Aletheia
WORKING PAPER SERIES

The Value of Remote Work: A Correspondence Experiment on Tutors

SOFOKLIS GOULAS

May 2025
GAPS Lab

Working Paper No. 04/2025
Aletheia Research Institution

The Value of Remote Work: A Correspondence Experiment on Tutors

Sofoklis Goulas[1]

May 13, 2025

Abstract

This study explores the preference for remote work by sending thousands of randomized messages to tutors advertising on an online platform across Greece. The messages requested either in-person or online tutoring. Requests for online lessons were roughly 50 percent more likely to receive a callback (10.7 vs. 7.3 percent). Female tutors, STEM tutors, and those in high-competition areas showed stronger preferences for online lessons. Tutors favoring remote work also demanded higher premiums for in-person sessions. Survey findings suggest that online tutoring aligns with higher job satisfaction, more employment opportunities, improved instructional effectiveness, and increased tutoring hours.

Keywords: Remote work, in-person wage premium, online learning, tutoring, experiment
JEL Codes: J2, J3, J4, J6, C93

[1]Brookings Institution, Yale University, Aletheia Research Institution, and IZA (email: sofoklis.goulas@yale.edu).
I would like to thank Lauren Bauren, Wendy Edelberg, Carol Graham, Mike Hansen, Sarah Reber, Jon Valant and seminar participants at the Brookings Institution for their helpful comments and suggestions. The content of this paper is solely the responsibility of the author. This project has been cleared by the Institutional Review Board of Health Media Lab, Inc. (protocol # 2644). This study has been pre-registered at the AEA RCT Registry (AEARCTR-0013801).

1 Introduction

The widespread adoption of remote work during the COVID-19 pandemic was made possible by recent technological advancements that enabled office tasks to be completed from home. This global experiment reshaped how businesses and workers approach work arrangements, leading to significant growth in the remote labor market post pandemic (Barrero, Bloom, and Davis, 2021). Currently, 12 percent of workers are fully or almost fully remote, while nearly 29 percent work in a hybrid arrangement, splitting time between home and their employer's site. In this evolving landscape, remote workers are often paid less than their in-person counterparts (Zarate, Dolls, Davis, Bloom, Barrero, and Aksoy, 2024).

Various theories have been proposed about why remote workers are paid less than in-person workers. First, remote work can be seen as an amenity that the workers prefer. Survey results support that most people prefer to work remotely part of the week, with the average worker willing to give up 20 percent of wages to avoid a schedule set by an employer on short notice, and eight percent for the option to work from home (Mas and Pallais, 2017). Second, as a newfound job amenity, remote or hybrid work raises the supply of labor at any given wage and puts downward pressure on real wages. Third, remote work may be associated with lower pressure for wage growth and might make it easier for companies in high-wage areas to hire workers from low-wage areas (Barrero, Bloom, Davis, Meyer, and Mihaylov, 2022). Fourth, work from home may influence the extent of spatial competition in labor markets. Especially in fully remote jobs, competition from workers in other locations can exert a powerful influence on wages (Barrero, Bloom, and Davis, 2023; Brinatti, Cavallo, Cravino, and Drenik, 2023).

This study combines information on tutor demographics, education, experience, location and ask hourly rate data from an online tutor board in Greece with a correspondence experiment on the same board to elicit worker preference for remote work and investigate the price for in-person and remote work. In the correspondence experiment, thousands of randomly created messages were sent by email in response to postings offering tutoring services across Greece in July and August 2024. The messages were designed to plausibly represent typical parents who inquire about tutoring services for their child. There were two treatment conditions: (1) a message that inquired about in-person lessons, and (2) a message that inquired about online lessons.

Tutors provide a valuable context for the study of the preference for remote work for three key reasons. First, they are self-employed. Fully remote work is four times as common for the self-employed as for employees (Barrero, Bloom, and Davis, 2023). This suggests that people who navigate toward self employment, including contract and gig work, might have a strong desire for work in fully remote capacity. Thus, measures of preference for remote work among employees may not represent those of workers in contract or gig industries. Second, tutors enjoy considerable flexibility in setting their own schedule even when offering lessons in person. Tutors usually negotiate the days and times that work best for them. Mas and Pallais (2017) show that employees value work from home more than other employee-friendly work arrangements. By comparing callbacks for requests for lesson online versus in person, this study captures the preference for remote work rather than scheduling flexibility.

Third, tutors' effort is constantly monitored by students and guardians. Previous work emphasizes the importance of agency in determining wages for individuals working from home. White (2019) suggests that the decreasing cost of monitoring employee effort has contributed to the narrowing wage differentials between in-person and at-home workers, from a 26 percent penalty in 1980 to a 5 percent premium in 2014. Tutor effort is more easily observed by employers than in other occupations, mitigating concerns about the influence of monitoring costs on the in-person wage premium.

The results reveal that tutors show a stronger preference for online tutoring, as indicated by a 3.9 percentage-point (or 53.4 percent) higher likelihood of receiving callbacks for online requests compared to in-person requests, after accounting for tutor characteristics. The preference for online lessons is stronger among female tutors, with a 4.7 percentage-point gap compared to 2.1 points for males. The gap between online and in-person requests is wider for STEM tutors (e.g., Biology, Chemistry, Mathematics, Physics) than for non-STEM tutors (7.1 vs. 2.6 percentage points), indicating a stronger preference for remote work among STEM tutors. Tutors in areas with higher local competition also show a greater gap in callback rates for online versus in-person lessons (5.8 vs. 2.6 percentage points), suggesting that increased competition may amplify their preference for remote work. I investigate the sensitivity of the results to various definitions of local competition. As the radius defining local competition widens, the preference for online lessons becomes even more pronounced, indicating that broader competition enhances the attractiveness of remote tutoring. Tutors' callback feedback indicates that their preference for online lessons is driven by time savings, reduced commuting, and the effectiveness of digital tools, which enhance both the quality and accessibility of remote learning.

I develop a simple theoretical framework to explain why ask rates for remote work are generally lower than for in-person work, emphasizing the roles of capacity expansion and demand elasticity. The framework provides a dual mechanism: (1) remote work increases tutors' capacity, prompting them to offer more hours and thus set rates at a lower point on the marginal revenue curve; and

(2) the greater competition in online markets increases demand elasticity, leading tutors to further reduce rates. However, it also accounts for the moderating effect of differentiation, which allows some tutors to maintain higher rates for remote services despite increased competition. Key implications of this framework are that remote work can be more profitable for tutors who capitalize on increased labor supply, and that the observed rate reductions in remote tutoring markets are not solely due to lower costs, but also strategic adjustments to demand conditions.

I use tutors' posted ask rates for in-person and online lessons on the tutor board to empirically investigate the model's predictions regarding tutors' pricing decisions. Tutors ask for higher rates for in-person lessons than online lessons, with an average in-person premium of 1.1 Euros. This premium is larger for STEM tutors, and in areas with more competition. I find a positive association between the in-person rate differential and callback rates, indicating that tutors who set a higher in-person rate premium also exhibit a stronger preference for remote work. Furthermore, the larger callback gap observed at higher levels of the in-person rate differential suggests that the true valuation of remote work might exceed the posted rates. This implies that the actual in-person premium could be higher than the descriptive average of 7.6 percent, which also aligns with prior research (Mas and Pallais, 2017).

Unless a job's tasks are largely unsuited for it, work-from-home intensity reflects choices in job design, management practices, culture, and lifestyle. These choices are influenced by shifting perceptions of productivity, remote work stigma, tool availability, and an organization's ability to manage remote work, as well as changing employee preferences. When tasks are more suitable for remote work, even small shifts in these factors can lead to significant increases in work-from-home adoption. To understand the drivers of preference for remote work, I collected qualitative information perceptions of productivity, stigma, and tool availability in a survey instrument disseminated in the same study population after the completion of the correspondence experiment.

I explore the reasons behind tutors' preference for online lessons using a survey deployed on the tutor board. The survey asked tutors to rate their agreement with 17 statements comparing online and in-person lessons, using a scale from -5 (completely disagree) to 5 (completely agree). To mitigate acquiescence bias, the statements were displayed in both positive and reverse wording. The survey results show that around 55 percent of respondents preferred teaching online, while 16 percent were indifferent, and less than 30 percent preferred in-person lessons. The top reasons driving a preference for online lessons include access to technological tools, increased tutoring hours, and job satisfaction. The mechanisms analysis identifies key factors like additional employment, teaching more hours, and recognition as significant in shaping tutors' preferences. I observe gender differences, with women placing more importance on access to technology and scheduling flexibility, while men prioritized personal teaching effectiveness and recognition. The survey findings validate the theoretical prediction that online lessons can increase profitability by expanding tutors' labor supply.

This study contributes to three key strands of the literature.[1] First, it relates to the rapidly expanding body of work on the rise of remote work and its implications (Barrero, Bloom, and Davis, 2021, 2023; Barrero, Bloom, Davis, Meyer, and Mihaylov, 2022; Brinatti, Cavallo, Cravino, and Drenik, 2023). Remote work, characterized by the absence of commuting and flexible scheduling, is increasingly seen as a desirable work arrangement. The literature documents workers' preference for such flexibility; for example, Mas and Pallais (2017) and He, Neumark, and Weng (2021) find that workers are willing to sacrifice part of their wages to gain the option of working from home. In this study, tutors can allocate their labor to either the in-person or online market, highlighting a unique aspect of remote work in this context: it allows tutors to offer more lessons by freeing up time otherwise spent commuting. Thus, remote work may not only be valued as an amenity but also as a means of increasing tutor profits through expanded labor supply in a market with somewhat differentiated tutors. Aksoy, Barrero, Bloom, Davis, Dolls, and Zarate (2023) supports this, noting that "*Workers allocate 40 percent of their time savings to their jobs.*"

This study contributes to the growing literature on remote work *after* COVID-19. The way employers and employees think about remote work has changed after COVID-19 (Barrero, Bloom, and Davis, 2023). In the beginning of COVID-19, remote workers worked primarily from home. Thus, this practice was called "work from home." Four years after the start of COVID-19 pandemic, remote work is no longer confined in the walls of one's own home. Remote workers can be anywhere, often working with clients or collaborating with teams in different time zones. This study offers the first post-COVID experimental look at preference for remote work.

Second, this study contributes to the growing literature on wage differences between in-person and online workers. Most of our current understanding of remote work and the higher wages often associated with in-person roles comes from survey data (Bick, Blandin, and Mertens, 2023; Dingel and Neiman, 2020; Zarate, Dolls, Davis, Bloom, Barrero, and Aksoy, 2024). Surveys suggest that a typical worker would accept a 6 percent salary reduction in exchange for the amenity of remote work (Barrero, Bloom, and Davis, 2021). This study goes beyond survey evidence by analyzing

[1] Methodologically, this study builds on prior correspondence studies (Ahmed, Andersson, and Hammarstedt, 2013; Bertrand and Mullainathan, 2004; Carlsson and Rooth, 2007; Lippens, Vermeiren, and Baert, 2023; Neumark, 2018; Rooth, 2010; Ruffle and Shtudiner, 2015). Riach and Rich (2002b) provides an overview of early correspondence experiments, while Riach and Rich (2002a) discusses ethical considerations in such studies.

asking price data from a real labor market, offering a more nuanced perspective on wage dynamics in remote versus in-person work. It also sheds light on how men and women value remote work differently and how these preferences contribute to the gender wage gap.

Third, this study enhances our understanding of how wages are shaped by local competition and worker productivity. Previous research by Pabilonia and Vernon (2021) and Emanuel and Harrington (2024) finds that the wage discount associated with remote work varies significantly with observable worker characteristics, suggesting that the in-person wage differential may partly reflect differences in productivity. Meanwhile, remote work may alter the impact of spatial competition in labor markets, especially in fully remote roles, where competition from workers in other locations can strongly affect wages (Barrero, Bloom, and Davis, 2023; Brinatti, Cavallo, Cravino, and Drenik, 2023). This study demonstrates that local labor market conditions are significant determinants of the in-person wage differential, independent of worker productivity.

More broadly, understanding tutors' willingness to teach remotely offers the potential to unlock a human capital repository to simultaneously address both the challenge of teacher retention (Bacher-Hicks, Chi, and Orellana, 2023; Devers, Duyar, and Buchanan, 2024; Goldhaber and Theobald, 2023; Ingersoll and Tran, 2023), and the challenge of accelerating student learning in the post-COVID-19 era (Alejo, Naguib, and Yao, 2023; Cohen, 2024; Gambi and De Witte, 2023; Goulas and Raymond, 2023).

2 Experimental Design

2.1 Experimental Setting

The experiment was carried out on the largest online tutor board in Greece, which hosts thousands of tutors who advertise their services. Tutors can register and create profiles free of charge. Tutor profiles are advertised free of charge. No registration or membership is required to contact tutors. All contact is done through email. A membership is required for tutors to see the contact information of the client messaging them, but they can see the subject and the content of the message free of charge. Tutor profiles feature information on their academic credentials, teaching experience, subjects taught, and rates for in-person and online lessons.

Figure S1 shows the counts of tutors in the study sample across regions. All regions are represented in the study sample. The wide reach of the tutor board across Greece, with tutors competing to offer similar services, allows for a robust comparison of prices. Since providing tutoring services online require minimal capital beyond a computer, this platform serves as an ideal marketplace for studying the dynamics of remote and in-person work. Moreover, the dataset is enriched with information on tutors' location, pedagogical approaches, methods used to assess learner needs, ratings, and academic certifications. This richness is crucial for analyzing the in-person wage premium, as it enables a comparison between various levels of experience, qualifications, and local labor markets.

Table 1 shows summary statistics of the characteristics of contacted tutors. A total of 4,254 tutors were contacted during the correspondence experiment. A little over 70 percent of tutors in the experiment are women. The median tutor has eight years of tutoring experience. Approximately 68 percent of tutors teach non-STEM subjects, while the remainder teach STEM subjects. Forty-five percent of tutors teach a foreign language. Less than six percent of tutors have training in special needs pedagogy. In terms of education, 37 percent of tutors in the sample have a college degree, while six percent of them have a master's degree. A little less than four percent of tutors are college students. On average, tutors charge 12.9 and 12.4 euros per hour for in-person and online tutoring, respectively. The average difference between in-person and online rates for the same tutor is 1.1 euros.

Table S1 shows the counts of tutors in the sample compared to those on the platform population by subject. Table S1 reveals rich variation in subjects taught and substantial coverage of the tutor population within and across subjects. About 91 percent of the tutor population was included in the study sample. Table S2 compares the characteristics of tutors in the sample to those of all tutors on the platform teaching the same subjects. The study sample captures a slightly higher percentage of tutors teaching STEM subjects than the platform population, but the difference is not statistically significant. Overall, tutor characteristics in the sample are statistically comparable to those in the tutor population on the platform.

2.2 Treatments

There were two treatment conditions: (1) a message asking about in-person lessons and (2) a message asking about online lessons. The messages were designed to plausibly represent typical parents who inquire about tutoring services for their child. The messages were constructed after consulting actual messages tutors receive through tutor boards.[2] Each message included an introduction sentence, a sentence mentioning where contact details were found, a sentence requesting tutoring lessons for the client's daughter, a sentence specifying the daughter's grade level, a sentence (in email type A1 and A2) or two (in email type B1 and B2) specifying the expectation the client has from the tutor,

[2]A focus group of two tutors, two school teachers, and two mental health professionals working with teachers provided very helpful advice and provided examples of language used in messages through tutor boards from parents asking for tutoring services for their children. The focus group also provided advice on the timing of the experiment.

two sentences regarding location, and one sentence regarding the rate tutors charge. Location was specified in the messages for three reasons: (1) to minimize the impact of commute time on callback rates by matching the location in the message with the first service area listed on the tutor's profile, (2) to confirm that the listed area reflects the tutor's residence, and (3) to mirror the natural inquiry a parent might make about location for in-person lessons, ensuring consistency in both the in-person and online versions of the message.

The experiment design addresses four key challenges in estimating workers' preferences for remote work arrangements. First, the design mitigates the influence of task and employer heterogeneity in remote work preferences. In-person and remote work may not look similar across industries or employers. In the experimental context, the task description and client characteristics are identical across requests for in-person and online services. Second, non-experimental data on remote work preferences often reflect self-selection, as workers may view remote roles as desirable amenities. In contrast, this experimental design controls for self-selection by framing the request for in-person or online work from the employer's side, preventing workers from sorting themselves based on job type. Third, the experimental approach offers more accurate and reliable estimates of remote work preferences compared to stated preference methods based on hypothetical scenarios.

Fourth, one may worry that workers may prefer to work remotely because they expect to be less productive. This means that tutors' callback rate might depend on the quality of expected service. If tutors believe that the value-add of online lessons is lower than that of in-person lessons, then they may be more inclined to prefer online lessons when the expected academic outcomes are unclear. The experimental messages clearly communicate consistent expectations for value added, ensuring that the measured preference for remote work is not influenced by differing productivity expectations. Specifically, a sentence was included in the message to specify the expected academic outcomes. In cases of middle school subjects, the treatment specified an expectation of academic support throughout the school year. In cases of foreign languages, the treatment specified an expectation of transitioning from a B1 level to a B2 level. Reaching a level B2 from a level B1 is a standard goal in language acquisition over the course of a school year. Obtaining a B2 level diploma in a foreign language at the end of grade 8 is also a standard expectation for students in Greece.

Table 2 shows the number of tutors contacted by treatment condition and subject taught. In total, 2,119 and 2,135 tutors were contacted in this correspondence experiment inquiring about in-person and online lessons, respectively. Tutors in 23 subjects were contacted.[3] Among those, four subjects are STEM related: Biology, Chemistry, Mathematics, and Physics. Greek language

[3]Languages such as Arabic, Bulgarian, Norwegian, Dutch, Polish, Portuguese, Serbian, Swedish are categorized as "Other languages" because there are fewer than 10 cases in at least one email treatment type.

and foreign languages are categorized as non-STEM subjects. Overall, the two treatment groups are well-balanced, supporting the validity of comparisons.

2.3 Experimental Procedure

Information on the entire tutor population on the board was web-scraped during the first week of July 2024 and randomly divided across conditions. Messages were sent over a six-week period, from the second week of July 2024 to the third week of August 2024. Table S3 displays the number of messages sent each week. The timing of the experiment was chosen based on the following considerations. First, all testing and retesting was completed by June 26$^{\text{th}}$, 2024, and schools started on September 11$^{\text{th}}$. This suggests that tutors are likely to seek students to fill their rosters for the upcoming academic year between early July and late August. Second, limiting the experiment to a six-week period helped mitigate potential cyclicality influences.

