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Abstract

We study the nature of home bias in online employment, wherein the employers prefer workers from their own home countries. Using a unique large-scale dataset from a major online labor platform, we identify employers' home bias in their online employment decisions. Moreover, we find that employers from countries with high traditional values, lower diversity, and smaller (user) population size, tend to have a stronger home bias. Further, we investigate the nature of employers' home bias using a quasi-natural experiment wherein the platform introduces a monitoring system to facilitate employers to keep track of workers' progress in time-based projects. After matching comparable fixed-price projects as a control group using propensity score matching, our difference-in-difference estimations show that the home bias does exist in online employment, and at least 40.93% of home bias is driven by statistical discrimination.

Keywords: home bias, employment, statistical discrimination, taste-based discrimination, quasi-natural experiment, Gig economy

1. Introduction

Firms usually make employment decisions under high uncertainty due to information asymmetry (Kugler and Saint-Paul 2000). Such decision uncertainty leads employers to employ heuristics to infer workers' capability and diligence (Hendricks et al. 2003; Fryer and Jackson 2008). Two heuristics commonly examined in the literature are discrimination based on the racial group membership and that based on gender. For example, employers were found to prefer white workers to black workers (the minority group), even though they have the same observable characteristics (Bertrand and Mullainathan 2004). While the discrimination against minority groups is well-known, little prior research has considered another form of discrimination - the minority group could have a preference for applicants from the same minority group. A notable example demonstrating the importance of the matching between managers and workers is that managers at Oracle, most of whom are Asians, were involved in a lawsuit because of their discrimination against qualified white workers and in favor of Asians who were belonged to the minority group in the previous discrimination literature.² This anecdote underscores that sometimes it is the similarity or closeness between two parties playing a critical role in determining the discrimination pattern and the employment choice.

The literature has documented one kind of this discrimination as *home bias*, which is people tend to prefer to conduct financial or trading transactions with agents with shorter geographic distance (Hortaçsu et al. 2009; Lin and Viswanathan 2015). Home bias has been extensively documented, in areas such as portfolio management (Coval and Moskowitz 1999), P2P lending (Lin and Viswanathan 2015), various products from the same city (Hortaçsu et al. 2009). The existence of home bias is plausible yet potentially detrimental in employment settings because it decreases the potential for global labor arbitrage (Roach 2003; Gefen and Carmel 2008) and leads to market inefficiency. Specifically, home bias adds friction to the labor markets and serves as one type of unconscious biases that makes the employment decisions unfair to some workers (Bertrand et al. 2005). Important as the question is, there is little academic evidence documenting home bias in employment. And the lack of evidence is not surprising, given the geographic homogeneity of workers in local employment relationships. And even when there is variation in worker home

² <http://fortune.com/2017/01/18/labor-department-oracle/>

country, the recruiting data is typically not available, due to the proprietary and confidential nature of recruiting.

Further, since workers' locations (countries) are highlighted in many leading global online labor platforms (e.g. Upwork, Freelancer), such geographic information might serve as a salient base for social categorization when employers evaluate workers. In such a case, employers may categorize worker candidates into different groups based on their locations, and further employ the group/country information to extrapolate workers' quality. Moreover, they may tend to overvalue domestic workers and trust them more owing to the in-group favoritism (Chen and Li 2009), which means that people show bias towards other agents in the same group with them. Further, though the literature regarding in-group favoritism is generally found to be positive, the magnitude of such bias may vary as multiple contingent factors, such as the group norms (Sagiv and Schwartz 1995), within-group similarity (diversity) (Luijters, Van der Zee, & Otten, 2008), and group size (Brewer and Kramer 1986; Simon and Hamilton 1994). Under the implication of such context-contingent nature of in-group favoritism, the strength of employers' home bias may also be depending on various contingent factors (such as the strength of group norms, diversity, and group size). Specifically, will employers from countries emphasizing the conformity of norms and traditional values tend to show stronger home bias, as the previous in-group favoritism literature suggests? Will they hold weaker home bias if the population composition is diverse and the population size is large? However, as far as we know, such potential heterogeneity of home bias has not been explored by the previous literature.

In this paper, we seek to fill this gap and investigate the discrimination based on the similarity of home country and its potential heterogeneity by using a unique data set from the online employment setting, wherein we are able to reliably observe both the employer and workers' countries, the employers' consideration set of workers who applied for the jobs, and the employers' hiring choices. The research setting is ideal for examining home bias in employment because online labor platforms are global, resulting in the desired variation in the workers' country (or city) of origin.

The literature has offered explanations for the home bias, in particular, for investment portfolios and international trade (Obstfeld and Rogoff 2000). Generally, home bias, as an example of employers' discrimination based on a heuristic cue (nationality) instead of individuals'

