addition of region, task category, and other controls.

In Column 6, the sample is restricted to a subset of 29 dominant countries, comprising 87% of the total sample, using country-level fixed-effects. The list of countries included are available in the Appendix.

Even in design tasks, the only task category where differences favored females, female hourly rates are lower after controlling for other factors

	Admin Support	AI	Design	IT	Engineering	Finance	HR	Legal	Sales/ Marketing	Writing/ Translation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr
Female	-0.089***	-0.19***	-0.049*	-0.0988***	-0.0455	-0.129***	-0.049	-0.21***	-0.082**	-0.0305
	(0.0279)	(0.044)	(0.030)	(0.037)	(0.049)	(0.035)	(0.04)	(0.038)	(0.036)	(0.0278)
Controls										
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency Association	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Achievement tags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.489***	3.979***	3.849***	4.033***	3.772***	4.064***	3.962***	4.186***	3.946***	3.549***
	(0.0469)	(0.0397)	(0.0363)	(0.0450)	(0.0638)	(0.0396)	(0.0415)	(0.0438)	(0.0433)	(0.0551)
N	2020	1815	1557	1729	1987	1987	2005	2005	1972	1986

Standard errors in parentheses. *p<0.10, ** p<0.05, *** p<0.01

Note: These results are from a linear regression using logarithmic hourly rates as the outcome variable.

Gender differences persist in quoted hourly rates across regions, with statistically significant disparities most robust in EAP, ECA, and North America

Note: These results are from a linear regression using logarithmic hourly rates as the outcome variable.

	East Asia & Pacific	Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	North America	South Asia	Sub-Saharan Africa
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr	Log $/ hr
Female	-0.130***	-0.0999***	-0.105**	-0.0893	-0.138***	-0.0547**	-0.0543
	(0.0260)	(0.0253)	(0.0494)	(0.0575)	(0.0242)	(0.0231)	(0.0468)
Controls							
Task category	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agency Association	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Achievement tags	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.190***	3.121***	2.562***	2.380***	3.547***	2.324***	2.314***
	(0.0311)	(0.0615)	(0.0831)	(0.152)	(0.0509)	(0.0358)	(0.0690)
N	3304	3178	879	942	3453	6226	1081

Standard errors in parentheses. *p<0.10, ** p<0.05, *** p<0.01

Discussion: What could explain gender differences in hourly rates?

Is it caused by gender-based disparities in information and education level? Information disparities are improbable, given freelancers' ready access to publicly available data on prevailing rates and skills. Educational differences are also unlikely, as the recent report does not find any gender disparity favoring men in education levels among online gig workers

Is it due to male dominance in premium-rate skills? While it is possible, it is unlikely to be the sole or primary driver of observed disparities, given the clear demarcation of task categories on the platform (such AI, Design, Architecture) representing varying skill sets

Do women employ a more strategic pricing strategy, quoting lower rates? While it is possible, this tendency, if at all, might become more apparent during negotiations and, even then, would not eliminate the potential influence of the confidence gap on pricing. Additionally, cumulative earnings do not necessarily indicate that women are working more than men on the platform.

Is it due to a 'confidence gap'? This is likely to be one of the channels and aligns with existing literature on competition and confidence disparities (Niederle and Vesterlund 2007; Lundberg 2022), emphasizing women's lower expectations. Actual hourly earnings between men and women on the platform may be narrower, as effective client negotiation could potentially drive women's rates down (Biasi and Sarsons 2022).

Encouragingly**, platform design can address such disparities**. Pre-filling the salary request field with the median bid salary of similar candidates effectively bridged gender 'ask gaps' (Roussille 2023), highlighting the potential of platform design to mitigate gender-based wage disparities.

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Appendix

Sample size and extraction across categories

- **Extraction Method:** Profiles from searches were extracted in .txt format and subsequently transformed into a matrix
- **Total Profiles**: The transformation process resulted in 19,092 profiles.
- **Exclusion Details**: There were minor exclusions (less than 5% of the intended sample) during scraping and transformation and were found to be random.
  - Manual verification was conducted on a stratified sample of 600 profiles (from the beginning, middle, and end of the list) to confirm accuracy
- **Duplicate Profiles**: Among the 19,092 profiles, 55 were identified as duplicates across task categories.
  - 53 profiles appeared in two tasks, while 1 profile showed up in three.
  - Given the task-specific nature of most data and the minimal impact of these duplicates, they have been retained in the sample

Task categories	Number of observations	%
Artificial Intelligence (AI)	1,819	9.53
Administrative Support	2,020	10.6
Design	1,559	8.17
Information Technology (IT)	1,729	9.06
Engineering	1,996	10.5
Finance	1,990	10.4
Human Resources (HR)	2,010	10.5
Legal Services	2,007	10.5
Sales/ Marketing	1,975	10.3
Writing/Translation services	1,987	10.4
Total	19,092	100