Two typical Greek names were used as parent names. A telephone number and an email account for each name were set up to collect responses from the tutors. Tutors who called a parent received the same message mentioning that the person they are trying to reach is not available and a request to leave a name and a message. Messages and e-mails were recorded. Responses were classified as callbacks if the tutor requested a parent to contact them. Responses that declined to offer services were not classified as callbacks.

2.4 Identification

I estimate the impact of a request for online lessons versus a request for in-person lesson on the likelihood of a callback using the following specification:

$$\mathbb{P}(Callback_i = 1) = F(\alpha + \beta Online\ Lessons_i + \gamma \mathbf{X}_i + \epsilon_i) \tag{1}$$

In this specification, $\mathbb{P}(Callback_i = 1)$ denotes the probability that the message sent to tutor i generated a callback. $Online\ Lessons_i$ is an indicator variable taking the value one for messages requesting online tutoring lessons. Messages requesting in-person tutoring lessons serve as the reference group. β is the parameter of interest and captures the difference in callback rates associated with remote work arrangements for tutors, holding all other variables constant. Vector $\mathbf{X}_i$ captures tutor characteristics. Tutor characteristics include a female indicator, an indicator of missing gender information to minimize record loss,[4] indicators for reported education (certification, bachelor,

[4]Table 1 shows that the dataset contains complete gender information for 98.4 percent of records.

master, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, indicators for above- and below-median age, as well as an indicators for missing information regarding years of experience or age,[5] an indicator for teaching STEM subjects, an indicator for having special learning needs training, an indicator for being recommended by platform users, location indicators, and indicators for week and day of the week messaged. Specification (1) is estimated using a logistic regression model.[6] Standard errors are corrected for possible heteroskedasticity.

Heterogeneity analyses are performed by replacing the treatment variable $Online\ Lessons_i$ in the specification (1) with group-specific treatment indicators. I investigate differential callback rate gaps based on tutor gender, whether tutors teach STEM or non-STEM subjects, and the population density and local competition in the tutors' areas. Specifically, I categorize tutors in areas above and below the median population density, as well as those facing above and below-median local competition. Local labor market competition is measured by the number of other tutors on the platform teaching the same subject within a 10-mile radius, divided by an estimate of school-age children (ages 3-17 in 2024) in that area (main definition). I also explore how sensitive the estimated effects are to different definitions of local tutor competition (Section 3.6). In the heterogeneity analyses regarding population density and local competition, the location indicators in specification (1) are replaced with specific indicators for population density and local competition to address collinearity. Data on population and area estimates are sourced from the 2021 census of the Hellenic Republic.

With random assignment, simple comparisons of callback rates can identify the relative effect of work arrangements. The main assumption for obtaining causal estimates of β in specification (1) is that there are no omitted variables correlated with both the assignment to the *Online Lessons* treatment condition and the outcome of interest. Table 3 compares tutors in the *in-person* and *online* treatment conditions across a comprehensive set of tutor and location-level characteristics to assess the potential existence of such factors and the validity of the empirical strategy. It shows no statistically significant differences in tutor characteristics between treatment conditions. This means that tutor characteristics are balanced across treatment conditions. The randomization of treatment assignment provides confidence that this assignment is orthogonal to unobservable tutor characteristics as well.

[5]Table 1 shows that the dataset contains complete information on age and years of experience for 79.2 and 20.0 percent of records, respectively.

[6]Table S4 explores robustness of the results when a linear probability model is used.

3 Results

3.1 Main Estimates

Table 4 shows the callback counts by treatment condition and subject. The average callback rate is nine percent. Table 5 shows the main results. The top panel reports the estimated parameter of interest across all tutors. Overall, requests for online lessons are 3.5 percentage points or 47.9 percent more likely to receive a callback than requests for in-person lessons (10.7 vs. 7.3 percent).[7] After accounting for tutor characteristics, subject type, location, and timing of the request, the estimated effect is 3.9 percentage points or 53.4 percent.[8] For the remainder of this section, I restrict attention to estimates that account for tutor characteristics.

3.2 By Gender

Le Barbanchon, Rathelot, and Roulet (2021) find that women value reductions in commuting time more than men do, potentially pointing to stronger preference for remote work among women than among men. The second panel of Table 5 presents heterogeneous results by tutor gender. Male tutors have a slightly higher overall callback rate than female tutors (10.1 vs. 8.8 percent). Requests for online lessons are more likely to receive a callback than requests for in-person lessons among both female and male tutors. However, the callback rate gap between requests for online and in-person lessons is larger among females than among males (4.7 vs. 2.1 percentage points).

3.3 STEM Vs. Non-STEM

Tutors with a STEM background may be more inclined to prefer remote work due to their positive predisposition towards information and communication technology (Howard, Chan, and Caputi, 2015; Xu and Zhu, 2020). The third panel of Table 5 explores heterogeneous estimated callback rate gaps for tutors teaching STEM- and tutors teaching non-STEM-related subjects. Tutors teaching STEM-related subjects have a lower overall callback rate than tutors teaching non-STEM-related subjects (9.8 vs. 7.5 percent). The type of subject taught is associated with tutor gender. Females tutors are more common in non-STEM subjects than STEM ones. Roughly 82 and 46 percent of tutors teaching non-STEM and STEM subjects, respectively, are women. Requests for online lessons are more likely to receive a callback than requests for in-person lessons among tutors teaching

[7] The overall response rate is more than an order of magnitude larger than that found in other experiments on job boards (He et al., 2021).

[8] Table S4 shows that the estimated marginal effects remain similar in magnitude and precision when a linear probability model is used.

STEM and non-STEM subjects. The estimated callback rate gap between requests for online and in-person lessons is larger among STEM tutors than among non-STEM tutors (7.1 vs. 2.6 percentage points). This indicates a stronger preference for remote work among tutors who teach STEM-related subjects.

3.4 By Population Density Levels

Prior research suggests that remote work is more prevalent in high-density areas (Barrero, Bloom, and Davis, 2023; Brueckner, Kahn, and Lin, 2023; Davis, Ghent, and Gregory, 2024; Ramani and Bloom, 2021). This may be due to the industry composition in these regions, as high-density areas often have a greater concentration of service-oriented industries where tasks can be performed remotely more easily than in low-density areas (Althoff, Eckert, Ganapati, and Walsh, 2022). I explore whether the preference for remote work varies among tutors located in areas with above-median and below-median population densities.[9]

The fourth panel of Table 5 displays the estimated callback rate gaps between tutors in the *Online Lessons* condition and those in the *In-person Lessons* condition. Tutors in above-median density areas (measured as population per square mile) have a lower overall callback rate than those in below-median density areas (8.1 vs. 9.9 percent). However, the unadjusted callback rate gap between online and in-person lesson requests is similar for tutors in high- and low-density areas (3.6 vs. 3.3 percentage points). When adjusting for tutor characteristics, this gap changes only slightly (3.7 vs. 3.2 percentage points), providing limited evidence of differential preferences for remote work across areas with varying population densities.

3.5 By Local Competition Levels

Brinatti, Cavallo, Cravino, and Drenik (2023) find that the price of remote work is associated with the conditions that workers face in their local labor markets. This suggests that workers may place different valuation on remote work based on how competitive their local labor market is. I explore the heterogeneity of the callback rate gap between requests for online and in-person lessons for tutors in areas with varying levels of local labor market competition. The bottom panel of Table 5 presents the estimates. Local labor market competition that each tutor faces is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area.[10] Tutors in areas with

[9] Figure S2 presents a histogram of the population density measure, with a mean of 28.6 and a median of 37.2 thousand people per square mile.

[10] Figure S3 plots the histogram of the local competition measure. The mean and median number of the main local

above median local labor market competition (i.e., other tutors per 1,000 school-age children) have a lower overall callback rate than tutors in areas with below median population density (7.9 vs. 10.1 percent). The estimated callback rate gap between online and in-person lessons is substantially larger for tutors in highly competitive labor markets compared to those in less competitive markets (5.8 vs. 2.6 percentage points). This suggests that tutors in high-competition areas are more likely to offer remote lessons than in-person ones, relative to tutors in low-competition areas. When facing intense local competition, tutors may be more inclined to explore alternative service delivery methods to expand their clientele.

3.6 Different Definitions of Local Competition

I conduct a robustness analysis using various definitions of local tutor competition. The main measure estimates the ratio of tutors on the platform teaching the same subject to the number of school-age children within a 10-mile radius. To test the sensitivity of the results, I adjust the radius downward to 5 miles and then to the smallest census-defined geographical unit, which corresponds to an area with a radius of approximately 1.7 miles. I also test the sensitivity by increasing the radius to 15 and 20 miles.[11] Table S6 shows the results of this sensitivity analysis across these different radii. The middle panel of Table S6 uses the main definition (10-mile radius) as a reference point.

Expanding the radius brings the analysis closer to identifying what constitutes a commutable distance versus what does not.[12] The estimated gap in callback rates between areas of above- and below-median local competition widens as we shift from a 1.7-mile radius to the 5- and 10-mile radius. This indicates that the preference for online lessons in more saturated markets increases as the geographical definition of competition broadens, up to a 10-mile radius.

However, increasing the radius beyond 10 miles does not significantly affect the estimated callback rate gap between above- and below-median competition areas. These results suggest that tutors within a 10-mile radius are more likely to serve the same student pool than those farther apart. In areas with above-median tutor saturation within a 10-mile radius, competition appears fiercer than in areas with above-median saturation in smaller radii (1.7 or 5 miles). This is because tutors in less saturated areas within a 1.7- or a 5-mile radius might still share access to the same student pool as those slightly farther away.

competition measure is 2.1 and 1 tutors, respectively.

[11] Table S5 shows summary statistics for the different definitions of local tutor competition investigated.

[12] The estimated time to commute 10 miles (e.g., a distance similar to commuting from the west suburbs to the east suburbs of Attica) is a little over 30 minutes after peak hours on a weekday evening.

4 Insights from Tutors' Replies

Tutors' replies allow us to gain perspective about their motivations to prefer giving lessons online versus in-person. Typical responses reflected one or more of the following three justifications. First, tutors seemed reluctant to commute. Typical responses were:

> *I teach lessons only online because I am very busy and do not want to waste time traveling between lessons.*
>
> *It is difficult to commute in Athens, so I work only online.*
>
> *I usually conduct lessons online, but if we live close and it is convenient, we can also do in-person lessons with your daughter.*

Some tutors mentioned that they face time constraints and view commuting for lessons as a waste of time. Moreover, some tutors also hold formal jobs alongside tutoring:

> *Unfortunately, I leave as a substitute teacher every year, so I cannot take on in-person lessons.*

Some tutors argued in favor of the efficacy of online tutoring:

> *I have been teaching online for many years with consistent success.*
>
> *What I can guarantee you is that the quality of the online lessons, at least the way I conduct them, is no different from the in-person lessons.*
>
> *I can take on your daughter remotely; very good work can be done as long as she is cooperative! It is a very effective method...*

Some tutors also mentioned the role of technology tools in the efficacy of remote lessons:

> *There is no need to worry that a lesson cannot be conducted online. I have my own material in Word and Excel formats with grammar and pronunciation rules, and there are also YouTube videos for these lessons.*
>
> *I use a stylus (instead of a board). Whatever I write appears on the screen, and at the end of the lesson, I save it as a PDF and send it via email to the student.*
>
> *Every week, I assign homework with exercises, which the students send back to me solved via email. I return them corrected and graded with comments. Additionally, I often give tests and exams in the same way.*

5 Pricing Decisions

5.1 Theoretical Framework

The experiment of Section 3 points to tutors preferring to work remotely rather than in person. Tutors' preference for remote work may be reflected in the price rate they charge for remote services versus in-person services. In this section, I develop a theoretical framework of pricing decisions to motivate an empirical investigation of the association between hourly rates and the preference for remote work as well as key mechanisms behind the preference for remote work. I start with the simplest formulation. Suppose that remote work is not possible and all tutoring is done in person. Tutor i faces the following profit-maximizing problem:

$$\max_{w_i} \quad \Pi = (w_i - c_i)h_i(w_i, \mathbf{w_{-i}}) \tag{2}$$

Tutor i's objective is to set a rate w_i to maximize the product of his profit margin $(w_i - c_i)$ and the number of tutoring sessions he can sell at rate w_i. Tutor i faces competition. This means that the number of tutoring sessions tutor i can sell, h_i, also depends on the wage rates of other tutors $-i$, $\mathbf{w_{-i}}$. Tutors face a capacity constraint in the sense that there are only so many hours in the day they can devote to tutoring. Tutor i's capacity limit is $\bar{h_i}$. The capacity constraint is reflected in the cost function:

$$c_i = \begin{cases} \tilde{c} & \text{if } h_i \leq \bar{h_i} \\ \infty & \text{if } h_i > \bar{h_i} \end{cases} \tag{3}$$

From the clients' perspectives, tutors are similar, but not identical. Specifically, clients view tutoring services as differentiated products. Thus, each tutor faces a distinct demand function:

$$h_i = h(w_i, \mathbf{w_{-i}}) \tag{4}$$

Tutors face a Marshallian demand curve in which demanded hours of tutoring from tutor i decrease when their own rate, w_i, increases, or when competitors' rate, $\mathbf{w_{-i}}$, decreases:

$$\frac{\partial h_i}{\partial w_i} < 0 \;\; and \;\; \frac{\partial h_i}{\partial \mathbf{w_{-i}}} > 0$$

Thus, tutor i may act like a monopolist in their own market segment but competition affects the demand curve they face. Tutor i will keep offering more hours of tutoring until the marginal revenue equals the cost (i.e., $MR = \tilde{c}$) or until they run out of capacity. At the margin, tutor i charges:

$$w_i^* = \frac{c_i e_i^D}{1 + e_i^D} \tag{5}$$

where e_i^D is the elasticity of the demand function tutor i faces. Now, suppose that remote tutoring is possible, and tutors can choose to work either exclusively in person or entirely remotely. Each tutor's cost changes when tutoring remotely because capacity increases ($\bar{h} \uparrow$). Also, the demand curve each tutor faces becomes more elastic because there are more substitutes ($|e_i^D| \uparrow$). Tutor i charges a lower rate for remote (r) vs. in-person services (p):

$$w_i^r < w_i^p \tag{6}$$

Tutor i prefers to work remotely vs. in-person if and only if

$$\Pi^r = h_i^r(w_i^r - \tilde{c}) \geq h_i^p(w_i^p - \tilde{c}) = \Pi^p \tag{7}$$

This theoretical framework has two implications. First, ask rates for remote work will be lower than for in-person work, driven by two factors: increased capacity allows tutors to offer more hours, shifting rates to a lower point on the marginal revenue curve; and greater online competition makes demand more elastic. A counter-argument is that sufficiently differentiated tutors may not need to lower their rates significantly to attract remote clients. Second, tutors may prefer remote work as it enables them to increase profits by expanding their labor supply. The first implication is investigated in the remainder of this section, while the second is explored in Section 6.

5.2 Hourly Rate Data

I use tutors' posted ask rates for in-person and online lessons on the tutor board to empirically examine the implications of Section 5.1.[13] Table 6 compares the hourly rates tutors ask for in-person and online lessons, both overall and by tutor and location characteristics. On average, in-person rates are higher than online rates (13.5 vs. 12.4 Euros), with a statistically significant difference of 1.1 Euros. Both male and female tutors exhibit a positive in-person premium, but male tutors experience a slightly larger premium (1.2 vs. 1.0 Euros). Although one might expect female tutors to have a greater in-person premium due to a stronger preference for remote work, as discussed in Section 3, floor effects could be influencing this outcome. Figure S5 shows that lower in-person rates are associated with smaller differences between in-person and online rates.[14] This

[13] About a quarter of callbacks included hourly rate information. Of those that did, roughly 70 percent matched the rate posted on the tutor board (Figure S4). The difference between ask rates in callbacks and those on the tutor board is statistically indistinguishable from zero. Moreover, this difference is not statistically significant when comparing tutors in the *Online* and *In-person* treatment conditions. This lends confidence to the validity of the ask rates posted on the tutor board.

[14] Importantly, Figure S5 shows that the in-person rate differential is a relatively fixed percentage of the in-person rate. In other words, tutors tend to apply a consistent discount rate for online lessons, using their in-person rate as

is consistent with female tutors generally setting lower rates than male tutors, with rates that are seven percent lower for in-person lessons and six percent lower for online lessons. The smaller rate gap in the online market suggests that remote work may be associated with a smaller gender wage gap.

For subjects, STEM tutors have a slightly higher in-person premium compared to non-STEM tutors (1.3 vs 1.0 Euros). The in-person rate premium is similar for tutors in both above-median and below-median population density areas (1.1 Euros). Tutors in areas with greater local competition tend to have higher in-person premiums (1.4 vs. 0.9 Euros). These results align with the findings in Section 3, which showed a higher preference for remote work among STEM tutors and tutors in areas with high local competition.

These empirical results also align well with the theoretical framework. The observed lower ask rates for online tutoring support the prediction that increased capacity under remote work drives rates to a lower point on the marginal revenue curve, as tutors may offer more hours remotely.

5.3 In-person Rate Differential

Figure 1 shows the distribution of ask rates for in-person and online lessons. The distribution of ask rates for online lessons is slightly to the left of the distribution of ask rates for in-person lessons. This suggests that overall tutors ask lower rates to offer tutoring services remotely versus in-person. Figure 2 compares the ask rates for in-person and online lessons within each tutor. The majority of tutors (59.5 percent) ask the same rate for in-person and online lessons. Approximately 39.5 percent of tutors post a higher rate for in-person than online lessons.

Brinatti, Cavallo, Cravino, and Drenik (2023) highlight the role of local market competition in shaping the price of remote work. Table S7 examines the effect of local tutor competition on the difference between in-person and online rates for each tutor. I find that a one standard deviation increase in local market competition raises the rate differential by approximately 1 to 5 percent. This suggests that local labor market conditions are a significant driver of the in-person rate differential, independent of worker characteristics related to productivity.