productivity-related attributes (Becker 2010), could be driven by either the statistical/rational discrimination mechanism (Cooper and Kaplanis 1994; Helliwell 2000) or the taste-based discrimination mechanism (Lewis 1999; Lin and Viswanathan 2015). For example, in the investment example, statistical discrimination refers to decision makers' higher preference for domestic portfolios or trade because of the associated higher expected utility inferred based on individual-specific and group-specific signals (Phelps 1972; Arrow 1973). In contrast, taste-based discrimination comes from the pre-existing liking for domestic portfolios or trade, which is not related to the signal exaction or utility function (Becker 2010). Based on the extant literature, home bias in investment portfolios might be driven by either statistical or taste-based discrimination. Specifically, it could come from established institutional factors (French and Poterba 1991), investors' rational desire to hedge specific sources of risk (Cooper and Kaplanis 1994), or simply their reluctance to share risks with foreigners (Lewis 1999). However, in the employment setting, these concerns about risk hedging or risk sharing do not appear applicable. Additionally, studies in international trade suggest that international trade barriers (Helliwell 2000; Brunetti et al. 1997), localized consumption of the goods (Hortaçsu et al. 2009) and the possibility of direct contract enforcement (Hortaçsu et al. 2009) are the major rational explanations for a home bias. However, because typically there is little barrier to entry for users from different countries and major platforms have well-established arbitration systems in online labor markets, these explanations do not appear to apply either. Meanwhile, home bias in employment also differs from the home bias in the financial markets or trade because of the hidden action issues in employment decisions. To be specific, unlike the financing or trade decision where standardized products are sold, online employment involves non-contractible elements of labor and thus has severe information asymmetry between the workers and employers. On the one hand, such information asymmetry and unpredictable project performance may render employers to elaborate more on the potential economic outcomes and be less likely to solely rely on simple heuristics. On the other hand, more asymmetric information might render the employment decision more effortful and resource-consuming, and subsequently strengthen managers' reliance on pre-existing stereotype-based or idiosyncratic taste. Therefore, the existence of home bias is more unpredictable and complex in the employment scenario. Bearing the above in mind, we seek to extend the previous literature in home bias by examining employment decisions in online labor markets (Chan and Wang 2017; Ghani et al. 2014), and specifically, we address the following three research questions:

- *Q1 (existence): Is there home bias towards workers based on nationality in online labor markets?*
- *Q2 (heterogeneity): If so, how does the strength of “home bias” vary with social-environmental factors across countries?*
- *Q3 (mechanism): Further, what drives home bias in this market? Is such home bias based on statistical discrimination or taste-based discrimination?*

In this study, we identify the existence of and explore the potential mechanism for employment home bias by leveraging a natural experiment -- the initial implementation of a monitoring system in Freelancer.com. This event serves as an exogenous shock to the level of information asymmetry by reducing worker hidden actions. Based on the different theoretical predictions of corresponding mechanisms, we seek to identify the underlying mechanism of discrimination. Specifically, on the one hand, because of the monitoring system lower employers' reliance on group-specific signal extraction by alleviating the ex post individual-specific information, the implementation of the monitoring system should lower the home bias driven by statistical discrimination. On the other hand, taste-based home bias should not be affected by the change in individual information availability and remain constant. Our econometric identification hinges on the fact that the monitoring system is only applicable to time-based contracts (online employment contracts) but not to fixed-price contracts (the sale contracts of outsourcing service), which allows us to use time-based contracts as the treatment group and fixed-price contracts as the control group. Based on a unique large-scale dataset from one of prevalent online labor markets, we document the existence of home bias towards workers in the employment setting. Further, our result suggests that at least 40.93% of employers' home bias is statistical-based.

Our paper contributes to the stream of literature in two ways. First, our study is among the first to investigate the existence of home bias in the employment setting and explore the discrimination mechanism with a quasi-natural experiment. It extends previous equity or trade home bias research, which mainly focuses on decisions under ex ante information asymmetry, to the employment decision threatened by both ex ante and ex post information asymmetry. Also, given that the online employment context provides us a rare opportunity to explore the home bias without the mixture of social referrals or organization culture, this paper advances the employment discrimination research by demonstrating the impact of the similarity between the managers and workers. Additionally, our study does not only broadly confirm the existence of home bias but also

highlight the cross-country heterogeneity in home bias from the perspective of traditional values, group size, ethnic and cultural diversity. Second, our paper adds to our understanding of potential discrimination in the “Gig” economy. During the last few years, “Gig” economy platforms provide the digital infrastructure that connects demand and on-demand service and brings reorganization of a wide variety of traditional markets. However, even though the “Gig” economy seems to provide a “frictionless” avenue of low entry barrier for the two-sided matching, some emerging research suggests that it also develops into a breeding ground of “racial discrimination” (Ge et al. 2016; Edelman et al. 2017), which is legally banned in the traditional markets but is out of reach of such antidiscrimination laws (Todisco 2015; Edelman et al. 2017; Belzer & Leong, forthcoming). Our study showcases the existence of another type of discrimination, home bias, and suggests that platforms’ information policies such as monitoring could help to alleviate the statistical home bias.

This paper proceeds as follows. In Section 2, we introduce the theoretical background. In the research methodology section, data description and empirical models of the existence and mechanism home bias are presented. Further, we provide additional analysis and robustness checks to lend support to our finding. Finally, we conclude the findings and implications.

2. Theoretical Background

2.1. Home Bias

Home bias has been reported in multiple contexts, such as financial markets (Forman et al. 2009, 2012; Sorenson and Stuart 2001; Lin and Viswanathan 2015) and trade (Brunetti et al. 1997; Ghani et al. 2014; Helliwell 2000; Hortaçsu et al. 2009).

Many papers on home bias focus on offline contexts (Obstfeld and Rogoff 2001). For instance, Lewis (1999) finds that the reluctance to share the international risk helps to explain the observed “equity-home-bias”. Moreover, Coval and Moskowitz (1999) suggest that the home bias phenomenon is not only limited to the preference for the equity at the home country, but also can be presented as the preference for equity in a shorter geographic distance without crossing the country borders.