Note: The exact names of the tasks/categories have been anonymized

Description of variables

- **Name** (which is used to determine gender)
- **Hourly Rate**: Quoted rate in USD.
- **Cumulative earnings on the platform in USD**. Exclusions: Freelancers associated with agencies don't display individual earnings and premium members can opt to hide their earnings from public view
- **Country**: Registered location of the freelancer
- **Task category/Skill**: Freelancer's specialized domain from a set of 10 tasks representing different skillsets
- **Achievement tags**:
  - The platform awards achievement tags to denote experience and expertise based on job completion rate, success rate, and recent earnings of the freelancer.
  - There are four possible tags, with the highest one involving an interview process and only given to a select few
- **Agency Association**: Whether a freelancer is affiliated with a formal agency that is registered on the platform

- **Gender Identification Process**: The data lacked a gender label. The team used a name-matching database combined with manual verification to establish gender for each profile. The primary method used is matching using the Onograph (Forbears) database, which assigns gender probabilities based on names and countries. Gender was identified for 19,063 profiles (over 99.8% of the sample)

- Women constitute 39.5% of the sample, aligning with the larger report and platform-specific estimates available online.

Gender Identification in the sample

- **Initial Identification:** Used the Onograph (Forbears) database, which provides gender probabilities for millions of names.
  - 80% of profiles were identified with 90% or higher gender probability.
  - 91% were identified with a gender probability greater than 75% (which was set as the threshold for automatic assignment)
- **Manual Validation**: 400 random entries were manually verified to confirm gender assignment, including at least 100 names from the 75-80% probability range.
  - Verification involved matching profile images, pronouns in profiles/reviews, and manual searches on the platform
- **Manual Gender Assignment**: For the almost 9% (or 1685 observations) not meeting the threshold, gender was assigned using the same manual verification methods.
- **Final Sample**: Total profiles with gender identification: 19,063. Profiles where gender couldn't be assigned: 29 (excluded from analysis)
- Females constitute 39.5% of freelancers in our data

Countries and Regions

- There are 159 countries and territories represented in the sample. These are categorized have been classified into seven regions and four income groups as per the World Bank classification system to ease the analysis

- **East Asia & Pacific (EAP):** Philippines, China, Malaysia, Indonesia, Australia, Singapore, Thailand, Japan, New Zealand, Vietnam, South Korea, Myanmar, Papua New Guinea, Taiwan, Hong Kong, Brunei Darussalam, Cambodia, Fiji, Mongolia, Laos, and French Polynesia.
- **Europe & Central Asia (ECA):** Turkey, Germany, United Kingdom, Kazakhstan, Ireland, Estonia, Netherlands, Hungary, France, Romania, Albania, Italy, Ukraine, Bosnia and Herzegovina, Czech Republic, Spain, Poland, Greece, Kyrgyzstan, Serbia, Macedonia, Armenia, Latvia, Slovenia, Switzerland, Denmark, Cyprus, Moldova, Uzbekistan, Austria, Portugal, Luxembourg, Croatia, Sweden, Georgia, Finland, Montenegro, Slovakia, Lithuania, Norway, Belgium, Azerbaijan, Bulgaria, Reunion, Iceland, Russia, Tajikistan, and Guadeloupe.
- **Latin America & Caribbean (LAC)**: Mexico, Jamaica, Argentina, Belize, Dominican Republic, Paraguay, Colombia, Brazil, Venezuela, Honduras, Costa Rica, Nicaragua, Uruguay, El Salvador, Chile, Peru, Guatemala, Ecuador, United States Virgin Islands, Dominica, Cayman Islands, Saint Lucia, Panama, Suriname, Haiti, Bolivia, Puerto Rico, Antigua and Barbuda, Guyana, Trinidad and Tobago, Saint Kitts and Nevis, and Barbados.
- **Middle East & North Africa (MENA)**: Egypt, Kuwait, United Arab Emirates, Algeria, Morocco, Qatar, Jordan, Saudi Arabia, Palestinian Territories, Oman, Tunisia, Lebanon, United Arab Emirates, Israel, Malta, Bahrain, Yemen, and Egyptian.
- **North America**: United States, Canada, and United States Minor Outlying Islands.
- **South Asia Region (SAR)**: Bangladesh, India, Pakistan, Nepal, Sri Lanka, and Maldives.
- **Sub-Saharan Africa**: South Africa, Nigeria, Tanzania, Kenya, Rwanda, Cameroon, Ethiopia, Madagascar, Uganda, Benin, Togo, Guinea, Ghana, Botswana, Burkina Faso, Swaziland, Sierra Leone, Mauritius, Zimbabwe, Namibia, Zambia, Malawi, Seychelles, Gabon, Angola, Cote d'Ivoire, Lesotho, Congo, Somalia, Senegal, and Mozambique.

Countries included in the country fixed-effects regression

Countries that have at least 100 observations and included in column (6) of the main regression table are United States, India, Pakistan, Philippines, Bangladesh, Nigeria, Ukraine, United Kingdom, Canada, Egypt, Turkey, Kenya, Germany, Indonesia, United Arab Emirates, France, Italy, Brazil, Spain, South Africa, Mexico, Poland, Australia, Vietnam, Argentina, China, Serbia, Colombia, Romania