For the remainder of this section, I use the percent difference in ask rates between in-person and online lessons as a proxy for their valuation of remote work arrangements:

$$\text{In-person Rate Differential} = \frac{Rate^{In-person} - Rate^{Online}}{Rate^{In-person}}$$

a reference point. This is evident in the upward-sloping fitted line between the in-person rate differential and the in-person ask rate (Panel A). Consequently, there is a relatively flat fitted line between the in-person rate differential and the online rate (Panel B).

Figure 3 plots the distribution of the in-person rate differential. The mean in-person rate differential stands at 7.6 percent. Among tutors with a positive in-person rate differential, the mean stands at 21.1 percent.

5.4 Heterogeneous Callback Rates by In-person Rate Differential Level

One might expect workers who prefer to work remotely to be willing to give up a greater share of their hourly wage to work remotely instead of in person (Mas and Pallais, 2017). Thus, tutors with stronger preference for online lessons might offer a greater rate discount for lessons online, reflected in a greater in-person rate differential. I investigate this hypothesis by exploring the association between the callback rate gap between requests for online and in-person lessons and the in-person rate differential. I pursue two approaches. First, I replace the *Online Lessons* treatment variable in specification (1) with a pair of treatment variables; one capturing the impact of requests for *Online Lessons* on callbacks for tutors with positive in-person rate differential ($Rate\ \Delta > 0$) and one capturing the impact of requests for *Online Lessons* on callbacks for everyone else ($Rate\ \Delta \leq 0$). The specification is as follows:

$$\begin{aligned} \mathbb{P}(Callback_i = 1) = F[&\alpha + \beta_1 \mathbb{1}(Rate\ \Delta > 0) \times Online\ Lessons_i \\ &+ \beta_2 \mathbb{1}(Rate\ \Delta \leq 0) \times Online\ Lessons_i + \gamma \mathbf{X}_i + \lambda \mathbb{1}(Rate\ \Delta > 0) + \epsilon_i] \end{aligned} \tag{8}$$

Table 7 presents estimates of heterogeneous callback rate gaps for online versus in-person requests, distinguishing between tutors with no in-person rate premium and those with a positive in-person rate premium, based on specification (8). The callback rate gap is larger for tutors with a positive in-person rate premium than for those with zero or negative in-person premiums. This finding suggests that a higher in-person wage premium is associated with a stronger preference for remote work. Tutors who prefer remote work may require a higher premium to offer in-person services.[15]

[15] In an alternative approach, I extend specification (1) to include controls for the in-person rate differential ($Rate\ \Delta$) and its interaction with the treatment variable *Online Lessons*.

$$\begin{aligned} \mathbb{P}(Callback_i = 1) = F[&\alpha + \beta_1 Rate\ \Delta \times Online\ Lessons_i \\ &+ \beta_2 Online\ Lessons_i + \gamma \mathbf{X}_i + \kappa Rate\ \Delta + \epsilon_i] \end{aligned} \tag{9}$$

Table S8 presents the estimates, showing that the callback rate gap attributed to the *Online Lessons* treatment condition grows as the in-person rate differential increases. To visually examine how the estimated callback rate gap varies across different levels of the in-person rate differential, I obtain the difference in fitted values (specification (9)) for tutors in the *Online Lessons* and In-person Lessons treatment conditions over the full range of the in-person rate differential. Figure S6 displays this variation, confirming a positive association between the preference for remote work (captured by a larger callback rate gap for online lessons) and the in-person rate differential.

Next, I examine nonlinearities in the relationship between the in-person rate differential and the callback rate gap. To do this, I modify specification (1) by replacing the *Online Lessons* treatment variable with five treatment variables, each reflecting the impact of requests for *Online Lessons* on callbacks within a specific quintile of the in-person rate differential, while also controlling for quintile indicators, as in specification (8). Figure 4 presents these estimates. I find substantially higher callback rate gaps at higher quintiles of the rate differential compared to lower quintiles, indicating a strong preference for remote work among tutors with larger rate differentials.

If posted rates accurately reflected reservation wages, the posted in-person premium would fully capture the valuation of the remote work modality, making tutors indifferent to offering services in-person or online. However, the observed positive and significant callback rate gap between requests for online and in-person lessons suggests that the actual in-person wage premium needed for indifference may be higher than the posted one. This implies that the descriptive measure of the in-person wage premium (7.6 percent), which aligns with the literature benchmark of eight percent (Mas and Pallais, 2017), might underestimate the true in-person wage premium.

6 Survey Evidence on the Reasons for Online Lessons Preference

6.1 Survey Design

Section 4 provided insights from callback content on the reasons tutors may prefer to offer lessons online rather than in person. I provide further evidence on the reasons driving tutors' preference for online lessons through an online survey instrument deployed on the same tutor board. The survey inquired about each tutor's agreement with 17 statements comparing online and in-person lesson modality, and then asked whether they prefer to give lessons online or in-person. Tutors rated their agreement with each on a -5 to 5 scale with -5 representing Completely Disagree and 5 representing Completely Agree. Zero represented neither agreeing nor disagreeing.

The goal of this investigation is to gauge tutors' perceptions about online lessons versus in-person lessons. Acquiescence bias (i.e., yes-saying) can be a potential challenge in designing a survey instrument that captures participants' true rate of agreement with depicted statements. For example, if tutors are asked to rate the degree to which they prefer to teach online versus in person, using positive language only can result in skewed results due to acquiescence bias. To mitigate this potential bias, each statement was randomly shown to respondents in either positive or reverse wording (Buchholz, 2022). Table S9 shows the positive and reverse wordings of each statement used to capture the reasons for online lessons preference. To limit potential respondents' confusion and fatigue from reverse wording, the survey instrument was kept short with an estimated completion time of 4 minutes. The full survey instrument is provided in the Online Appendix.

6.2 Survey Results

Table 8 reports the average agreement score among all participants for each reason statement about online tutoring. The statement with the highest agreement score refers to access to technological tools and knowledge to conduct online lessons. This finding underscores that access to technology and digital fluency are vital for successful online teaching, as they enable effective collaboration and communication through digital platforms. The statement with the second highest agreement score refers to the online lessons modality allowing tutors to expand their hours of tutoring relative to in-person lessons. The result of the survey on the increase in tutoring hours under the online lessons modality validates the implication of the theoretical framework in Section 5.1 that online lessons may allow greater profitability because it increases the capacity of tutors in terms of hours of labor supply.

I gauge tutors' preference for online lessons by asking survey participants their level of agreement with the following statement: "I prefer teaching online lessons over in-person lessons." Similar with the preceding statements, positive and reverse wording was randomly displayed to survey participants to limit the influence of acquiescence bias. Survey participants reporting an agreement score of more than zero with the positively worded statement or less than zero with the negatively worded statement were classified as preferring online lessons to in-person lessons. Figure S7 plots the distribution of the agreement score for online lessons preference among surveyed tutors. Roughly 55 percent of respondents prefer to give lessons online. Approximately 16 percent of respondents are indifferent between giving lessons online or in person. This means that less than 30 percent of surveyed tutors prefer to teach in person. These results corroborate the experimental evidence in this study indicating a strong preference for tutoring online.

6.3 Mechanisms Investigation

Tutors may prefer teaching in-person in some situations and online in others, influenced by various factors. The survey investigates 17 potential reasons behind these preferences. Presenting these reasons before asking about online lesson preference could prime participants to consider them as key influences (Chaudoin et al., 2021; Wells and Windschitl, 1999). This setup enables a mechanisms investigation: If both online and in-person tutors give similar agreement scores to a reason, it likely is not a key driver of their preferences. Conversely, if scores differ significantly between the two groups, the reason may be an important factor driving their choices.

Table 9 provides descriptive statistics of the agreement scores of surveyed tutors who report a preference for in-person teaching, a preference for online teaching, or being indifferent between in-person and online teaching. I compare the agreement scores of surveyed tutors who prefer to teach in person and those of tutors who prefer to teach online to infer potential drivers of the preference for online versus in-person lessons. Statements with large differences in agreement scores between tutors who prefer online teaching and those who prefer in-person teaching indicate potentially important driving reasons for the preference for online lessons.

The factors of *greater job satisfaction*, *effectiveness of online instruction*, *additional employment*, *teaching more hours*, and *recognition and respect* are the top-5 drivers for the online lesson preference among surveyed tutors. The result of strong predicting influence of *additional employment* and *teaching more hours* validate the theoretical predictions of Section 5.1 that online lessons may allow tutors to increase their profit by expanding their labor supply. The list of statistically significant drivers for the preference for online lessons is completed by the factors of *scheduling control*, *personal teaching effectiveness*, *better mental health*, *patience as teacher*, *access to job opportunities*, and *access to tech tools and skills*. Five factors were found not be statistically significant drivers of the preference for online lessons: *lower exposure to diseases*, *location flexibility*, *less commute-related stress*, *more time for loves ones or personal interests*, and *lower commuting expenses*. The factor associated with online tutoring requiring more cooperation from the student is found to be a statistically significant drivers of the preference for in-person lessons.

I investigate the driving factors of the preference for online lessons among men and women. Table S10 shows the agreement scores reported by men tutors for each of the reason statement and the difference in scores between those who prefer to tutor online versus in person.[16] Similarly, Table S11 reports the agreement scores reported by women tutors for each reason statement and the difference in the scores between those who prefer online versus in-person lessons. Table 10 summarizes and compares the results of the mechanisms investigation between female and male tutors. The results reveal substantial differences between men and women in the factors driving their preference for online lessons. Among women, *access to tech tools and skills*, *increased job satisfaction*, and *teaching more hours* are found to be the three most important drivers of preference for online lessons. Among men, *recognition and respect*, *increased job satisfaction*, and *personal teaching effectiveness* emerge as the top drivers of their preference for online lessons.

I compare the differences in agreement scores between women and men who prefer tutoring

[16] Panel A of Figure S7 plots the distribution of the agreement score for online lessons preference among surveyed female and male tutors.

online versus in-person. This comparison highlights gender differences in the factors driving preferences for online tutoring. For women, the preference for online lessons is more strongly associated with access to *technological tools and knowledge* (3.261 vs. -0.936), *job opportunities* (2.369 vs. 1.400), *scheduling control* (2.706 vs. 1.791), and *tutoring more hours* (3.195 vs. 1.964) than it is for men. This suggests that access to tech tools and skills plays a key role in women's preference for online tutoring. Moreover, women who prefer tutoring online may view the larger client base and increased capacity for lessons as significant advantages. The importance women place on scheduling flexibility may reflect their greater family and caregiving responsibilities compared to men, as well as the pressure to manage family emergencies. On the other hand, for men, preference for online tutoring is more strongly linked to *personal teaching effectiveness* (3.391 vs. 1.741) and *recognition and respect* (4.600 vs. 1.888) compared to women.

Table S12 summarizes results of the mechanisms investigation between tutors who teach STEM-related subjects and those teaching non-STEM subjects.[17] Among tutors in STEM subjects, the preference for online lessons is most strongly associated with *scheduling control*, *additional employment*, and *increased job satisfaction*. Among non-STEM tutors, *personal teaching effectiveness*, *increased job satisfaction*, *increased job satisfaction*, and *recognition and respect* are found to be the three most important drivers of preference for online lessons. The belief that teaching online requires more student cooperation drives tutors' preference for in-person lessons both in STEM and non-STEM subjects.

7 Transferability, Implications, and Scalability

7.1 Transferability

Are the insights of this study applicable to tutors in other parts of the world or to non-tutor workers? To evaluate the transferability of these insights to teacher populations and the general workforce outside Greece, I provide demographic benchmarks for K-12 teachers and the general workforce in the European Union (EU), OECD countries, and the United States. The characteristics of the tutor sample reveal both meaningful similarities and some differences when compared to these benchmarks, as outlined in Table S15.

In terms of gender composition, the tutor sample comprises 70 percent women, closely align-

[17]Panel B of Figure S7 plots the distribution of the agreement score for online lessons preference among surveyed STEM and non-STEM tutors. Tables S13 and S14 show detailed agreement scores reported by tutors in STEM and non-STEM subjects, respectively, for each of the reason statement and the difference in scores between those who prefer to tutor online versus in person.

ing with the proportions of female K-12 teachers in the EU (72 percent) and OECD (69 percent) (UNESCO Institute for Statistics, 2023; World Bank, 2023), as well as the US (77 percent) (National Center for Education Statistics, 2021). This similarity suggests that the sample could provide insights into broader educational settings, where female educators are predominant. However, compared to the general working-age population, where women represent only about 45-46 percent (Eurostat, 2023b; World Bank, 2023), the tutor sample is significantly more female-dominated, reflecting the gendered nature of both K-12 teaching and tutoring professions. This suggests that findings related to female participation and experiences may have broader applicability in the education sector, while generalizations to the overall labor market could be limited by this demographic skew.

Regarding educational attainment, 39 percent of the tutor sample have post-high school education, which is roughly comparable to the benchmarks for the working-age population in the EU (43 percent) (Eurostat, 2023a), OECD (40 percent) (Organisation for Economic Co-operation and Development (OECD), 2023a), and the US (47 percent) (U.S. Census Bureau, 2023). This suggests that the tutor sample represents a sizable segment of the workforce with some level of tertiary education, supporting the generalizability of findings to similar educational levels in the broader population.

Lastly, reported tutor age suggests a median age of 30 years in the sample.[18] This is considerably younger than both K-12 teachers in the US (42 years) (National Center for Education Statistics, 2021) and the general working-age population across all three regions (EU: 44 years (Eurostat, 2023b), OECD: 40 years (Organisation for Economic Co-operation and Development (OECD), 2023b), US: 42 years (U.S. Bureau of Labor Statistics, 2023)). This age difference suggests that tutors in the sample represent a younger, potentially more dynamic segment of the workforce, which could influence their perspectives, preferences, and adaptability in teaching practices. While this limits direct comparability to older teaching populations, it also offers insights into emerging trends in educational workforces.

The tutoring industry offers three distinct advantages that make it a more suitable context for studying workers' preference for remote work than other industries. First, while most workers are employees (Bracha and Burke, 2019; Dokko, Mumford, and Schanzenbach, 2015), remote work may not lead to increased labor supply for employees in the same way it does for self-employed workers,

[18]Median tutor age was indirectly validated by cross-referencing the reported education level and years of experience. The following assumptions about the likely starting age for tutoring were applied to verify consistency with the reported age: tutors with less than a bachelor's degree were assumed to have started at 18, those with a bachelor's degree at 22, a master's degree at 24, and those with a doctoral degree at 27.

such as tutors. This is because contract workers or self-employed individuals can often increase their earnings by providing additional man-hours, whereas employees may not have this flexibility (Aksoy, Barrero, Bloom, Davis, Dolls, and Zarate, 2023). As a result, employees may view remote work more as an amenity provided by employers, rather than as an alternative means of trading labor. Second, while in-person work in most industries often involves limited flexibility, tutors generally set their own schedules even for in-person work. As a result, the estimated preference for remote work among tutors is less likely to be confounded by a preference for scheduling flexibility. Third, in the market for tutoring, tutor effort is monitored in the same fashion regardless of whether the lesson is conducted in person or online. The learner looks at the tutor for the duration of the tutoring session. This implies comparable monitoring cost of tutoring online and in person. This may not be the case in every industry. A higher monitoring cost of the remote worker compared with the in-person workers may decrease labor demand (White, 2019). This suggests that it may be harder to disentangle the impact of remote work on labor supply, when remote work may also affect labor demand or the perceived/expected labor demand.

A potential limitation is that there may be tutors who may not advertise their services on the internet. These professionals may have limited computer or internet literacy. They may also rely on informal networks of neighbors, friends, or family to advertise their services. These professionals may be less likely to prefer to teach lessons online than their counterparts with an online presence.

7.2 Implications

This study produces insights with implications in four directions. First, the finding that tutors prefer to offer lessons online rather than in person suggests that tutors—and professionals with comparable characteristics to tutors—may be willing to pay for remote work arrangements. Second, this positive valuation of remote work may not be solely associated with the view of remote work as an amenity. If remote work induces tutors to increase labor supply—rather than spend time with their loves ones or on personal interests—as the survey results suggest, then remote work may not *only* be viewed as an amenity, but also as an individual capacity expander. Under this perspective, increased labor supply due to remote work may lead to higher number of hours worked and higher social welfare, since both sides of the market may extract positive surplus from the additional transactions.

Third, since existing survey evidence on wage differentials between in-person and online work may target contract workers (Barrero, Bloom, and Davis, 2021), the estimated valuation of remote work may primarily capture an amenity-related component of remote work rather than its impact on individual supply of labor hours. Thus, the current estimates of the value of remote work may underestimate its potential value to workers who can work more if they work remotely.

Fourth, the findings align with the policy recommendations of Carlana and La Ferrara (2024) and Gortazar, Hupkau, and Roldán-Monés (2024), who argue that remote tutoring can transform education by making it more accessible and inclusive through its scalability and cost-effectiveness. The online modality reduces costs by eliminating commuting and lowering rates. It also improves student-tutor matching, enabling broader outreach to students in need. Remote tutoring could address two major challenges in education systems: motivating and retaining qualified teachers, and increasing teacher supply in specific subjects.

7.3 Scaling

A key factor in determining the external validity and scalability potential of an experiment is its *naturalness*—how closely the experimental setting, tasks, and behaviors resemble real-world environments and interactions (List, 2020). The correspondence experiment in this study replicated realistic market conditions, meaning the callbacks represent genuine economic decision-making under real circumstances. This enhances confidence in the transferability of the findings to broader real-world contexts.

One opportunity for scalability in remote tutoring is that locations with limited tutor supply or high commuting costs can recruit tutors from farther away. This broadens the marketplace, potentially lowering the cost of tutoring services and enhancing welfare by enabling sessions that might not be feasible in person. In the survey, tutors were asked whether they preferred working as private tutors over holding a permanent full-time position.[19]

Fifty-five percent of survey respondents (48 out of 87) reported preferring to work as private tutors rather than holding a permanent full-time position. Roughly 16 percent (14 respondents) were indifferent between the two options, while approximately 29 percent (25 respondents) preferred a permanent full-time position over private tutoring. This suggests that remote tutoring, with its increased flexibility to be combined with other professional commitments (as reported by tutors, see Table 8), may tap into a reserve of potential tutors. Some of these individuals may not even participate in the in-person tutoring market because they prefer a permanent full-time job that cannot be easily combined with in-person tutoring.