As the development of online trade and online financial markets, recent work starts to explore whether the geography-based preference still holds in the online setting. Specifically, most the related studies focus on how the geography-based explanation and culture factors might lead to home bias. On the one hand, some studies suggest that the shorter geographic distance per se is associated with a higher preference because of rational considerations or pre-existing taste. For instance, Hortaçsu et al. (2009) find that the city-limits, goods needed to locally consume, the possibility of contract enforcement and cultural factors might jointly contribute to the concentration of local trade on eBay. Lin and Viswanathan (2016) explore the home bias in online peer-to-peer markets and find it might be driven by taste-based preference. On the other hand, there is also a stream of literature suggesting that the culture factor plays an important role in the country-level home bias. However, the extant findings of the mechanism of culture-related home country bias are still mixed. For instance, Ghani et al. (2014) find that Indians show ethnical discrimination when making the outsourcing decisions. Moreover, Gefen and Carmel (2008) find that most employers prefer to purchase the outsourcing service from parties in their home countries. Burtch et al. (2013) suggest that there exists a substitutional relationship between cultural differences and physical distance in the online pro-social lending context. Overall, the aforementioned explanations and the mechanisms of home bias are still inclusive (Lewis 1999; Lin and Viswanathan 2015). Additionally, given that the rich literature on of home bias in the online and offline financial markets and trade, none of the previous literature explore the home bias in the employment setting.

Regarding the methodology of home bias, scholars tend to employ different methods according to their levels of analysis. When the available data is at the macro-level, a typical test would be the gravity equation (Bergstrand 1985). Similar to a Cobb-Douglas production function, the gravity equation is a power function of the distance between two parties, the economy volume traded between two parties and other related factors. This method is more applicable to the macro economy research, especially the trading between two countries or cities. When micro-level data is accessible, some alternative methods would be the choice models (Ghani et al. 2014) or the potential-dyads approach used in Lin and Viswanathan (2015). Especially, when the decision makers' consideration sets are not well-specified, potential dyads analysis enables scholars to include all the available alternatives into the model and explore whether the decision makers have a stronger preference for parties from their home country (Lin and Viswanathan 2015).

2.2. In-group Favoritism

The home bias phenomenon is in line with the in-group favoritism (Chen and Li 2009), which emphasizes how people treat in-group members and out-group member differently and show preference for in-group members (Allen and Wilder 1975; Efferson et al. 2008; DiDonato et al. 2011), such as in-group bias (Chen and Li 2009), in-group altruism (Brewer and Kramer 1986), in-group trust (Falk and Zehnder 2013), and out-group comparison, etc. Specifically, in most online labor markets, workers' countries are highlighted by the platform. Therefore, located countries are expected to be salient bases for social categorization. In such as case, employers might consider domestic workers as in-group members and show a significant preference for them compared to foreign workers with similar working experience and reputation. In this study, we intend to explore the potential heterogeneity of home bias across different employer countries under the implication of in-group favoritism (Chen and Li 2009).

First, in-group social norms encourage in-group preference and collaboration and discourage contacts with out-group members (Sagiv and Schwartz 1995). In the context of the online labor market, employers from countries with deep-rooted nationalistic mindsets and a strong tendency to conformity to cultural norms are more likely to show in-group favoritism and show preference to workers from the same group (country). Therefore, we expect that employers brought up in cultures which emphasize traditional³ and nationalistic values more tend to hold a home bias owing to their strong social norms and national identity. As such, social norms within each country may contribute to a strong employer's trust in domestic workers and increase home bias. To measure the emphasis of social norms and nationalistic mindset across countries, we employ the traditional value reported in the World Values Survey (WVS)⁴.

³ According to the World Values Survey (WVS), country culture can be categorized based on the extent to which a society emphasizes traditional rather than secular values. Countries with high traditional values emphasize the importance of religion, deference to authority, traditional family values and have high levels of national pride (Inglehart and Welzel 2010). Given that the WVS is less subject to selection bias and it has been employed to measure country culture in the IS literature (e.g. Hofstede 1991, 2001; Burtch et al. 2014).

⁴ WVS is a worldwide survey which mainly rely on face-to-face interviews. By now, WVS has been conducted in almost 100 countries which occupy around 90 percent of the global population. It covers multiple thematic sub-sections, such as social values and stereotypes; societal well-being; trust and organizational membership, economic values. It mainly adopts the full probability sampling on Primary Sampling Units (PSU) and requires no replacements. Since the WVS is a longitudinal data set and the traditional values of different countries may slightly fluctuate, we calculate the average traditional values (denoted as "Trad value") for each country by combing multiple waves of WVS.

Second, within-group diversity tends to erode the importance of the shared social identity, and reduce in-group favoritism (e.g. Luijters, Van der Zee, & Otten, 2008). As a result, the home bias of employers from countries with greater diversity might be weaker. Moreover, to measure the diversity among residents within each country, we use the country-specific ethnic fractionalization and cultural diversity⁵ (Fearon 2003; Fearon and Laitin 2003) to capture the within-country diversity. Specifically, ethnic fractionalization measures the probability that each two people (who are randomly drawn from a country) belong to the same ethnic group (Fearon 2003), while cultural diversity denotes the probability that each two persons randomly chosen from the country speak the similar language (Fearon 2003). If different ethnic groups in the country speak structurally unrelated languages, the ethnic fractionalization will be highly correlated with cultural diversity (Fearon 2003). Within our sample, we find that there exists a high correlation between these two diversity measures, so we enter these two measures separately. High ethnic fractionalization or cultural diversity implies the potential low resemblance between employers and workers from this country and the lower home bias.

Third, the in-group favoritism may be influenced by the group size. Specifically, the smaller the group size is, the more prosocial and generous people would be (Brewer and Kramer 1986; Simon and Hamilton 1994). In this sense, home bias is likely to be weaker for more populous countries. In light of these previous findings on Social Identity Theory, we further explore how employers' home bias would vary by the traditional values, diversity, and population size of their countries. To construct the measure of group size, we use two different variables to represent the group size, including the log-transformed population size of each country⁶ in 2014 and the log-transformed number of workers on this platform.

2.3. Mechanisms of Discrimination

Discrimination is derived from the information asymmetry between workers and employers in online labor markets. Given the limited information regarding workers' capability and effort, employers rely on the observable signal to extrapolate the individual workers' characteristics. There are a lot of mechanisms proposed by researchers to explain the discrimination. Based on the

⁵ Ethnic fractionalization and cultural diversity are both measures of the diversity within the national population.