[19] One might wonder about tutors' preference rankings between in-person tutoring, online tutoring, and a permanent full-time position, rather than just the comparison between tutoring and full-time employment. Because the question specifies "if I cannot combine the two," the premise is that in-person tutoring would be harder to combine with a full-time position than online tutoring, allowing us to gauge the potential increase in labor supply under the online lesson modality.

A key limitation to scalability is that remote tutoring may not be suitable for all learners. In the survey, tutors' preferences for in-person versus online lessons were influenced by the belief that online lessons require greater student cooperation compared to in-person lessons. This may reflect the association between remote learning and poorer behavioral outcomes (Hanno, Fritz, Jones, and Lesaux, 2022; Hollister, Nair, Hill-Lindsay, and Chukoskie, 2022), and the potential role of self-motivation and self-determination in online learning success (Chen and Jang, 2010; Hartnett and Hartnett, 2016; Mendoza, Yan, and King, 2023)

Another factor affecting scalability is access to computers, high-speed internet, and the knowledge to use them. Limitations in access can hinder both the potential pool of tutors capable of teaching remotely and the reach of remote tutors. However, in a world with high digital penetration, obstacles related to access to broadband internet, devices, and digital literacy, crucial components for the success of remote tutoring, may be less prominent than they used to be.

8 Conclusion

This study presents evidence on the preference for remote work from a correspondence experiment in which thousands of randomized messages were sent to tutors, inquiring about in-person or online lessons. The results show that online tutoring requests are significantly more likely to receive callbacks than in-person requests, with a 3.9 percentage-point or 53.4 percent higher likelihood after accounting for tutor characteristics.

Female tutors receive fewer callbacks overall compared to male tutors, but the online versus in-person gap is larger for them (4.7 vs. 2.‘ percentage points). Similarly, STEM tutors have lower callback rates than non-STEM tutors, yet their gap is wider (7.1 vs. 2.6 percentage points). Tutors facing higher local competition also experience lower overall callback rates, with a more pronounced gap between online and in-person requests (5.8 vs. 2.6 percentage points). Tutors' callback content suggests that their preference for online lessons is motivated by time constraints and commuting challenges, with many citing the efficiency and effectiveness of online instruction.

Examining tutors' ask rates for in-person and online lessons, I find a positive association between the in-person rate differential and callback rates. This suggests that tutors setting a higher in-person rate premium exhibit a stronger preference for remote work. If posted rates accurately reflected reservation wages, tutors would be indifferent between offering services in-person or online. However, the significant callback rate gap indicates that the actual in-person wage premium needed for such indifference may exceed the posted rate. Consequently, the measured in-person wage premium (7.6 percent), consistent with the literature benchmark of eight percent (Mas and Pallais, 2017), could be an underestimate.

I conducted a survey of the same tutor population to explore why tutors prefer online lessons. The survey asked tutors to rate their agreement with 17 statements comparing online and in-person tutoring. About 55 percent of tutors preferred teaching online, while less than 30 percent preferred in-person tutoring. Key drivers for this preference included job satisfaction, perceived effectiveness of online instruction, additional employment, and increased tutoring hours. These findings, particularly the role of increased labor supply, align with a simple theoretical framework predicting pricing decisions in both in-person and remote labor markets. Gender differences also play a significant role in the preference for remote work. Women who prefer online tutoring value tech tools, job opportunities, and scheduling flexibility more than women who favor in-person work. In contrast, men who prefer online teaching prioritize recognition, respect, and personal teaching effectiveness compared to those who prefer in-person tutoring.

This study provides novel insights into the potential of remote work, particularly within the education sector, emphasizing its advantages for expanding labor supply. The tutor sample, being younger and predominantly female, aligns with broader educational workforce demographics, underscoring its relevance to the field. The strong preference among tutors for online work suggests that remote work functions not only as an amenity but also as a capacity booster, effectively increasing labor supply. The study uniquely demonstrates that tutoring, with its consistent monitoring costs across in-person and online settings, provides a clear lens to assess workers' preference for remote work—something less feasible in other industries. Moreover, remote tutoring presents a scalable model for reaching underserved areas, offering flexibility and accessibility that traditional in-person models cannot match. While challenges like digital access and learner engagement remain, this research underscores the transformative potential of remote tutoring in addressing educational disparities and enhancing teacher retention.

References

Ahmed, A. M., L. Andersson, and M. Hammarstedt (2013). Are Gay Men and Lesbians Discriminated Against in the Hiring Process? *Southern Economic Journal 79*(3), 565–585.

Aksoy, C. G., J. M. Barrero, N. Bloom, S. J. Davis, M. Dolls, and P. Zarate (2023). Time Savings When Working From Home. In *AEA Papers and Proceedings*, Volume 113, pp. 597–603. American Economic Association.

Alejo, A., K. Naguib, and H. Yao (2023). Education in a Post-COVID World: Towards a RAPID Transformation. *UNICEF*.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2022). The Geography of Remote Work. *Regional Science and Urban Economics 93*, 103770.

Bacher-Hicks, A., O. L. Chi, and A. Orellana (2023). Two Years Later: How COVID-19 Has Shaped the Teacher Workforce. *Educational Researcher 52*(4), 219–229.

Barrero, J. M., N. Bloom, and S. J. Davis (2021). Why Working From Home Will Stick. Technical report, National Bureau of Economic Research.

Barrero, J. M., N. Bloom, and S. J. Davis (2023). The Evolution of Work From Home. *Journal of Economic Perspectives 37*(4), 23–49.

Barrero, J. M., N. Bloom, S. J. Davis, B. H. Meyer, and E. Mihaylov (2022). The Shift to Remote Work Lessens Wage-Growth Pressures. Technical report, National Bureau of Economic Research.

Bertrand, M. and S. Mullainathan (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review 94*(4), 991–1013.

Bick, A., A. Blandin, and K. Mertens (2023). Work From Home Before and After the COVID-19 Outbreak. *American Economic Journal: Macroeconomics 15*(4), 1–39.

Bracha, A. and M. A. Burke (2019). How Big Is the Gig? *Federal Reserve Bank of Boston*.

Brinatti, A., A. Cavallo, J. Cravino, and A. Drenik (2023). The International Price of Remote Work. Technical report, National Bureau of Economic Research.

Brueckner, J. K., M. E. Kahn, and G. C. Lin (2023). A New Spatial Hedonic Equilibrium in the Emerging Work-From-Home Economy? *American Economic Journal: Applied Economics 15*(2), 285–319.

Buchholz, J. (2022). Mixed-Worded Scales and Acquiescence in Educational Large-Scale Assessments. Technical report, OECD, Paris, France.

Carlana, M. and E. La Ferrara (2024). Apart but Connected: Online Tutoring, Cognitive Outcomes, and Soft Skills. Technical report, National Bureau of Economic Research.

Carlsson, M. and D.-O. Rooth (2007). Evidence of Ethnic Discrimination in the Swedish Labor Market Using Experimental Data. *Labour Economics 14*(4), 716–729.

Chaudoin, S., B. J. Gaines, and A. Livny (2021). Survey Design, Order Effects, and Causal Mediation Analysis. *The Journal of Politics 83*(4), 1851–1856.

Chen, K.-C. and S.-J. Jang (2010). Motivation in Online Learning: Testing a Model of Self-Determination Theory. *Computers in Human Behavior 26*(4), 741–752.

Cohen, L. (2024). Learning Curve: Lessons From the Tutoring Revolution in Public Education. Technical report, National Student Support Accelerator.

Davis, M. A., A. C. Ghent, and J. Gregory (2024). The Work-From-Home Technology Boon and Its Consequences. *Review of Economic Studies*, rdad114.

Devers, K., I. Duyar, and K. Buchanan (2024). Examining Teacher Attrition Through the Experiences of Former Teachers Before and During the COVID-19 Pandemic. *Education Sciences 14*(2), 184.

Dingel, J. I. and B. Neiman (2020). How Many Jobs Can Be Done at Home? *Journal of Public Economics 189*, 104235.

Dokko, J., M. Mumford, and D. W. Schanzenbach (2015). Workers and the Online Gig Economy. Technical report, The Hamilton Project, Brookings Institution, Washington, DC.

Emanuel, N. and E. Harrington (2024). Working Remotely? Selection, Treatment, and the Market for Remote Work. *American Economic Journal: Applied Economics 16*(4), 528–559.

Eurostat (2023a). Educational Attainment Statistics. Technical report, Eurostat, Luxembourg City, Luxembourg.

Eurostat (2023b). Population: Structure Indicators. Technical report, Eurostat, Luxembourg City, Luxembourg.

Gambi, L. and K. De Witte (2023). *The Uphill Battle: The Amplifying Effects of Negative Trends in Test Scores, COVID-19 School Closures and Teacher Shortages.* KU Leuven, Department of Economics.

Goldhaber, D. and R. Theobald (2023). Teacher Attrition and Mobility in the Pandemic. *Educational Evaluation and Policy Analysis 45*(4), 682–687.

Gortazar, L., C. Hupkau, and A. Roldán-Monés (2024). Online Tutoring Works: Experimental Evidence From a Program With Vulnerable Children. *Journal of Public Economics 232*, 105082.

Goulas, S. and M. E. Raymond (2023). Meta-analysis of Academic Recovery after COVID-19. Technical report, Center for Research on Education Outcomes at Stanford University, Stanford, CA.

Hanno, E. C., L. S. Fritz, S. M. Jones, and N. K. Lesaux (2022). School Learning Format and Children's Behavioral Health During the COVID-19 Pandemic. *JAMA Pediatrics 176*(4), 410–411.

Hartnett, M. and M. Hartnett (2016). The Importance of Motivation in Online Learning. *Motivation in Online Education*, 5–32.

He, H., D. Neumark, and Q. Weng (2021). Do Workers Value Flexible Jobs? A Field Experiment. *Journal of Labor Economics 39*(3), 709–738.

Hollister, B., P. Nair, S. Hill-Lindsay, and L. Chukoskie (2022). Engagement in Online Learning: Student Attitudes and Behavior During COVID-19. In *Frontiers in Education*, Volume 7, pp. 851019. Frontiers Media SA.

Howard, S. K., A. Chan, and P. Caputi (2015). More Than Beliefs: Subject Areas and Teachers' Integration of Laptops in Secondary Teaching. *British Journal of Educational Technology 46*(2), 360–369.

Ingersoll, R. M. and H. Tran (2023). Teacher Shortages and Turnover in Rural Schools in the US: An Organizational Analysis. *Educational Administration Quarterly 59*(2), 396–431.

Le Barbanchon, T., R. Rathelot, and A. Roulet (2021). Gender Differences in Job Search: Trading Off Commute Against Wage. *The Quarterly Journal of Economics 136*(1), 381–426.

Lippens, L., S. Vermeiren, and S. Baert (2023). The State of Hiring Discrimination: A Meta-Analysis of (Almost) All Recent Correspondence Experiments. *European Economic Review 151*, 104315.

List, J. A. (2020). Non Est Disputandum de Generalizability? A Glimpse Into the External Validity Trial. Technical report, National Bureau of Economic Research.

Mas, A. and A. Pallais (2017). Valuing Alternative Work Arrangements. *American Economic Review 107*(12), 3722–3759.

Mendoza, N. B., Z. Yan, and R. B. King (2023). Supporting Students' Intrinsic Motivation for Online Learning Tasks: The Effect of Need-Supportive Task Instructions on Motivation, Self-Assessment, and Task Performance. *Computers & Education 193*, 104663.

National Center for Education Statistics (2021). Public School Teacher and Private School Teacher Data Files. Technical report, U.S. Department of Education, National Center for Education Statistics, Washington, DC.

Neumark, D. (2018). Experimental Research on Labor Market Discrimination. *Journal of Economic Literature 56*(3), 799–866.

Organisation for Economic Co-operation and Development (OECD) (2023a). Education at a Glance 2023. Technical report, OECD, Paris, France.

Organisation for Economic Co-operation and Development (OECD) (2023b). Working Better with Age. Technical report, OECD, Paris, France.

Pabilonia, S. and V. Vernon (2021). Telework, Wages, and Time Use in the United States (Working Paper 546 [rev.]). Technical report, GLO Discussion Paper.

Ramani, A. and N. Bloom (2021). The Donut Effect of COVID-19 on Cities. Technical report, National Bureau of Economic Research.

Riach, P. A. and J. Rich (2002a). Ethical Issues in Deceptive Field Experiments of Discrimination in the Market Place. Technical report, Monash University.

Riach, P. A. and J. Rich (2002b). Field Experiments of Discrimination in the Market Place. *The Economic Journal 112*(483), F480–F518.

Rooth, D.-O. (2010). Automatic Associations and Discrimination in Hiring: Real World Evidence. *Labour Economics 17*(3), 523–534.

Ruffle, B. J. and Z. Shtudiner (2015). Are Good-Looking People More Employable? *Management Science 61*(8), 1760–1776.

UNESCO Institute for Statistics (2023). World Bank Open Data. Technical report, UNESCO Institute for Statistics, Paris, France.

U.S. Bureau of Labor Statistics (2023). Employment Projections Program. Technical report, U.S. Bureau of Labor Statistics, Washington, DC.

U.S. Census Bureau (2023). Census Bureau Releases New Educational Attainment Data. Technical report, U.S. Census Bureau, Suitland, MD.

Wells, G. L. and P. D. Windschitl (1999). Stimulus Sampling and Social Psychological Experimentation. *Personality and Social Psychology Bulletin 25*(9), 1115–1125.

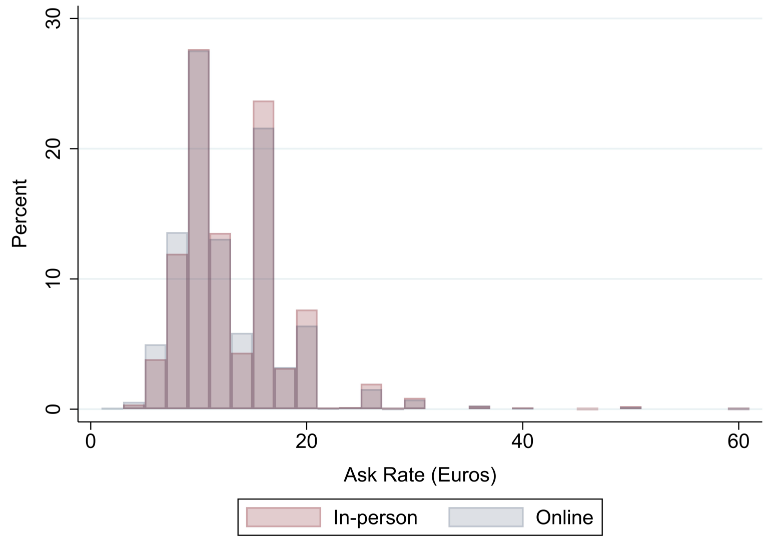
White, D. R. (2019). Agency Theory and Work From Home. *Labour 33*(1), 1–25.

World Bank (2023). World Development Indicators Database. Technical report, World Bank, Washington, DC.

Xu, S. and S. Zhu (2020). Factors Influencing K-12 Teachers' Intention to Adopt Mobile Devices in Teaching. *Computers in the Schools 37*(4), 292–309.

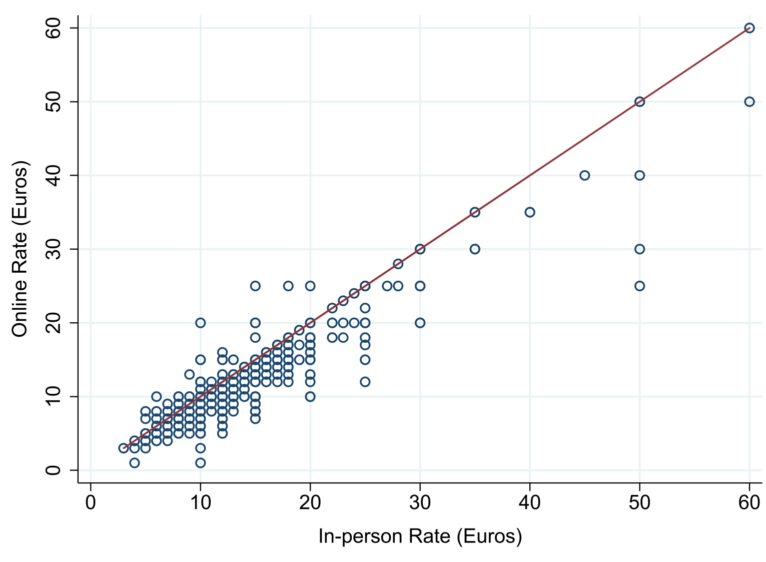
Zarate, P., M. Dolls, S. J. Davis, N. Bloom, J. M. Barrero, and C. G. Aksoy (2024). Why Does Working From Home Vary Across Countries and People? Technical report, National Bureau of Economic Research.

Figure 1: Ask Rates



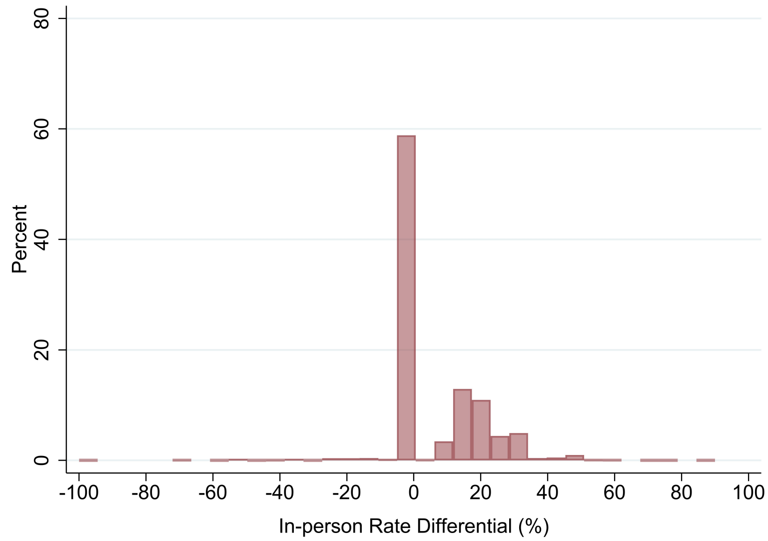
Notes: This figure plots the histogram of hourly rates tutors ask for in-person and online lessons.

Figure 2: Ask Rates Comparison



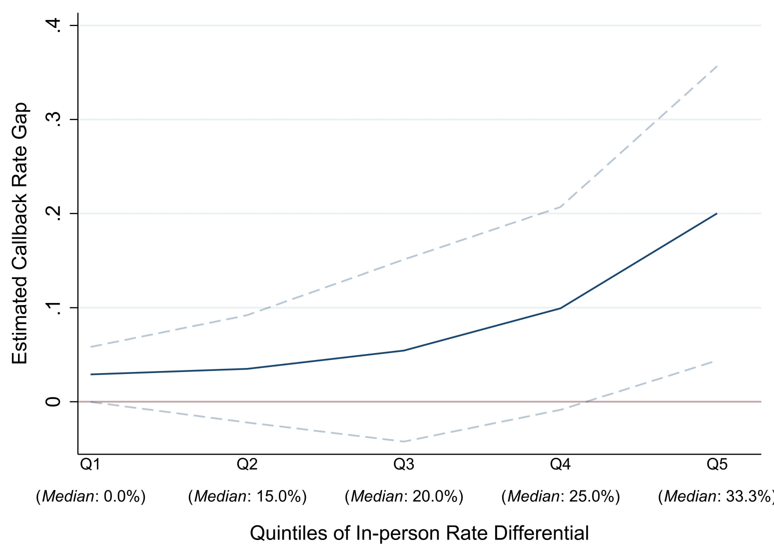
Notes: This figure shows the scatterplot between hourly rates tutors ask for in-person and online lessons. Each marker represents a tutor. Tutors with the same rate for in-person and online lessons lie on the 45-degree line (red line).

Figure 3: In-person Rate Differential



Notes: This figure plots the histogram of the in-person rate differential tutors ask, defined as the percent difference between their individual rates for online and in-person lessons.

Figure 4: Nonlinearity Between In-person Rate Difference and Preference for Remote Work



Notes: This figure shows the estimated callback rate gap between requests for online and in-person lessons across different levels of the in-person rate differential. It is based on estimated marginal effects from a logistic regression of callback on the *Online Lessons* treatment variable within each quintile of the in-person rate differential. The specification includes controls for the logarithms of both in-person and online rates. Dashed lines indicate the 95-percent confidence intervals.

Table 1: Summary Statistics

	Mean	Median	Std. Dev.	5 pct	95 pct	N
Panel A: Ask hourly rates (euro)						
In-person Rate	12.9	12.0	5.2	7.0	20.0	4,250
Online Rate	12.4	12.0	4.9	6.0	20.0	2,869
Diff. (In-person - online rate)	1.1	0.0	1.9	0.0	5.0	2,869
Panel B: Tutor characteristics						
Age (Yrs)	34.1	30.0	9.0	20.0	50.0	3,370
Experience (Yrs)	10.3	8.0	8.0	1.0	27.0	852
Local Competition	2.1	1.0	5.0	0.0	9.0	4,254
(Other Tutors/ 1,000 School-age Children)						
Population Density	28.6	37.2	17.0	2.0	44.0	4,254
(Thousands/Square Mile)						
			%			N
Female			70.3			4,187
Teach STEM Subjects			32.5			4,254
Teach Non-STEM Subjects			67.5			4,254
Teach Foreign Language			44.9			4,254
Special Needs Training			5.6			4,254
Recommended			6.1			4,254
Education						
Certification			9.0			4,254
Bachelor's Degree			37.1			4,254
Master's Degree			6.2			4,254
Doctoral Degree			1.5			4,254
College Student			3.8			4,254

Notes: Panel A reports moments of ask rates for in-person and online services and their difference for tutors in the sample. Panel B reports characteristics for tutors in the sample. Each tutor was contacted only once. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic.

Table 2: Number of Tutoring Requests Sent by Treatment Condition and Subject

	Treatment Condition			
	In-person		*Online*	
	Parent Name		Parent Name	
Subject	*Maria Georgiou*	*Anna Papageorgiou*	*Maria Georgiou*	*Anna Papageorgiou*
Biology	65	66	58	65
Chemistry	100	85	85	109
Chinese	12	16	14	16
English	198	187	206	202
French	70	62	47	43
German	56	62	60	54
Greek language	245	225	239	250
Italian	26	20	25	38
Mathematics	111	116	99	105
Other languages	27	31	27	31
Physics	68	88	93	70
Russian	24	35	41	37
Spanish	38	40	29	39
Turkish	30	16	17	36
Total	1,070	1,049	1,040	1,095
Combined Total	2,119		2,135	

Notes: This table shows the number of messages through the platform requesting in-person or online lessons from tutors in each subject. Each tutor was contacted only once.

Table 3: Tutor Characteristics

	In-person		Online			
	Mean	N	Mean	N	Diff.	P-value
Panel A: Ask Hourly Rates (Euro)						
In-person Rate	12.8	2,119	12.9	2,131	-0.089	0.573
Online Rate	12.4	1,428	12.4	1,441	0.025	0.890
Diff. (In-person - online rate)	1.0	1,428	1.1	1,441	-0.097	0.180
Panel B: Tutor Characteristics						
Age (Yrs)	34.1	1,683	34.0	1,687	0.079	0.800
Experience (Yrs)	10.0	437	10.5	415	-0.526	0.353
Local Competition	2.2	2,119	2.0	2,135	0.201	0.196
(Other Tutors/ 1,000 School-age Children)						
Population Density	28.6	2,119	28.5	2,135	0.145	0.778
(Thousands/Square Mile)						
	%	N	%	N		
Female	71.1	2,091	69.5	2,096	1.649	0.243
Teach STEM Subjects	33.0	2,119	32.0	2,135	0.950	0.509
Teach Non-STEM Subjects	67.0	2,119	68.0	2,135	-0.950	0.509
Teach Foreign Language	44.8	2,119	45.1	2,135	-0.226	0.882
Special Needs Training	5.9	2,119	5.4	2,135	0.419	0.554
Recommended	6.2	2,119	6.0	2,135	0.140	0.849
Education						
Certification	9.3	2,119	8.7	2,135	0.632	0.471
Bachelor's Degree	36.8	2,119	37.5	2,135	-0.755	0.610
Master's Degree	6.6	2,119	5.7	2,135	0.893	0.226
Doctoral Degree	1.2	2,119	1.7	2,135	-0.506	0.172
College Student	3.8	2,119	3.7	2,135	0.075	0.897

Notes: Panel A reports moments of ask rates for in-person and online services and their difference in each treatment condition. Panel B reports tutor characteristics in each treatment condition. Each tutor was contacted only once.

Table 4: Number of Callbacks Received by Treatment Condition and Subject

	Treatment Condition			
	In-person		*Online*	
	Parent Name		Parent Name	
Subject	*Maria Georgiou*	*Anna Papageorgiou*	*Maria Georgiou*	*Anna Papageorgiou*
Biology	5	1	4	8
Chemistry	4	8	7	15
Chinese	0	0	1	2
English	18	8	24	22
French	8	8	8	8
German	3	4	5	3
Greek language	17	14	27	17
Italian	4	2	7	4
Mathematics	2	7	10	7
Other languages	3	10	7	5
Physics	3	4	11	8
Russian	1	3	3	2
Spanish	5	5	4	2
Turkish	5	3	2	6
Total	78	77	120	109
Combined Total	155		229	

Notes: This table shows the number of callbacks received from tutors by treatment condition and subject. Each tutor was contacted only once.

Table 5: Estimated Callback Rates

	Means		Without Controls		With Controls		
	In-person	Online	$\hat{\beta}$	SE	$\hat{\beta}$	SE	N
All	0.073	0.107	0.035***	0.009	0.039***	0.009	4,254
By Gender							
Females	0.069	0.106	0.040***	0.011	0.047***	0.011	2,943
Males	0.088	0.116	0.025	0.016	0.021	0.016	1,244
STEM vs. Non-STEM							
STEM	0.049	0.102	0.066***	0.018	0.071***	0.019	1,383
Non-STEM	0.085	0.110	0.023**	0.010	0.026**	0.011	2,871
By Population Density							
Above Median	0.065	0.097	0.036***	0.013	0.037***	0.013	2,085
Below Median	0.081	0.117	0.033***	0.012	0.032***	0.012	2,169
By Local Competition Definition: 10-mile Radius							
Above Median	0.052	0.094	0.052***	0.014	0.058***	0.015	2,077
Below Median	0.093	0.120	0.023**	0.011	0.026**	0.012	2,177

Notes: This table reports estimated marginal effects from logistic regressions. Controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users, as well as location indicators and indicators for the week and day of the week messages were sent. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic. $\hat{\beta}$ is the estimated marginal effect from a logistic regression model. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: Heterogeneity of In-person Rate Differential

	In-person		Online				
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	Std. Err.	N
All	13.5	5.2	12.4	4.9	1.1***	0.1	2,869
By Gender							
Females	13.2	4.7	12.2	4.4	1.0***	0.1	1,999
Males	14.2	6.1	13.0	5.9	1.2***	0.3	851
STEM vs. Non-STEM							
STEM	14.0	6.1	12.7	5.7	1.3***	0.3	851
Non-STEM	13.3	4.7	12.3	4.5	1.0***	0.1	2,018
By Population Density							
Above Median	13.5	5.3	12.4	5.1	1.1***	0.2	1,428
Below Median	13.5	5.1	12.4	4.7	1.1***	0.2	1,441
By Local Competition							
Above Median	13.5	5.5	12.2	5.1	1.4***	0.2	1,333
Below Median	13.5	5.0	12.6	4.7	0.9***	0.2	1,536

Notes: This table reports summary statistics of the the ask rates (in Euros) for in-person and online lessons, overall, and by gender, by subject taught (i.e., STEM vs. non-STEM), by population density in the area of each tutor, and by the local competition each tutor faces. Column *Diff.* shows the mean difference between rates for in-person and online lessons. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Heterogeneous Callback Rate Gap by In-person Rate Differentials

	Callback			
	(1)	(2)	(3)	(4)
Online Lessons × Rate Differential≤0	0.029*	0.035**	0.038**	0.039**
	(0.015)	(0.016)	(0.016)	(0.016)
Online Lessons × Rate Differential>0	0.068***	0.074***	0.069***	0.065***
	(0.021)	(0.023)	(0.023)	(0.022)
Observations	2,869	2,869	2,869	2,869
Location FE	No	Yes	Yes	Yes
Log Rate Controls	No	No	Yes	Yes
Tutor Controls	No	No	No	Yes

Notes: This table reports estimated marginal effects from logistic regressions. Controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users, as well as location indicators and indicators for the week and day of the week messages were sent. An indicator that takes the value when a tutor's in-person rate differential is positive and zero otherwise is also included. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Online Lessons Preference and Associated Reasons

Reason	Statement	Mean	Std. Dev.
Tech Tools and Skills	I have all the technological tools and knowledge I need to conduct online lessons.	2.839	2.816
Teach More Hours	Online lessons allow me to teach more hours than in-person lessons.	2.678	2.626
Location Flexibility	Online lessons give me more freedom to choose where I work compared to in-person lessons.	2.494	3.087
Lower Commuting Expenses	With online lessons, I spend less money on commuting expenses than with in-person lessons.	1.425	4.161
Less Commute-related Stress	I feel less stressed when I don't have to commute to give lessons.	2.103	2.977
Job Satisfaction	I am more satisfied with my work when I have the flexibility to teach remotely.	1.977	2.873
Additional Employment	Online lessons make it easier for me to have other professional engagements than in-person lessons.	2.034	2.843
Scheduling Control	Online lessons give me greater control over my work schedule compared to in-person lessons.	1.851	2.935
Less Exposure to Diseases	Online lessons reduce my exposure to illnesses like the common cold and flu compared to in-person lessons.	1.529	3.621
More Time for Loved Ones/Personal Interests	With online lessons, I spend more time with my loved ones or on personal interests than with in-person lessons.	1.368	3.376
Online Requires More Student Cooperation	Online lessons require more collaboration from the student compared to in-person lessons.	1.092	3.269
Job Opportunities	I find more opportunities for online lessons than for in-person lessons.	0.552	3.238
Can be More Effective	A student taking online lessons can learn more than one taking in-person lessons.	0.356	3.447
Better Mental Health	I have better mental health when I teach online than in-person.	0.241	2.719
Recognition and Respect	I feel greater recognition and respect as a professional when I offer online lessons compared to in-person lessons.	0.149	3.112
More Patient Teacher	I am more patient when I teach online than with in-person lessons.	0.138	3.024
More Effective Teacher	I am more effective when I teach online than in-person.	-0.310	3.134
Online Lessons Preference	I prefer teaching online lessons over in-person lessons.	1.218	3.332
Tutoring vs. Permanent Job	I prefer to work as a private tutor over holding a permanent full-time position, if I cannot combine the two.	0.874	3.139

Notes: Reasons/Statements are ordered by magnitude of agreement score. The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree). Observations: 87. This table presents the positive wording used to investigate the reasons for preferring online lessons. Randomized positive and reverse wordings were used across two versions of the instrument (versions A and B, which appear at the end of the Online Appendix). In each version, roughly half of the questions were phrased positively, while the other half were phrased in reverse. Table S9 shows the positive and reverse wording of the reasons investigated for the preference to deliver online versus in-person lessons.

Table 9: Reasons Driving Online Lessons Preference

	Preference							
	In-person		*Online*		*Either*			
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	P-value
Reason	(1)	(2)	(3)	(4)	(5)	(6)	(3) − (1)	
Job Satisfaction	0.120	3.018	3.417	2.152	0.357	1.985	3.297	0.000
Can be More Effective	-1.320	3.567	1.583	3.134	-0.857	2.656	2.903	0.001
Additional Employment	0.280	2.762	3.042	2.501	1.714	2.644	2.762	0.000
Teach More Hours	0.800	2.915	3.542	2.103	3.071	2.056	2.742	0.000
Recognition and Respect	-1.400	3.014	1.167	3.144	-0.571	1.604	2.567	0.001
Scheduling Control	0.280	2.542	2.771	2.912	1.500	2.534	2.491	0.000
More Effective Teacher	-1.640	3.094	0.667	2.970	-1.286	2.730	2.307	0.004
Better Mental Health	-1.240	2.241	1.146	2.775	-0.214	2.082	2.386	0.000
More Patient Teacher	-1.120	3.004	0.896	2.919	-0.214	2.778	2.016	0.008
Job Opportunities	-0.560	3.318	1.542	3.155	-0.857	2.214	2.102	0.012
Tech Tools and Skills	1.520	3.255	3.313	2.651	3.571	1.651	1.792	0.022
Less Exposure to Diseases	1.000	3.122	1.708	4.000	1.857	3.183	0.708	0.408
Location Flexibility	1.920	2.943	2.500	3.458	3.500	1.454	0.580	0.455
Less Commute-related Stress	1.640	2.343	2.188	3.474	2.643	2.023	0.548	0.428
More Time for Loved Ones/Personal Interests	1.120	3.219	1.479	3.579	1.429	3.131	0.359	0.665
Lower Commuting Expenses	1.960	3.813	1.104	4.387	1.571	4.146	-0.856	0.392
Online Requires More Student Cooperation	2.640	2.464	0.208	3.525	1.357	2.649	-2.432	0.001
N	25		48		14			

Notes: Reasons are ordered by magnitude of the difference in agreement score between tutors who report preferring to teach online and tutors who report preferring to teach in person (i.e., difference (3)-(1)). P-values correspond to tests of significance of the difference (3)-(1). The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree). Observations: 87.

Table 10: Online Preference Mechanisms by Gender

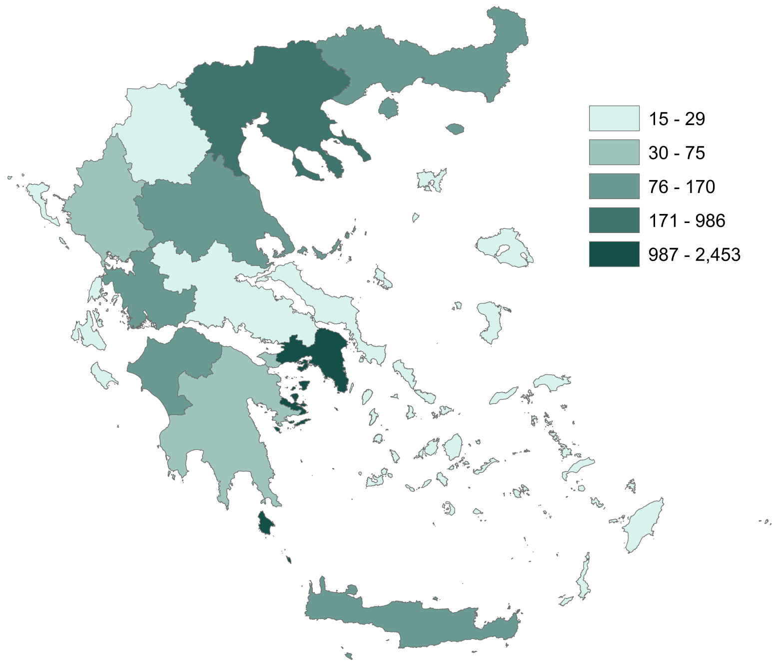
	Score Difference Between Online and In-person			
	Females		Males	
Reason	Diff.	Rank	Diff.	Rank
Additional Employment	2.683***	7	2.555**	5
Better Mental Health	2.760***	5	2.045*	6
Can be More Effective	2.969**	4	2.582*	4
Job Opportunities	2.369**	8	1.400	12
Job Satisfaction	3.202***	2	3.964***	2
Less Commute-related Stress	0.279	14	1.400	12
Less Exposure to Diseases	1.050	12	0.055	14
Location Flexibility	0.422	13	0.591	13
Lower Commuting Expenses	−1.148	16	−0.073	15
More Effective Teacher	1.741	11	3.391**	3
More Patient Teacher	2.342**	9	1.936*	8
More Time for Loved Ones/Personal Interests	−0.052	15	1.718	10
Online Requires More Student Cooperation	−2.661***	17	−2.455	17
Recognition and Respect	1.888*	10	4.600***	1
Scheduling Control	2.706***	6	1.791	9
Teach More Hours	3.195***	3	1.964*	7
Tech Tools and Skills	3.261***	1	−0.936	16
N	52		21	

Notes: Agreement score ranges from -5 (Completely Disagree) to 5 (Completely Agree). Eight out of 60 female survey participants were indifferent between online and in-person lessons. Six out of 27 male survey participants were indifferent between online and in-person lessons. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Supplementary Appendix