⁶ The population size of each country is measured in thousand persons per country.

decision rule, discrimination can be classified as rational/statistical discrimination and taste-based discrimination (Bertrand and Mullainathan 2004). Specifically, rational or statistical discrimination means employers are profit-maximizing actors, who use the group-specific signal to infer the characteristics of individual workers (Arrow 1973). For instance, if the employer learns that domestic workers are more skillful and diligent based on his/her private information, he/she might use the country as the signal to infer the workers' quality later, given the limited information and cognitive resource. On the other hand, taste-based discrimination captures employers' pure preference which does not involve any rational inference or the utility function (Becker 2010; Heckman 1998; Ghani et al. 2014).

Regarding how to disentangle statistical discrimination from the taste-based counterpart, the most common method employed in the previous discrimination literature is comparing the different gaps between groups under different scenarios (Bertrand and Duflo 2017) and verifying the predictions. Generally, it could be classified into two types of predictions, namely, the static and dynamic predictions (Rubineau and Kang 2012). First, the static predictions are about the static difference across between-group pairs when other observable productivity characteristics are unfavorable or favorable (Bertrand and Duflo 2017). In line with this logic, we could predict that statistical discrimination would be weaker when between-group parties with high observable productivity characteristics are compared, while the magnitude of discrimination would be stronger when between-group parties with low observable productivity characteristics are compared. Second, the dynamic prediction refers to the prediction about when and how the discrimination within the similar pairs of minor and non-minor groups will change (Rubineau and Kang 2012). For instance, when people can have chances to correct their beliefs because of the market competition or more information, they are expected to change accordingly if they hold statistical discrimination (Rubineau and Kang 2012). For instance, Rubineau and Kang (2012) state that the medical training should help students to learn to obtain more hard-to-observe characteristics and lower their statistical discrimination. However, they observe that students tend to show a strong discrimination after a year of training, which suggests that it is not statistical discrimination that drives the racial disparities (Rubineau and Kang 2012). Based on the dynamic predictions of statistical discrimination, information changes such as the removal of gender information (Goldin and Rouse 1997) or criminal background information (Doleac and Hansen 2016) will lead to a change in the magnitude of discrimination. On the whole, checking the result

if it is consistent with the dynamic prediction is an emerging way to identify statistical discrimination.

2.4. Online Labor Markets and Contract Types

Online labor markets facilitate the procurement of on-demand labor services across the borders of cities or countries (Hong and Pavlou 2017). Recently, online labor markets have experienced a tremendous boost and are estimated to account for around 25 percentages of workers in the US.⁷

Generally, in online labor markets, there are two prevalent ways to buy service from unknown parties, namely, sales contracts (fixed-price contracts) or employment contracts (time-based contracts) (Simon 1951; Banerjee and Duflo 2000). Sales contracts (fixed-price contracts) are outcome-driven, and the agent gets a fixed payment until he/she can provide a given amount of output (Mani et al. 2012). On the other hand, employment contracts (time-based contracts), or cost-plus contracts, require that the payment should be calculated based on the worker's hourly wage and his/her actual work hours in the work process (Mani et al. 2012). Because usually workers' compensation is not depending on their performance in time-based projects, the hidden actions issues related to ex post information asymmetries (e.g. their carefulness, their effort spent on the projects) tend to pose a big threat to incentive design and employers' benefit. Moral hazard problems are prevalent in the traditional offline employment relationship and online employment relationship wherein the problems might be even more serious because of the spatial and temporal separation between employers and workers.

When information about workers' characteristics is limited and hard to observe, one way to reduce the uncertainty of employment decision is statistical inference (Hendricks et al. 2003; Fryer and Jackson 2008). For instance, by combining the average characteristics of the specific group and the observable individual information, employers can better predict workers' behaviors, which might lead to statistical discrimination (Aigner and Cain 1977). It is also found that sometimes statistical discrimination might help to increase efficiency (Schwab 1986). Another major way to reduce moral hazard problems by alleviating hidden action issues is acquiring more actual performance information, such as monitoring (Bolton and Dewatripont 2005). By tracking

⁷ <http://www.forbes.com/sites/groupthink/2014/10/21/the-next-big-thing-in-e-commerce-online-labor-marketplaces/#5f62eb9c6117>

and verifying workers' behaviors, monitoring could provide more procedural progress information and alleviate employers' uncertainty about workers' shirking (Pierce et al. 2015).

3. Research Context

To hire workers from online labor markets, an employer first posts a project on a broker platform such as Upwork, Amazon Mechanical Turk, and Freelancer. Detailed information about the project such as requirements and budget can be provided in the dedicated Web page for the project. Then, workers can bid for this project if they are interested.. After that, the employer decides who to hire based on the bids and characteristics (e.g., reputation) of the bidders. Finally, a contract is reached the designated worker(s)⁸ accept the offer.

Compared to conventional offline labor markets, online labor market is a more suitable to explore employers' home bias because of the following reasons: First, it is almost impossible to disentangle employers' home bias from the decrease in the productivity owing to the long distance between employers and workers. For instance, if employers and workers use the same language, they can have lower communication costs, which subsequently increases workers' productivity while performing this task. Second, another recurring challenge in estimating employers' home bias might be mainly driven by domestic employers' information advantage. In other words, there are some potential unobservable variables which are known by employers (especially domestic employers) but not researchers. Since the lack of personally identifiable information in the online labor market, the existence of the social relationship between would-be employers and workers is very unlikely. Moreover, because of the lack of field interviews, employers' hiring choices should be mainly based on the observable variables which are available to the authors. Given that the appearing advantages of online labor markets for the estimation of home bias, we obtained a dataset from www.freelancer.com (Freelancer), one of the largest online labor market platforms.