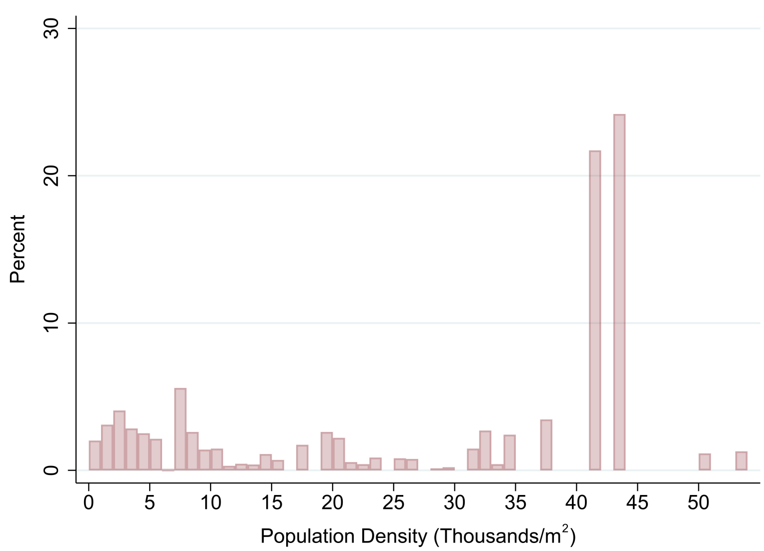
The Value of Remote Work

Figure S1: Study Sample



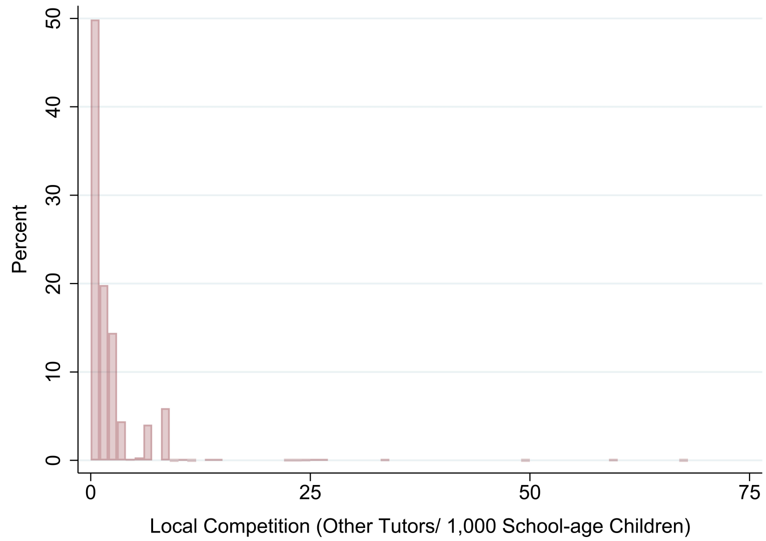
Notes: This map shows the counts of tutors in the study sample across regions.

Figure S2: Histogram of Population Density



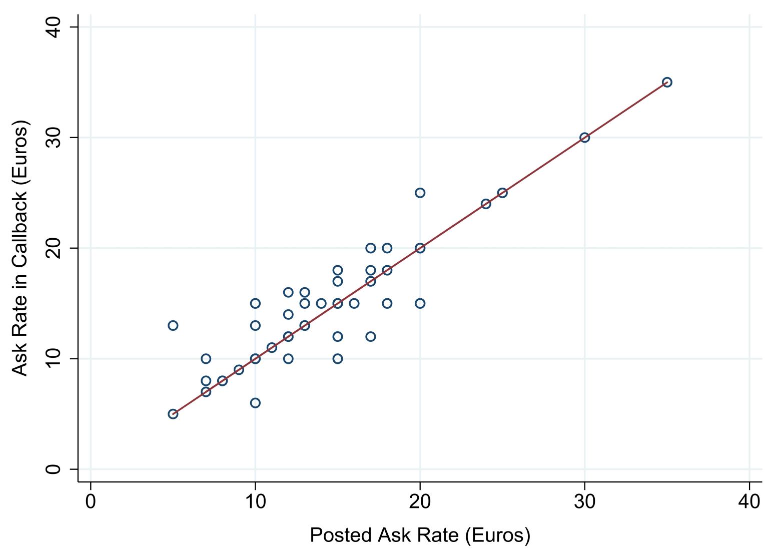
Notes: Population density is measured as the overall population in the smallest census-related geographical unit divided by the area of that unit in m^2. Population and area estimates come from the 2021 census of the Hellenic Republic.

Figure S3: Histogram of Local Competition



Notes: Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic.

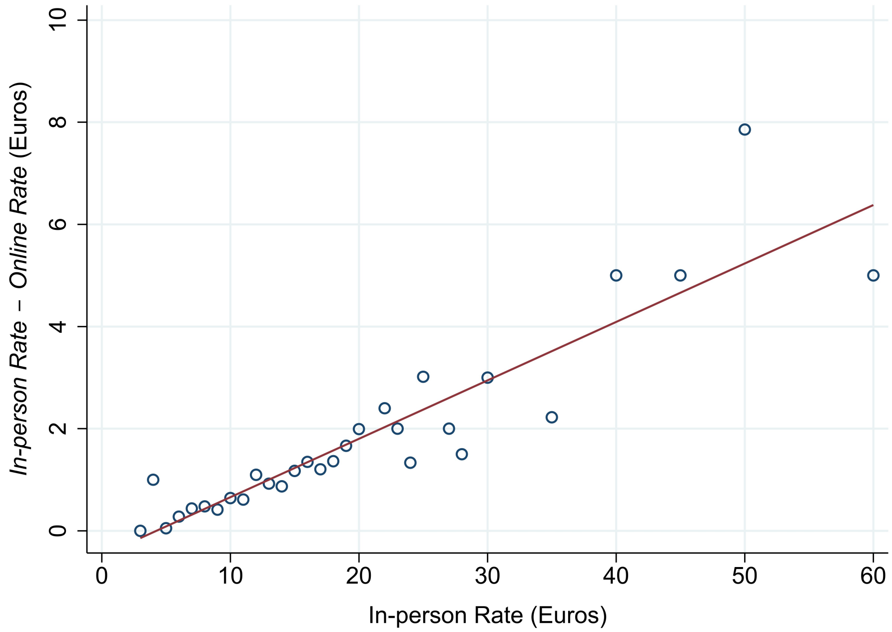
Figure S4: Association Ask Rates in Callbacks Posted Ask Rates



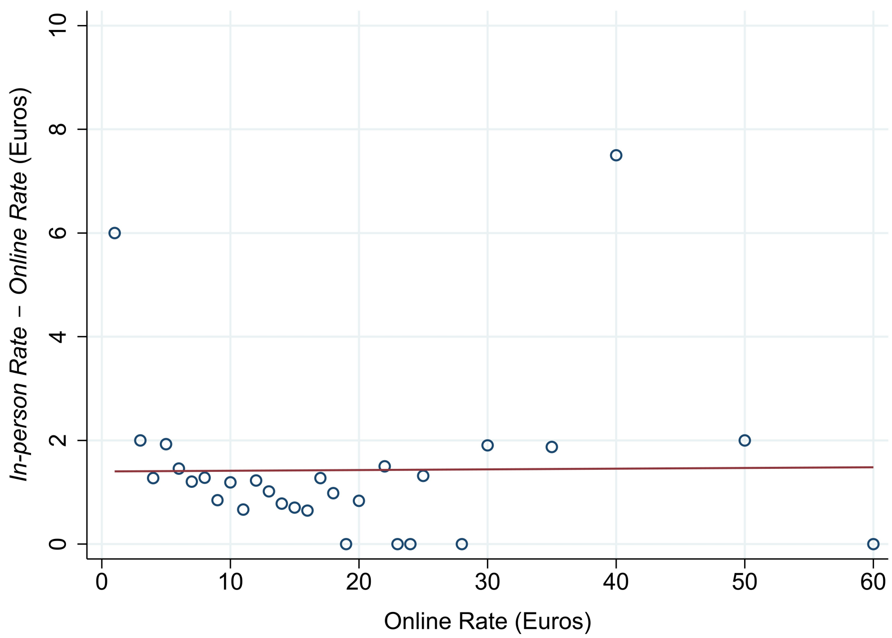
Notes: This figure shows the scatterplot and the 45-degree regression line between the ask rates in callbacks and the ask rates on the tutor board. Each marker represents a tutor.

Figure S5: Association Between Ask Rates and the Rate Difference Between In-person and Online Rates

Panel A: Relative to In-person Rate

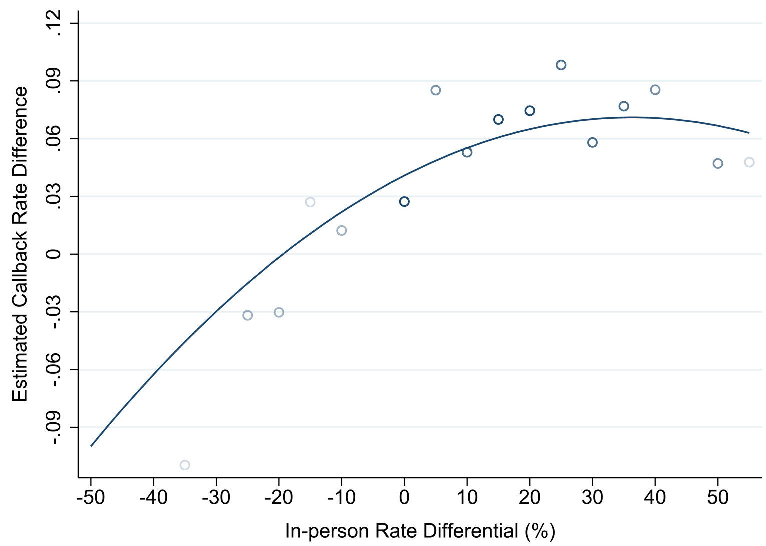


Panel B: Relative to Online Rate



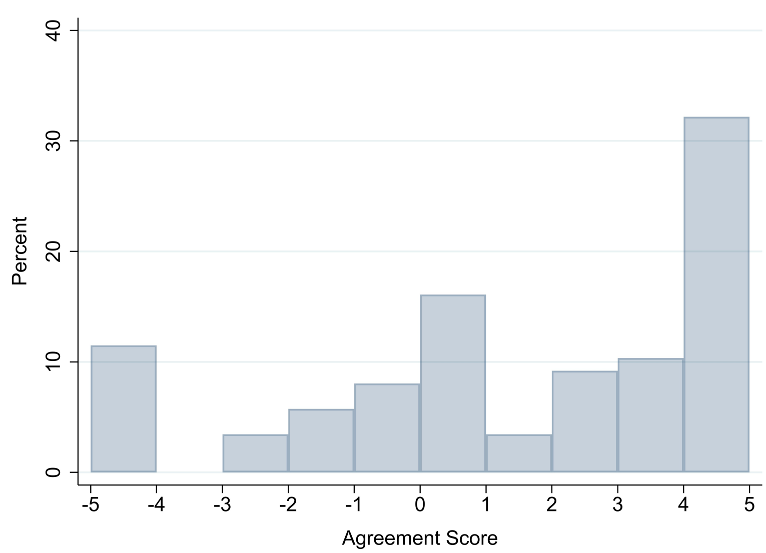
Notes: Panel A shows the scatterplot and the fitted regression line between the hourly rate tutors ask for in-person lessons and the difference in their asks rates for in-person and online lessons. Panel A shows the scatterplot and the fitted regression line between the hourly rate tutors ask for online lessons and the difference in their asks rates for in-person and online lessons. Each marker represents a tutor.

Figure S6: In-person Rate Difference and Preference for Remote Work



Notes: This figure displays the estimated callback rate gap between requests for online and in-person lessons at different levels of the in-person rate differential. It uses fitted values from a logistic regression of callback on the *Online Lessons* treatment variable, the in-person rate differential, and their interaction. The specification includes controls for the logarithms of both in-person and online rates. A quadratic fitted line is shown. The color shading of the markers indicates the number of observations in each bin, with darker shades representing higher observation counts and greater estimation precision.

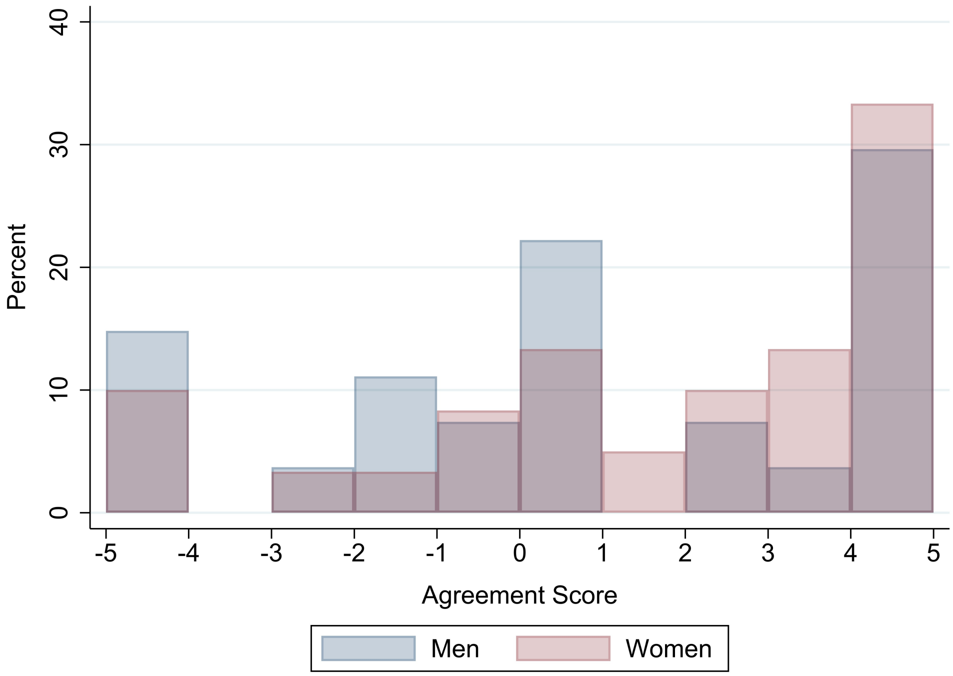
Figure S7: Histogram of Agreement Score for Online Lessons Preference



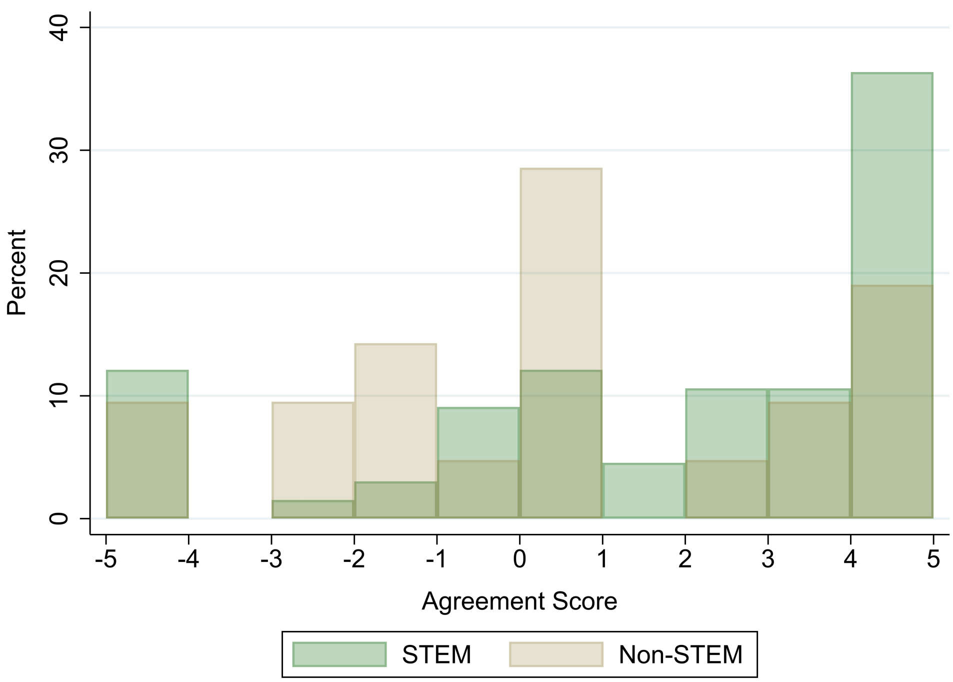
Notes: Agreement score ranges from -5 (Completely Disagree) to 5 (Completely Agree). Observations: 87.

Figure S8: Heterogeneity in the Agreement Score for Online Lessons Preference

Panel A: By Gender



Panel B: STEM vs. Non-STEM



Notes: Agreement score ranges from -5 (Completely Disagree) to 5 (Completely Agree). Observations: 87.

Table S1: Subjects in Sample and Population

Subject	Sample	Population
Biology	254	255
Chemistry	379	384
Chinese	58	61
English	793	925
French	222	239
German	232	246
Greek language	959	1,090
Italian	109	133
Mathematics	431	483
Other languages	116	116
Physics	319	327
Russian	137	141
Spanish	146	152
Turkish	99	103
Total	4,254	4,655

Notes: This table shows the number of tutors teaching each subject in the sample and the population. Each tutor is assigned the first subject they list. Each tutor was contacted only once.