On Freelancer.com, the employer may specify the project as a fixed-price project which pays hourly wages to the hired worker (i.e., time-based project). Workers could browse the active or ongoing projects on the website and selectively bid for some of them. Due to the limit on the

⁸ All these projects with more than one winners are dropped from our sample. The result of our main analysis is consistent if we keep all the projects with more than one winners.

number of bids, one can submit each month⁹, it is in the interest of the works to bid for projects that maximize their expected total rewards on the projects they are likely to be hired.

To rule out the effect of the auction format on employers' choices, we limit our analysis to projects using the most common public auction form¹⁰. Further, to construct a sample of homogenous projects, we focus on projects in the most popular category, i.e., "IT, software & website". The definition and basic statistics of the key variables in our final sample are provided in Tables 1.

Table 1. Definitions and Summary Statistics of Key Variables

Variable	Variable definition	Mean	SD	Min	Max
<i>A. Bids' Characteristics</i>					
Bid Price	The bid price posted by the worker	306.70	491.00	2.00	5000.00 ¹¹
Milestone percentage	A feature provided by Freelancer, it denotes the percentage of controlled payments paid to the worker during the project	73.72	33.31	0.00	120.00
Bidder tenure	the worker's tenure at Freelancer measured in months	31.60	28.70	0.00	183.00
Homecountry	A dummy variable (0,1), =1 if the worker and the employer live in the same country	0.05	0.22	0.00	1.00
Bid order rank	The sequence order of the worker's bid	19.63	20.07	1.00	263.00
Preferred freelancer	A dummy variable (0,1), =1 if the worker won the "Preferred Freelancer Badge"	0.21	0.41	0.00	1.00
Count rating	The number of reviews entered by previous employers	81.67	175.14	0.00	3937.00
Same language	A dummy variable (0,1), =1 if the employer's primary language is the same as that of the worker on this platform	0.76	0.43	0.00	1.00
Same time zone	A dummy variable (0,1), =1 if the time zone wherein the employer live is the same as that of the worker inferred based on the IP address	0.45	0.50	0.00	1.00
Same currency	A dummy variable (0,1), =1 if the employer's primary currency is the same as that of the worker on this platform	0.02	0.14	0.00	1.00

⁹ Free members could submit 8 bids per month. Golden members could submit more. However, the percentage of golden members in our dataset is less than 0.1%.

¹⁰ In such a case, projects like special contracts with NDA, featured projects, sealed projects, fulltime jobs, those using the non-dollar currency, those written in non-English are dropped from our sample.

¹¹ Because there are unreasonable large values in the maximum of bid prices and the win rate of these bids are all zeros, we chose to drop the top 1%. The result of our main analysis is consistent if we keep all the bids in our full sample.

B. Project Characteristics

Time-based	A dummy variable (0,1), =1 if the project is a time-based project; =0 if it is a fixed-price project	0.09	0.29	0.00	1.00
Log (employer overall rating)	The average overall worker-entered ratings for the employer (log-transformed)	1.77	0.15	0.00	1.79
Language Eng	A dummy variable (0,1), =1 if the project is described in English	0.88	0.32	0.00	1.00
Log (paid amount)	Amount of dollars paid by the employer after the project was completed (log-transformed)	4.44	1.31	0.00	11.00
Log (budget max)	The maximum of bid prices for this project set by the employer (log-transformed)	4.74	1.44	0.69	11.78
Log (title length)	Number of characters in the project title (log-transformed)	1.61	0.52	0.00	3.85
Log (description length)	Number of characters in the project description posted by the employer (log-transformed)	2.77	0.30	0.00	3.26
Employer developed	A dummy variable (0,1), =1 if the employer comes from a developed country	0.80	0.40	0.00	1.00

C. Country Characteristics

Trad value	The average traditional value reported in World Value Survey (Inglehart and Welzel 2010)	-0.36	0.59	-1.58	1.48
Ethnic factionalization	The ethnic factionalization index measured by Fearon and Laitin (2003)	0.35	0.21	0.05	0.85
Cultural diversity	The cultural diversity index measured by Fearon and Laitin (2003)	0.26	0.15	0.02	0.67
User perc	The percentage of workers from each country	0.05	0.06	0.00	0.33
Log popu	The Log-transformed population size (/thousand) reported by the World Bank ¹²	11.39	1.37	8.41	14.13

4. Existence of Home Bias**4.1. Model-free Evidence of Employers' Home Bias**

To provide some model-free evidence on the existence of home bias, we choose eight countries which are on the list of the top 20 employer countries and that of the top 20 worker countries, and then summarize the basic statistic for the employment choice made by employers from these

¹² <https://data.worldbank.org/indicator/SP.POP.TOTL?page=2>

countries¹³ in Table 3. For each country, we first identify all employers from this country and then calculate the ratio of their projects assigned to bidders in his/her home country for each employer. Meanwhile, we also calculate the average ratio of projects assigned to bidders from each country on the whole. By checking the difference between these two ratios (the last column of Table 3), we find that most employers tend more to hire bidders from the their home countries. This finding suggests that employers may have a home bias. Next, we corroborate this finding using an difference-in-difference model with propensity score matching, which not only controls for the characteristics of employers and workers, but also explores how home bias are moderated by the characteristics of employers. For this purpose of this study, we limit to the 25 countries which are on the top-30 list in terms of both the numbers of employers and workers.

Table 3. Country Distribution of International Employers' Employment Decisions

Employer's country	The awarded bidder's country								Share of projects assigned to bidders from that country	Diff ¹⁴
	Australia	Bangladesh	Canada	China	India	Pakistan	UK	US		
Australia	2.57%	4.79%	0.88%	3.31%	43.12%	10.30%	1.38%	1.30%	0.66%	1.92%
Bangladesh	0.78%	29.09%	0.26%	1.56%	29.61%	9.09%	0.00%	2.34%	5.10%	24.00%
Canada	0.39%	4.53%	2.36%	1.91%	36.77%	13.00%	1.26%	1.81%	1.02%	1.34%
China	0.29%	3.75%	0.29%	12.39%	43.80%	7.20%	0.00%	0.58%	2.34%	10.05%
India	0.09%	5.12%	0.40%	1.29%	59.65%	5.42%	0.70%	1.19%	40.95%	18.70%
Pakistan	0.47%	7.30%	0.35%	1.88%	32.39%	21.91%	1.53%	1.88%	11.34%	10.57%
UK	0.28%	4.82%	1.05%	1.81%	40.48%	12.04%	2.09%	2.41%	1.27%	0.83%
US	0.43%	4.77%	1.02%	2.37%	38.26%	11.93%	1.21%	4.11%	3.12%	0.98%

¹³ Employment decision is a two-sided matching process, if there are no domestic workers bidding for the project, employers' hiring decision in this specific project will not influence the identification of employers' home bias.

¹⁴ "Diff" Denotes the difference between the share of projects assigned to bidders from country X among all the projects posted by employers from country X and the share of projects assigned to bidders from country X among all the projects.

Figure 1 Model-free Evidence of Employers' Home Bias

4.2. Identification Challenges

To identify the existence of employers' home bias, we employ a comprehensive data from Freelancer, one of the prevalent online labor markets. Since we can clearly observe employers' consideration set, their location, reputation and other individual-specific information, the identification of our study is more fine-grained and the omitted variable bias should be a smaller concern, compared to the previous gravity-equation based home bias analysis (Hortaçsu et al. 2009). Though we can control for the effect of some unobserved factors by employing models with individual-specific or project-specific fixed effects, there are several main sources of bias that might affect our identification of home bias. First, geographical distance is confounded with not just the concept of "home," in online employment it can potentially add to friction between the employer and the worker (Hong and Pavlou 2017). For this, we controlled for key differences other than home country (language, time zone, currency). Second, workers from some countries with low GDP are more desired, because they offer low prices, and those countries (e.g., India) could be very different from where employers reside. To tackle this problem, we control for bidders' country dummies. Moreover, in the robustness check section, we also control for the country-month two-way fixed effect and the potential time-varying variation in levels of

competitiveness and “market tightness”¹⁵ from a worker’s fellow countrymen in different projects. We still find employers show a preference for domestic workers. Third, employers from different countries could exhibit very different behavior and the strength of home bias may not be constant across countries. As such, we explore heterogeneous effects based on the traditional value, diversity, and population size of the employer country. This analysis serves to lend support to our finding in two ways. For one thing, when the heterogeneous effects are consistent with our predictions based existing in-group favoritism theory, this lends support to the existence of home bias by increasing the internal validity. For another, the heterogeneity of home bias informs us about different populations’ hiring preference, which increases the external validity of our finding.

4.3. Identifying the Existence of Home Bias

Following Ghani et al. (2014) and Lin et al. (2016), we estimate the extent of home bias withwith a conditional logit model, as well as a linear probability model (LPM) with project-level fixed-effects. Taking the conditional logit model as an example, the utility that the employer of project i obtains from hiring bidder j is constructed as follows:

$$U(Project_i_by_bidder_j) = \alpha_i + \beta_1 Homecountry_{ij} + controls(Bidder_j) + \varepsilon_{ij} \quad (1)$$

where α_i represents the project-level fixed effect, which nests the employer-level fixed effects as every project has only one employer. The focal variable, $Homecountry_{ij}$, denotes whether the employer of project i and bidder j are from the same country. $controls(Bidder_j)$ include various bidders’ related characteristics¹⁶. ε_{ij} is assumed to follow the type-I extreme value distribution (Train 2009). A significantly positive effect of $Homecountry_{ij}$ (captured by $\hat{\beta}_1$) suggests that employers hold a home bias.

There are two potential threats to our identification of the above model. First, there might be time-invariant differences across countries. For example, some workers from some countries may be more competitive or acquire lower wage on average. In response to this issue, we include

¹⁵ We assume that as the number of bidders increase, the market competition becomes more fierce and the market tightness increases.

¹⁶ Within data, a worker’s average rating is almost constant during our observational period. Therefore, we didn’t treat the worker rating as a time-variant variable here.

25 dummies for the 25 selected countries and one dummy for all the rest countries. Second, the productivity of workers? might suffer from the difference in languages and time-zones. , which may result in a spurious home bias. To alleviate this concern, we use additional dummies to control for whether employers and workers use the same primary language, currency, and time zone.

As Model (1) in Table 2 suggests, without controlling for the “closeness” or “similarity” in language, currency and time zone, employers show a preference for domestic workers. Though employers’ home bias slightly decreases after controlling for the language, currency and time zone effect (see model x), the magnitude of home bias is still not negligible. To better understand the impact of home bias, we monetarize its value using Equation (2), in a similar way with previous studies (Leung 2017; Dahl and Sorenson 2010). According to result estimated by the Conditional Logit Model in Model (3) of Table 2, employers are willing to pay domestic workers 25% more than an alien worker.

$$\Delta Bid\ price = \exp^{\frac{\beta_{homecountry}}{\beta_{log\ bid\ price}}} \quad (2)$$