Table S2: Sample Representativeness

	Sample		Population			
	Mean	N	Mean	N	Diff.	P-value
Panel A: Ask Hourly Rates (Euro)						
In-person Rate	12.9	4,250	13.2	4,655	-0.337	0.290
Online Rate	12.4	2,869	12.6	3,103	-0.239	0.485
	1.1	2,869	1.1	3,103	-0.019	0.706
Panel B: Tutor Characteristics						
Age (Yrs)	34.1	3,370	34.1	3,662	0.027	0.900
Experience (Yrs)	10.3	852	12.4	922	-2.110	0.336
Local Competition	2.1	4,254	2.1	4,655	-0.004	0.971
(Other Tutors/ 1,000 School-age Children)						
Population Density	28.6	4,254	28.6	4,655	0.020	0.955
(Thousands/Square Mile)						
	%	N	%	N		
Female	70.3	4,187	70.5	4,579	-0.229	0.815
Teach STEM Subjects	32.5	4,254	31.1	4,655	1.383	0.162
Teach Non-STEM Subjects	67.5	4,254	68.9	4,655	-1.383	0.162
Teach Foreign Language	44.9	4,254	45.5	4,655	-0.511	0.629
Special Needs Training	5.6	4,254	5.5	4,655	0.099	0.839
Recommended	6.1	4,254	5.6	4,655	0.462	0.355
Education						
Certification	10.2	4,254	10.0	4,655	0.281	0.660
Bachelor's Degree	37.1	4,254	36.5	4,655	0.665	0.516
Master's Degree	6.2	4,254	5.8	4,655	0.337	0.503
Doctoral Degree	1.5	4,254	1.4	4,655	0.085	0.738
College Student	3.8	4,254	3.8	4,655	-0.061	0.881

Notes: Panel A reports moments of ask rates for in-person and online services and their difference in the sample and the population of tutors on the platform. Panel B reports treatment characteristics in the sample and the population of tutors on the platform. Each tutor in the sample was contacted only once. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic. Targeted population refers to tutors teaching STEM or non-STEM subjects in secondary education, or foreign languages.

Table S3: Messages Sent by Week

Week	Count	Percent
July 8, 2024 – July 14, 2024	1,229	28.89
July 15, 2024 – July 21, 2024	791	18.59
July 22, 2024 – July 28, 2024	1,093	25.69
July 29, 2024 – August 4, 2024	44	1.03
August 5, 2024 – August 11, 2024	263	6.18
August 19, 2024 – August 25, 2024	834	19.61
Total	4,254	100.00

Notes: No messages were sent during the week of August 12, 2024 - August 18, 2024 because of a major holiday on August 15.

Table S4: Robustness Check: Estimated Callback Rates Using a Linear Probability Model

	Means		Without Controls		With Controls		
	In-person	Online	$\hat{\beta}$	SE	$\hat{\beta}$	SE	N
All	0.073	0.107	0.034***	0.009	0.036***	0.008	4,254
By Gender							
Females	0.069	0.106	0.038***	0.010	0.042***	0.010	2,943
Males	0.088	0.116	0.028	0.017	0.023	0.016	1,244
STEM vs. Non-STEM							
STEM	0.049	0.102	0.055***	0.014	0.055***	0.014	1,383
Non-STEM	0.085	0.110	0.024**	0.011	0.026**	0.011	2,871
By Population Density							
Above Median	0.065	0.097	0.033***	0.012	0.033***	0.011	2,085
Below Median	0.081	0.117	0.035***	0.013	0.036***	0.012	2,169
By Local Competition							
Above Median	0.052	0.094	0.043***	0.011	0.041***	0.011	2,077
Below Median	0.093	0.120	0.026**	0.013	0.029**	0.012	2,177

Notes: Controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users, as well as location indicators and indicators for the week and day of the week messages were sent. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Population and area estimates come from the 2021 census of the Hellenic Republic. $\hat{\beta}$ is the estimated parameter of interest from a linear probability model. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S5: Summary Statistics of Different Definitions of Local Competition

Local Competition Definition	Mean	Median	Std. Dev.	5 pct	95 pct	N
Census Block ($\approx$ 1.7-mile Radius)	2.1	1.0	5.0	0.0	9.0	4,254
5-mile Radius	1.1	0.7	2.0	0.0	3.0	4,254
10-mile Radius (Main)	0.6	0.3	2.0	0.0	1.0	4,254
15-mile Radius	0.4	0.2	1.0	0.0	1.0	4,254
20-mile Radius	0.2	0.1	1.0	0.0	1.0	4,254

Notes: This table reports summary statistics for local tutor competition measures using different definitions. The unit of local tutor competition measures is the number of other tutors per one thousand school-age children. Local competition under the census block definition for each tutor is measured as the number of other tutors in the platform teaching the same subject within the radius of the smallest census-related geographical unit (i.e., census block) divided by an estimate of school-age children (age 3-17 in 2024) in the same unit. Local competition under the 5-mile radius definition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 5-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in that area using population information at the census-block level. Similarly for the local competition definitions using a 10-, 15-, or 20-mile radius.

Table S6: ESTIMATED CALLBACK RATES USING DIFFERENT DEFINITIONS OF LOCAL COMPETITION

	Means		Without Controls		With Controls		
	In-person	Online	$\hat{\beta}$	SE	$\hat{\beta}$	SE	N
Local Competition Definition: Census Block (Roughly Equivalent to 1.7-mile Radius)							
Above Median	0.062	0.096	0.040***	0.014	0.038***	0.014	2,096
Below Median	0.084	0.118	0.031***	0.012	0.041***	0.013	2,158
By Local Competition Definition: 5-mile Radius							
Above Median	0.059	0.095	0.041***	0.014	0.045***	0.014	2,104
Below Median	0.087	0.119	0.030**	0.012	0.034***	0.012	2,150
By Local Competition Definition: 10-mile Radius							
Above Median	0.052	0.094	0.052***	0.014	0.058***	0.015	2,077
Below Median	0.093	0.120	0.023**	0.011	0.026**	0.012	2,177
By Local Competition Definition: 15-mile Radius							
Above Median	0.051	0.092	0.052***	0.014	0.055***	0.015	2,081
Below Median	0.095	0.122	0.023**	0.011	0.028**	0.012	2,173
By Local Competition Definition: 20-mile Radius							
Above Median	0.052	0.094	0.052***	0.014	0.055***	0.015	2,105
Below Median	0.094	0.120	0.023**	0.011	0.027**	0.012	2,149

Notes: This table reports estimated marginal effects from logistic regressions. The unit of local tutor competition measures is the number of other tutors per one thousand school-age children. Controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users, as well as location indicators and indicators for the week and day of the week messages were sent. Local competition under the census block definition for each tutor is measured as the number of other tutors in the platform teaching the same subject within the radius of the smallest census-related geographical unit (i.e., census block) divided by an estimate of school-age children (age 3-17 in 2024) in the same unit. Local competition under the 5-mile radius definition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 5-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in that area using population information at the census-block level. Similarly for the local competition definitions using a 10-, 15-, or 20-mile radius. $\hat{\beta}$ is the estimated marginal effects from a logistic regression model. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S7: Effect of Local Competition on the In-person Rate Differential

	Logarithm of (*In-person Rate* − *Online Rate*)			
	(1)	(2)	(3)	(4)
Local Competition	0.010***	0.012***	0.035**	0.046***
	(0.004)	(0.004)	(0.014)	(0.014)
Observations	2,807	2,807	2,807	2,807
Location FE	No	No	Yes	Yes
Log Rate Controls	Yes	Yes	Yes	Yes
Tutor Controls	No	Yes	No	Yes

Notes: This table reports estimates coefficients from OLS regressions. The outcome is the logarithm of the difference between the ask rates for in-person and online lessons. Local competition for each tutor is measured as the number of other tutors in the platform teaching the same subject within a 10-mile radius divided by an estimate of school-age children (age 3-17 in 2024) in the same area. Log rate controls include controls for the logarithm of rates each tutor asks for in-person and online lessons. The local competition measure is standardized to have a mean of zero and a standard deviation of one. Location fixed effects (FE) refer to indicators for each tutor's reported location. Tutor controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S8: Effect of the In-person Rate Differential on Callback

	Callback			
	(1)	(2)	(3)	(4)
Online Lessons × In-person Rate Differential	1.945**	2.233**	2.679**	2.465**
	(0.792)	(0.874)	(1.076)	(1.149)
Online Lessons	0.284**	0.308**	0.291**	0.330**
	(0.128)	(0.136)	(0.143)	(0.151)
In-person Rate Differential	-1.751***	-1.731***	4.532	3.038
	(0.588)	(0.645)	(4.115)	(4.624)
Observations	2,869	2,869	2,869	2,869
Location FE	No	Yes	Yes	Yes
Log Rate Controls	No	No	Yes	Yes
Tutor Controls	No	No	No	Yes

Notes: This table reports estimates coefficients from logistic regressions. The in-person rate differential is the difference between the ask rates for in-person and online lessons divided by the rate for in-person lessons. Location fixed effects (FE) refer to indicators for each tutor's reported location. Log rate controls include controls for the logarithm of rates each tutor asks for in-person and online lessons. Tutor controls include a female indicator, an indicator for missing gender information, indicators for reported education levels (certification, bachelor's, master's, or doctoral degree), an indicator for being a college student, indicators for above- and below-median years of experience, an indicator for missing information regarding years of experience, indicators for above- and below-median age, an indicator for missing age information, indicators for teaching non-STEM subjects, having special learning needs training, and being recommended by platform users. All specifications control for indicators for the week and day of the week messages were sent. Heteroskedasticity-robust standard errors are reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S9: Wording of Statements About Reasons for Online Lessons Preference

Positive Wording	Reverse Wording
Online lessons give me greater control over my work schedule compared to in-person lessons.	In-person lessons give me greater control over my work schedule compared to online lessons.
I am more satisfied with my work when I have the flexibility to teach remotely.	I am more satisfied with my work when I don't have the flexibility to teach remotely.
I feel greater recognition and respect as a professional when I offer online lessons compared to in-person lessons.	I feel greater recognition and respect as a professional when I offer in-person lessons than online.
I find more opportunities for online lessons than for in-person lessons.	I find more opportunities for in-person lessons than online lessons.
Online lessons allow me to teach more hours than in-person lessons.	In-person lessons allow me to teach more hours than online lessons.
With online lessons, I spend less money on commuting expenses than with in-person lessons.	With in-person lessons, I spend less money on commuting expenses than with online lessons.
With online lessons, I spend more time with my loved ones or on personal interests than with in-person lessons.	With in-person lessons, I spend more time with my loved ones or on personal interests than with online lessons.
I am more effective when I teach online than in-person.	I am more effective when I teach in person than online.
I am more patient when I teach online than with in-person lessons.	I am more patient when I teach in person than with online lessons.
I have better mental health when I teach online than in-person.	I have better mental health when I teach in person than online.
Online lessons reduce my exposure to illnesses like colds and flu compared to in-person lessons.	In-person lessons reduce my exposure to illnesses like colds and flu compared to online lessons.
I feel less stressed when I don't have to commute to give lessons.	I feel less stressed when I need to commute to teach a lesson.
Online lessons give me more freedom to choose where I work compared to in-person lessons.	In-person lessons give me more freedom to choose where I work compared to online lessons.
Online lessons make it easier for me to have other professional engagements than in-person lessons.	In-person lessons make it easier for me to have other professional engagements than online lessons.
Online lessons require more collaboration from the student compared to in-person lessons.	In-person lessons require more cooperation from the student compared to online lessons.
A student taking online lessons can learn more than one taking in-person lessons.	A student taking in-person lessons can learn more than one taking online lessons.
I have all the technological tools and knowledge I need to conduct online lessons.	I don't have all the technological tools and knowledge I need to conduct online lessons.
I prefer teaching online lessons over in-person lessons.	I prefer teaching in-person lessons to online lessons.
I prefer to work as a private tutor over holding a permanent full-time position, if I cannot combine the two.	I prefer holding a permanent full-time position over working as a private tutor, if I cannot combine the two.

Notes: This table presents the positive and reverse wordings used to investigate the reasons for preferring online lessons. The positive and reverse wordings were randomized across two versions of the instrument (versions A and B, which appear at the end of the Online Appendix). In each version, roughly half of the questions were phrased positively, while the other half were phrased in reverse.

Table S10: Reasons Driving Online Lessons Preference, Men

	Preference							
	In-person		*Online*		*Either*			
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	P-value
Reason	(1)	(2)	(3)	(4)	(5)	(6)	(3) − (1)	
Recognition and Respect	-1.600	2.875	3.000	2.864	0.167	1.602	4.600	0.001
Job Satisfaction	0.400	3.204	4.364	1.120	0.500	2.588	3.964	0.003
More Effective Teacher	-2.300	2.163	1.091	3.534	-0.833	2.137	3.391	0.015
Can be More Effective	-1.400	3.239	1.182	2.926	-0.833	1.941	2.582	0.070
Additional Employment	-0.100	2.470	2.455	2.979	2.333	1.506	2.555	0.044
Better Mental Health	-0.500	0.972	1.545	3.236	0.000	0.632	2.045	0.068
Teach More Hours	1.400	2.633	3.364	2.292	3.167	2.137	1.964	0.085
More Patient Teacher	-0.300	2.163	1.636	2.873	-0.167	1.602	1.936	0.095
Scheduling Control	0.300	2.359	2.091	3.910	2.500	2.074	1.791	0.216
More Time for Loved Ones/Personal Interests	1.100	2.961	2.818	3.401	0.500	2.739	1.718	0.230
Job Opportunities	-0.400	3.534	1.000	3.406	-1.167	2.787	1.400	0.367
Less Commute-related Stress	1.600	2.366	3.000	3.066	2.167	2.317	1.400	0.253
Location Flexibility	1.500	2.953	2.091	3.727	3.000	1.549	0.591	0.690
Less Exposure to Diseases	1.400	3.239	1.455	4.204	2.500	2.074	0.055	0.974
Lower Commuting Expenses	1.800	3.910	1.727	4.429	2.833	3.920	-0.073	0.969
Tech Tools and Skills	3.300	2.710	2.364	3.722	4.167	1.602	-0.936	0.515
Online Requires More Student Cooperation	2.000	2.944	-0.455	3.751	0.833	2.041	-2.455	0.109
N	10		11		6			

Notes: Reasons are ordered by magnitude of the difference in agreement score between tutors who report preferring to teach online and tutors who report preferring to teach in person (i.e., difference (3)-(1)). P-values correspond to tests of significance of the difference (3)-(1). The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree).

Table S11: Reasons Driving Online Lessons Preference, Women

	Preference							
	In-person		*Online*		*Either*			
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	P-value
Reason	(1)	(2)	(3)	(4)	(5)	(6)	(3) − (1)	
Tech Tools and Skills	0.333	3.109	3.595	2.229	3.125	1.642	3.261	0.001
Job Satisfaction	-0.067	2.987	3.135	2.311	0.250	1.581	3.202	0.001
Teach More Hours	0.400	3.112	3.595	2.074	3.000	2.138	3.195	0.002
Can be More Effective	-1.267	3.882	1.703	3.222	-0.875	3.227	2.969	0.015
Better Mental Health	-1.733	2.712	1.027	2.661	-0.375	2.774	2.760	0.002
Scheduling Control	0.267	2.738	2.973	2.576	0.750	2.712	2.706	0.003
Additional Employment	0.533	2.997	3.216	2.359	1.250	3.284	2.683	0.005
Job Opportunities	-0.667	3.288	1.703	3.108	-0.625	1.847	2.369	0.024
More Patient Teacher	-1.667	3.416	0.676	2.935	-0.250	3.536	2.342	0.029
Recognition and Respect	-1.267	3.195	0.622	3.049	-1.125	1.458	1.888	0.061
More Effective Teacher	-1.200	3.590	0.541	2.824	-1.625	3.204	1.741	0.107
Less Exposure to Diseases	0.733	3.127	1.784	3.994	1.375	3.889	1.050	0.320
Location Flexibility	2.200	3.005	2.622	3.419	3.875	1.356	0.422	0.663
Less Commute-related Stress	1.667	2.410	1.946	3.590	3.000	1.852	0.279	0.746
More Time for Loved Ones/Personal Interests	1.133	3.482	1.081	3.578	2.125	3.399	-0.052	0.962
Lower Commuting Expenses	2.067	3.882	0.919	4.418	0.625	4.307	-1.148	0.361
Online Requires More Student Cooperation	3.067	2.086	0.405	3.484	1.750	3.105	-2.661	0.001
N	15		37		8			

Notes: Reasons are ordered by magnitude of the difference in agreement score between tutors who report preferring to teach online and tutors who report preferring to teach in person (i.e., difference (3)-(1)). P-values correspond to tests of significance of the difference (3)-(1). The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree).

Table S12: Online Preference Mechanisms by STEM vs. STEM Subjects

	Score Difference Between Online and In-person			
	STEM		Non-STEM	
Reason	Diff.	Rank	Diff.	Rank
Additional Employment	3.268*	3	2.254***	9
Better Mental Health	1.857	5	2.548***	6
Can be More Effective	−0.411	13	3.902***	1
Job Opportunities	−0.857	14	2.775***	5
Job Satisfaction	3.268***	3	3.528***	2
Less Commute-related Stress	−0.964	15	0.989	13
Less Exposure to Diseases	−2.554	16	1.603	12
Location Flexibility	0.089	10	0.875	14
Lower Commuting Expenses	0.107	9	−0.783	16
More Effective Teacher	2.125*	4	2.192**	10
More Patient Teacher	0.768	8	2.377**	8
More Time for Loved Ones/Personal Interests	0.911	7	0.341	15
Online Requires More Student Cooperation	−3.571*	17	−2.129***	17
Recognition and Respect	−0.036	11	3.056***	3
Scheduling Control	4.179***	1	1.894**	11
Teach More Hours	1.750	6	3.046***	4
Tech Tools and Skills	−0.036	12	2.473***	7
N	15		58	

Notes: Agreement score ranges from -5 (Completely Disagree) to 5 (Completely Agree). Eight out of 60 female survey participants were indifferent between online and in-person lessons. Six out of 27 male survey participants were indifferent between online and in-person lessons. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table S13: Reasons Driving Online Lessons Preference, STEM

	Preference							
	In-person		*Online*		*Either*			
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	P-value
Reason	(1)	(2)	(3)	(4)	(5)	(6)	(3) − (1)	
Scheduling Control	-0.750	2.550	3.429	1.718	3.000	1.673	4.179	0.002
Additional Employment	-1.125	2.900	2.143	3.024	2.667	1.033	3.268	0.051
Job Satisfaction	0.875	1.727	4.143	1.464	0.833	2.639	3.268	0.001
More Effective Teacher	-2.125	1.458	0.000	2.708	-1.333	2.251	2.125	0.094
Better Mental Health	-1.000	1.773	0.857	3.237	-0.333	1.033	1.857	0.206
Teach More Hours	1.250	3.012	3.000	2.517	3.667	1.506	1.750	0.239
More Time for Loved Ones/Personal Interests	1.375	3.204	2.286	3.450	0.333	2.733	0.911	0.606
More Patient Teacher	-0.625	1.996	0.143	2.911	-0.500	1.761	0.768	0.568
Lower Commuting Expenses	2.750	3.412	2.857	3.671	1.667	4.179	0.107	0.954
Location Flexibility	2.625	2.615	2.714	3.684	3.000	1.549	0.089	0.958
Tech Tools and Skills	2.750	3.955	2.714	3.684	3.833	1.602	-0.036	0.986
Recognition and Respect	-1.250	2.550	-1.286	3.592	-0.167	1.835	-0.036	0.983
Job Opportunities	0.000	3.024	-0.857	2.795	-0.833	3.061	-0.857	0.577
Can be More Effective	0.125	3.482	-0.286	3.147	-1.167	1.941	-0.411	0.814
Less Commute-related Stress	2.250	1.669	1.286	3.302	2.167	2.317	-0.964	0.502
Less Exposure to Diseases	2.125	2.642	-0.429	4.577	2.167	2.639	-2.554	0.222
Online Requires More Student Cooperation	3.000	2.777	-0.571	4.541	1.167	2.041	-3.571	0.099
N	8		7		6			

Notes: Reasons are ordered by magnitude of the difference in agreement score between tutors who report preferring to teach online and tutors who report preferring to teach in person (i.e., difference (3)-(1)). P-values correspond to tests of significance of the difference (3)-(1). The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree).