Table 2. Estimation Results of Employers’ Home Bias

Sample	Full sample		Full sample	
Model	(1) Logit	(2) LPM	(3) Logit	(4) LPM
Homecountry	0.516*** (0.041)	0.042*** (0.004)	0.387*** (0.047)	0.032*** (0.004)
Same language			0.416*** (0.026)	0.018*** (0.001)
Same currency			0.062*** (0.021)	0.004*** (0.001)
Same time zone			0.255*** (0.057)	0.025*** (0.005)
Log bid price	-1.735*** (0.018)	-0.090*** (0.001)	-1.736*** (0.018)	-0.090*** (0.001)
Log milestone percentage	-0.068*** (0.016)	-0.003*** (0.001)	-0.067*** (0.016)	-0.003*** (0.001)
Log count rating	0.099*** (0.007)	0.005*** (0.000)	0.096*** (0.007)	0.005*** (0.000)
Log avg rating	0.102*** (0.009)	0.003*** (0.000)	0.103*** (0.009)	0.003*** (0.000)
Log bid order rank	-0.327*** (0.013)	-0.017*** (0.001)	-0.313*** (0.014)	-0.016*** (0.001)
Preferred freelancer	0.499*** (0.018)	0.027*** (0.001)	0.471*** (0.018)	0.026*** (0.001)
Bidder country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	371,968	371,968
R-squared		0.043		0.044
Number of projects	23,943	23,943	23,943	23,943

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker’s fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-

typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Even after controlling for the effect of language, currency, and time zone, employers still show significant positive preference for domestic workers. This is in line with the in-group favoritism (Chen and Li 2009), which emphasizes the importance of group or category in people’s perception and behaviors (Allen and Wilder 1975; Efferson et al. 2008; DiDonato et al. 2011). Moreover, it has been found that the magnitude of in-group bias may vary as multiple contingent factors, such as the group norms (Sagiv and Schwartz 1995), within-group similarity (diversity) (Luijters, Van der Zee, & Otten, 2008), and group size (Brewer and Kramer 1986; Simon and Hamilton 1994). Under the implication of such context-contingent nature of in-group favoritism, we will further explore whether and how employers’ home bias might vary by these contingent factors of each group (country).

4.4. Heterogeneity of Home Bias

As the model-free evidence in Figure 1 shows, the preference of employers toward workers from home countries tends to vary across countries. However, since the model-free evidence might be confounded by multiple existing differences across worker countries (e.g. lower labor costs), whether there exists heterogeneity of home bias still need to be formally tested. Therefore, we further investigate how the strength of home bias may be associated with the traditional value, diversity and population size of the employer country in both the LPM and the Conditional Logit Model. Based on the result in Table 3-5, we find that the strength of employers’ home bias 1) is positively related to the traditional value of the employer country which represents the importance of a nationalistic outlook among residents (Inglehart and Welzel 2010); 2) is negatively related to the user (population) size of the employer country; 3) is negatively associated with the country-specific ethnic fractionalization and cultural diversity¹⁷ (Fearon and Laitin 2003). Moreover, the result is highly consistent after controlling for the competition within workers from the same country.

Table 3. Estimation Results of Heterogeneity regarding Traditional Values

Sample	Full sample

¹⁷ Ethnic fractionalization and cultural diversity are both measures of the diversity within the national population.

Model	Logit	LPM
Homecountry	0.670***(0.070)	0.060***(0.008)
Trad value*Homecountry	0.440***(0.090)	0.044***(0.011)
Same language	0.415***(0.029)	0.018***(0.001)
Same currency	0.059***(0.023)	0.004***(0.001)
Same time zone	0.317***(0.059)	0.031***(0.005)
Log bid price	-1.740***(0.020)	-0.092***(0.001)
Log milestone percentage	-0.063***(0.018)	-0.003***(0.001)
Log count rating	0.095***(0.008)	0.005***(0.000)
Log avg rating	0.103***(0.010)	0.003***(0.000)
Log bid order rank	-0.318***(0.015)	-0.017***(0.001)
Preferred freelancer	0.482***(0.020)	0.027***(0.001)
Bidder country dummy	yes	yes
Project fixed effects	yes	yes
Observations	371,968	371,968
R-squared		0.045
Number of projects	23,943	23,943

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Estimation Results of Heterogeneity regarding Diversity

Sample Model	Full sample		Full sample	
	Logit	LPM	Logit	LPM
Homecountry	1.170***(0.113)	0.104***(0.011)	0.831***(0.090)	0.072***(0.008)
Ethnic Fractionalization *homecountry	-1.447***(0.191)	-0.133***(0.019)		
Cultural Diversity*homecountry			-1.176***(0.204)	-0.107***(0.019)
Same language	0.412***(0.026)	0.017***(0.001)	0.412***(0.026)	0.017***(0.001)
Same currency	0.059***(0.021)	0.004***(0.001)	0.061***(0.021)	0.004***(0.001)
Same time zone	0.223***(0.057)	0.023***(0.005)	0.236***(0.057)	0.024***(0.005)
Log bid price	-1.738***(0.018)	-0.090***(0.001)	-1.737***(0.018)	-0.090***(0.001)
Log milestone percentage	-0.067***(0.016)	-0.003***(0.001)	-0.067***(0.016)	-0.003***(0.001)
Log count rating	0.096***(0.007)	0.005***(0.000)	0.096***(0.007)	0.005***(0.000)
Log avg rating	0.103***(0.009)	0.003***(0.000)	0.103***(0.009)	0.003***(0.000)
Log bid order rank	-0.314***(0.014)	-0.016***(0.001)	-0.314***(0.014)	-0.016***(0.001)
Preferred freelancer	0.472***(0.018)	0.026***(0.001)	0.472***(0.018)	0.026***(0.001)
Bidder country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	371,968	371,968
R-squared		0.044		0.044
Number of projects	23,943	23,943	23,943	23,943

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original

bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 5. Estimation Results of Heterogeneity regarding Group Sizes