Table S14: Reasons Driving Online Lessons Preference, Non-STEM

	Preference							
	In-person		*Online*		*Either*			
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	P-value
Reason	(1)	(2)	(3)	(4)	(5)	(6)	(3) − (1)	
Can be More Effective	-2.000	3.500	1.902	3.056	-0.625	3.204	3.902	0.000
Job Satisfaction	-0.235	3.456	3.293	2.239	0.000	1.414	3.528	0.001
Recognition and Respect	-1.471	3.281	1.585	2.907	-0.875	1.458	3.056	0.002
Teach More Hours	0.588	2.938	3.634	2.046	2.625	2.387	3.046	0.001
Job Opportunities	-0.824	3.504	1.951	3.057	-0.875	1.553	2.775	0.008
Tech Tools and Skills	0.941	2.817	3.415	2.480	3.375	1.768	2.473	0.004
Better Mental Health	-1.353	2.473	1.195	2.731	-0.125	2.696	2.548	0.001
More Patient Teacher	-1.353	3.408	1.024	2.937	0.000	3.464	2.377	0.018
Additional Employment	0.941	2.512	3.195	2.411	1.000	3.295	2.254	0.004
More Effective Teacher	-1.412	3.641	0.780	3.029	-1.250	3.196	2.192	0.038
Scheduling Control	0.765	2.463	2.659	3.071	0.375	2.560	1.894	0.018
Less Exposure to Diseases	0.471	3.262	2.073	3.837	1.625	3.701	1.603	0.115
Less Commute-related Stress	1.353	2.597	2.341	3.519	3.000	1.852	0.989	0.243
Location Flexibility	1.588	3.104	2.463	3.465	3.875	1.356	0.875	0.352
More Time for Loved Ones/Personal Interests	1.000	3.317	1.341	3.624	2.250	3.327	0.341	0.731
Lower Commuting Expenses	1.588	4.032	0.805	4.468	1.500	4.408	-0.783	0.519
Online Requires More Student Cooperation	2.471	2.375	0.341	3.373	1.500	3.162	-2.129	0.009
N	17		41		8			

Notes: Reasons are ordered by magnitude of the difference in agreement score between tutors who report preferring to teach online and tutors who report preferring to teach in person (i.e., difference (3)-(1)). P-values correspond to tests of significance of the difference (3)-(1). The agreement scores range from -5 (Completely Disagree) to 5 (Completely Agree).

Table S15: External Validity Benchmarks

		K-12 Teachers			Working-Age Population		
	Tutor Sample	EU	OECD	US	EU	OECD	US
Women (%)	70[§1]	72[§2]	69[§3]	77[§4]	46[§5]	45[§6]	46[§7]
Post-HS Education (%)	39[§8]	N/A	N/A	N/A	43[§9]	40[§10]	47[§11]
Median Age (Yrs)	30[§12]	N/A	N/A	42[§13]	44[§14]	40[§15]	42[§16]

Sources:

§1: Across all tutors in the sample.

§2, §3: The ratio of female teachers in primary and secondary education over the total number of teachers in primary and secondary education. Author's calculation using data from the UNESCO Institute for Statistics, World Bank Open Data, Washington, DC, accessed [October 2024], https://data.worldbank.org/indicator/SE.SEC.TCHR.FE

§4, §13: "Public School Teacher and Private School Teacher Data Files," 2021, National Teacher and Principal Survey (NTPS), U.S. Department of Education, National Center for Education Statistics, Washington, DC, accessed [October 2024], https://nces.ed.gov/surveys/ntps/estable/table/ntps/ntps2021_fl02_t12n.

§5, §6, §7: Female labor force (% of total labor force). Labor force comprises people ages 15 and older who supply labor for the production of goods and services during a specified period. Estimates are based on data obtained from International Labour Organization and United Nations Population Division. World Development Indicators Database, World Bank (2023), Washington, DC, accessed [October 2024], https://data.worldbank.org/indicator/SL.TLF.TOTL.FE.ZS.

§8: Across all tutors in the sample. Post-HS stands for post-high school. Includes tutors with certifications but not those who are still college students.

§9: "Educational Attainment Statistics," 2023, Eurostat, Luxembourg City, Luxembourg, accessed [October 2024], https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Educational_attainment_statistics.

§10: "Education at a Glance 2023," 2023, Organisation for Economic Co-operation and Development (OECD), Paris, France, accessed [October 2024], https://www.oecd-ilibrary.org/education/educational-attainment-of-25-64-year-olds-2022_c5373fc9-en.

§11: "Census Bureau Releases New Educational Attainment Data," 2023, U.S. Census Bureau, Suitland, MD, accessed [October 2024], https://www.census.gov/newsroom/press-releases/2023/educational-attainment-data.html.

§12: Across all tutors in the sample. Median tutor age was indirectly validated through reported educational attainment and years of experience for each tutor in the sample. Validation assumptions regarding the likely age at which tutors started tutoring: tutors with educational attainment below a bachelor's degree started tutoring at age 18; tutors with a bachelor's degree at 22; tutors with a master's degree at 24; and tutors with a doctoral degree at 27.

§14: "Population: Structure Indicators," 2023, Eurostat, Luxembourg City, Luxembourg.

§15: "Working Better with Age," 2023, Organisation for Economic Co-operation and Development (OECD) Paris, France, accessed [October 2024], https://www.oecd.org/en/publications/working-better-with-age_c4d4f66a-en.html.

§16: "Employment Projections Program," 2024, U.S. Bureau of Labor Statistics, Washington, DC, accessed [October 2024], https://www.bls.gov/emp/tables/median-age-labor-force.htm.

S1 Treatments

There are two treatment conditions: emails requesting in-person tutoring services and emails requesting online tutoring services. Two types of *firstname* and *lastname* parameters were used. First and last names were chosen to reflect relatively common Greek names. The same set of *firstname* and *lastname* parameters was used for tutors assigned to the in-person or the online treatment condition. Parameter *location* was populated to match the first location each tutor lists as an area they serve. Parameter *subject* was populated to match the subject each tutor lists. Each tutor was contacted only once.

Email Treatment A1 (English)

Subject: [subject] lessons in person

Hello,

My name is [firstname lastname]. I found your contact information on [platform name].

I am interested in private [subject] lessons at our home for my daughter. She has just completed the first year of junior high school.

She has reached approximately level B1. We would like her to take the exam for the B2 level diploma next year.

We live in [location]. Which area are you located in?

I would also like to ask how much you charge per hour.

Thank you very much,

[firstname lastname]

Email Treatment A2 (English)

Subject: [subject] lessons online

Hello,

My name is [firstname lastname]. I found your contact information on [platform name].

I am interested in private online [subject] lessons for my daughter. She has just completed the first year of junior high school.

She has reached approximately level B1. We would like her to take the exam for the B2 level diploma next year.

We live in [location]. Which area are you located in?

I would also like to ask how much you charge per hour.

Thank you very much,

[firstname lastname]

Email Treatment B1 (English)

Subject: [subject] lessons in person

Hello,

My name is [firstname lastname]. I found your contact information on [platform name].

I am interested in private [subject] lessons at our home for my daughter. She has just completed the first year of junior high school.

We would like her to have academic support throughout the next year.

We live in [location]. Which area are you located in?

I would also like to ask how much you charge per hour.

Thank you very much,

[firstname lastname]

Email Treatment B2 (English)

Subject: [subject] lessons online

Hello,

My name is [firstname lastname]. I found your contact information on [platform name].

I am interested in private online [subject] lessons for my daughter. She has just completed the first year of junior high school.

We would like her to have academic support throughout the next year.

We live in [location]. Which area are you located in?

I would also like to ask how much you charge per hour.

Thank you very much,

[firstname lastname]

Email Treatment A1 (Greek)

Subject: Μαθήματα [subject] δια ζώσης

Χαίρετε,

Ονομάζομαι [firstname lastname]. Βρήκα τα στοιχεία σας από το [platform name].

Ενδιαφέρομαι για ιδιαίτερα μαθήματα [subject] στο σπίτι μας για την κόρη μου. Μόλις τελείωσε την Α’

Γυμνασίου.

Έχει φτάσει περίπου στο επίπεδο B1. Θα θέλαμε να δώσει εξετάσεις για δίπλωμα επιπέδου B2 την επόμενη χρονιά.

Μένουμε [location]. Εσείς σε ποια περιοχή βρίσκεστε;

Θα ήθελα επίσης να ρωτήσω πόσο χρεώνετε την ώρα.

Σας ευχαριστώ πολύ,

[firstname lastname]

Email Treatment A2 (Greek)

Subject: Μαθήματα [subject] online

Χαίρετε,

Ονομάζομαι [firstname lastname]. Βρήκα τα στοιχεία σας από το [platform name].

Ενδιαφέρομαι για ιδιαίτερα μαθήματα [subject] online για την κόρη μου. Μόλις τελείωσε την Α' Γυμνασίου.

Έχει φτάσει περίπου στο επίπεδο B1. Θα θέλαμε να δώσει εξετάσεις για δίπλωμα επιπέδου B2 την επόμενη χρονιά.

Μένουμε [location]. Εσείς σε ποια περιοχή βρίσκεστε;

Θα ήθελα επίσης να ρωτήσω πόσο χρεώνετε την ώρα.

Σας ευχαριστώ πολύ,

[firstname lastname]

Email Treatment B1 (Greek)

Subject: Μαθήματα [subject] δια ζώσης

Χαίρετε,

Ονομάζομαι [firstname lastname]. Βρήκα τα στοιχεία σας από το [platform name].

Ενδιαφέρομαι για ιδιαίτερα μαθήματα [subject] στο σπίτι μας για την κόρη μου. Μόλις τελείωσε την Α' Γυμνασίου.

Θα θέλαμε να στηριχθεί σχολικά όλη την επόμενη χρονιά.

Μένουμε [location]. Εσείς σε ποια περιοχή βρίσκεστε;

Θα ήθελα επίσης να ρωτήσω πόσο χρεώνετε την ώρα.

Σας ευχαριστώ πολύ,

[firstname lastname]

Email Treatment B2 (Greek)

Subject: Μαθήματα [subject] online

Χαίρετε,

Ονομάζομαι [firstname lastname]. Βρήκα τα στοιχεία σας από το [platform name].

Ενδιαφέρομαι για ιδιαίτερα μαθήματα [subject] online για την κόρη μου. Μόλις τελείωσε την Α' Γυμνασίου.

Θα θέλαμε να στηριχθεί σχολικά όλη την επόμενη χρονιά.

Μένουμε [location]. Εσείς σε ποια περιοχή βρίσκεστε;

Θα ήθελα επίσης να ρωτήσω πόσο χρεώνετε την ώρα.

Σας ευχαριστώ πολύ,

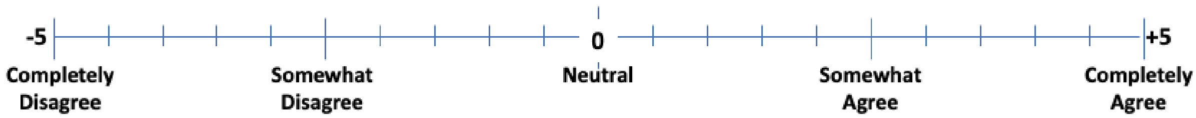
[firstname lastname]

Survey on Preference for Online Lesson Delivery [Version A]

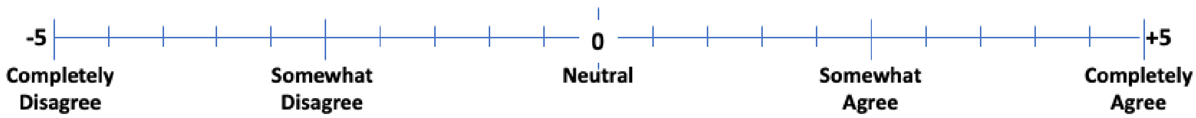
Please rate how much you agree with the following statements.

-5 means that you Completely Disagree and +5 means that you Completely Agree.

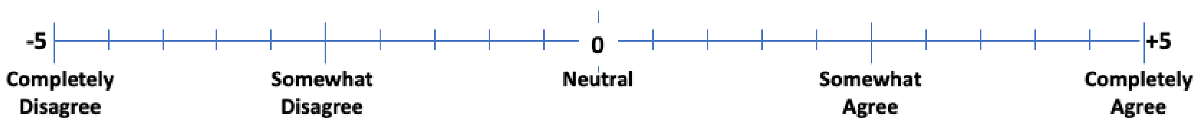
1. Online lessons give me greater control over my work schedule compared to in-person lessons.



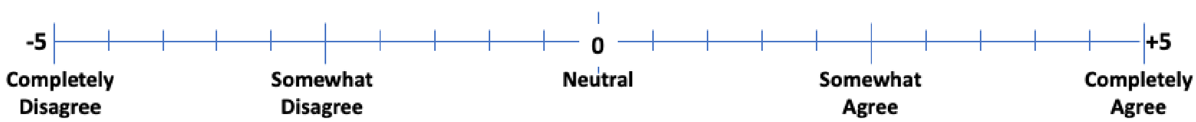
2. I am more satisfied with my work when I have the flexibility to teach remotely.



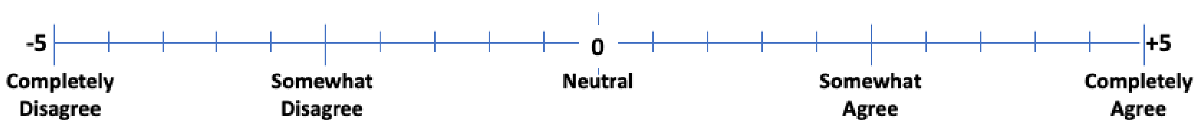
3. I feel greater recognition and respect as a professional when I offer online lessons compared to in-person lessons.



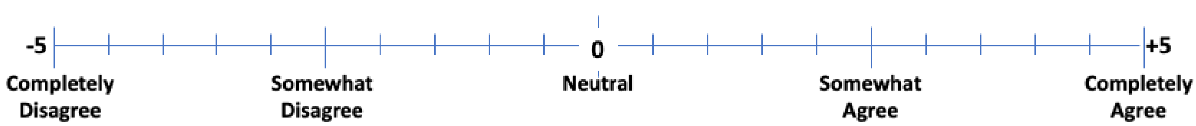
4. I find more opportunities for online lessons than for in-person lessons.



5. Online lessons allow me to teach more hours than in-person lessons.



6. With in-person lessons, I spend less money on commuting expenses than with in-person lessons.



7. With in-person lessons, I dedicate more time to my loved ones or personal interests than with online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

8. I am more effective when I teach in person than online.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

9. I am more patient when I teach in person than with online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

10. I have better mental health when I teach in person than online.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

11. In-person lessons reduce my exposure to illnesses like colds and flu compared to online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

12. I feel less stressed when I need to commute to teach a lesson.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

13. In-person lessons give me more freedom to choose where I work compared to online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

14. Online lessons make it easier for me to have other professional engagements than in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

15. In-person lessons require more cooperation from the student compared to online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

16. A student taking online lessons can learn more than one taking in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

17. I have all the technological tools and knowledge I need to conduct online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

18. I prefer teaching online lessons over in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

19. I prefer to work as a private tutor over holding a permanent full-time position, if I cannot combine the two.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

---

What is your gender?

- ☐ Male
- ☐ Female
- ☐ Other/Prefer not to say

What subject(s) do you teach?

- ☐ Foreign languages
- ☐ Greek language and literature
- ☐ Mathematics or Natural Sciences
- ☐ Other

Survey on Preference for Online Lesson Delivery [Version B]

Please rate how much you agree with the following statements.

-5 means that you Completely Disagree and +5 means that you Completely Agree.

1. With online lessons, I spend less money on commuting expenses than with in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

2. With online lessons, I spend more time with my loved ones or on personal interests compared to in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

3. I am more effective when I teach online than in-person.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

4. I am more patient when I teach online than in-person.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

5. I have better mental health when I teach online than in-person.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

6. Online lessons reduce my exposure to illnesses like the common cold and flu compared to in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

7. I feel less stressed when I don't have to commute to give lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

8. Online lessons give me more freedom to choose where I work compared to in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

9. In-person lessons give me greater control over my work schedule compared to online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

10. I am more satisfied with my job when I don't have the flexibility to teach remotely.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

11. I feel more recognized and respected as a professional when offering in-person lessons than online.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

12. I find more opportunities for in-person lessons than online.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

13. In-person lessons allow me to teach more hours than online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

14. In-person lessons make it easier for me to have other professional engagements than online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

15. Online lessons require more collaboration from the student compared to in-person lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

16. A student who takes in-person lessons can learn more than one who takes online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

17. I don't have all the technological tools and knowledge I need to conduct online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

18. I prefer teaching in-person lessons to online lessons.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

19. I prefer holding a permanent full-time position over working as a private tutor, if I cannot combine the two.

-5		0		+5
Completely Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Completely Agree

---

What is your gender?

- ☐ Male
- ☐ Female
- ☐ Other/Prefer not to say

What subject(s) do you teach?

- ☐ Foreign languages
- ☐ Greek language and literature
- ☐ Mathematics or Natural Sciences
- ☐ Other