Sample Model	Full sample		Full sample	
	Logit	LPM	Logit	LPM
Homecountry	0.650*** (0.064)	0.055*** (0.006)	2.789*** (0.392)	0.259*** (0.038)
User perc*homecountry	-1.912*** (0.321)	-0.173*** (0.029)		
Log popu size*homecountry			-0.191*** (0.031)	-0.018*** (0.003)
Same language	0.413*** (0.026)	0.018*** (0.001)	0.412*** (0.026)	0.018*** (0.001)
Same currency	0.061*** (0.021)	0.004*** (0.001)	0.059*** (0.021)	0.004*** (0.001)
Same time zone	0.243*** (0.057)	0.025*** (0.005)	0.226*** (0.057)	0.023*** (0.005)
Log bid price	-1.737*** (0.018)	-0.090*** (0.001)	-1.738*** (0.018)	-0.090*** (0.001)
Log milestone percentage	-0.067*** (0.016)	-0.003*** (0.001)	-0.067*** (0.016)	-0.003*** (0.001)
Log count rating	0.096*** (0.007)	0.005*** (0.000)	0.096*** (0.007)	0.005*** (0.000)
Log avg rating	0.103*** (0.009)	0.003*** (0.000)	0.103*** (0.009)	0.003*** (0.000)
Log bid order rank	-0.314*** (0.014)	-0.016*** (0.001)	-0.313*** (0.014)	-0.016*** (0.001)
Preferred freelancer	0.472*** (0.018)	0.026*** (0.001)	0.472*** (0.018)	0.026*** (0.001)
Bidder country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	371,968	371,968
R-squared		0.044		0.044
Number of projects	23,943	23,943	23,943	23,943

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we limit our sample to bids submitted by workers who bid for both fixed-price and time-based project (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure 2. Heterogeneity of Marginal Effects of the Homecountry Dummy¹⁸

As Figure 2 shows, higher traditional value employers' home country has, the stronger home bias employers hold. Meanwhile, the larger population size of employers' home country occupies or the larger percentage of worker accounts employers' home country occupies, the weaker home bias employers hold. Further, employers from countries with high ethnical fractionalization and cultural diversity also tend to show weak home bias. The heterogeneity of home bias indicates that employers' home bias is influenced by the context-contingent factors within the country, which

¹⁸ All the marginal plots are generated with the assumption that fixed effect is zero.

seems to suggest that employers' home bias is related to their stereotyped liking and preference. Though the analysis of heterogeneity deepens our understanding of potential country characteristics associated with home bias, this still provides limited insight into the underlying mechanism of employers' home bias. Since the mechanism of home bias could indicate potential approaches to alleviate the discrimination issue without loss of market efficiency, it is pivotal to understand the underlying driver of home bias. To further casually identify the mechanism of employers' home bias, we take advantage of a quasi-natural experiment wherein the risk of employers' hiring decisions have been exogenously decreased by the IT-enabled monitoring system. We will explain the research setting and our identification strategy in next section.

5. Does Home Bias Come from Taste-based or Statistical Discrimination?

5.1. Identifying the Mechanism of Home Bias: A Quasi-Natural Experiment

On February 5th, 2014, Freelancer rolled out its monitoring system for the first time, which enables employers to conveniently monitor the progress of time-based projects. Such a monitoring system automatically takes screenshots and keeps track of workers' effort input. This monitoring system could affect employers in the following two ways: 1) monitoring system can ensure and improve production of quality work, especially when hiring foreign workers. The monitoring system automatically takes a screenshot every few minutes and enables employers to provide detailed instructions or comments regarding any step of work. As such, the monitoring system improves the efficiency for employers to collaborate with freelancers. 2) the monitoring system enables employers to keep track of each individual worker's work, so that employers could have more verified information about individual worker's capability and effort. Owing to such information change driven by the exogenous shock---the implementation of the monitoring system¹⁹, employers would less rely on the signal extraction based on workers' country. Since the monitoring system is mandatory for all time-based projects and is not available for fixed-price projects, we use the fixed-price projects as the control group to study the treatment effect of monitoring system on time-based projects.

¹⁹ We confirm with employees of Freelancer that the implementation of the monitoring system is not publicly pre-announced.

Figure 3. Screenshots of the Monitoring System²⁰

According to the previous literature on statistical discrimination (Arrow 1973) and taste-based discrimination (Becker 2010), two distinct predictions can be made based on different assumptions about the underlying mechanisms of home bias. First, since statistical discrimination is contingent on the availability of individual-specific information, monitoring might lower the need for information extraction based on group-specific signals and hence lower the extent of statistical home bias (Altonji and Blank 1999; Rubineau and Kang 2012). For one thing, the implementation of the monitoring system, as a vital change in technology in online labor markets, has altered the effects of physical or cultural closeness on producing (Altonji and Blank 1999; Fang and Moro 2010; Autor 2003). In other words, the monitoring system smooths the collaboration between employers and workers, especially when they are spatially separated. It increases the average productivity of foreign workers relative to domestic workers. Thus, the implementation of monitoring system tends to decrease the productivity difference and reduce employers' statistical home bias. For another, the monitoring system effectively provides more

²⁰ <https://www.freelancer.com/community/articles/what-you-need-to-make-remote-collaboration-work>

individual-level information and lowers employers' reliance on group-level signal extraction. Therefore, employers will tend to lower their weight on the group (country) signal and emphasize more on workers' individual signals based on the reputation and monitoring system. As such, employers' statistical home bias based on the rational signal extraction tends to be decreased. Overall, the information change brought by the monitoring system will decrease employers' statistical home bias.

For another, given that taste-based discrimination is merely based on preference, which is irrelevant to the availability of information and the expected productivity (Becker 2010; Rubineau and Kang 2012). Models of taste-based discrimination usually assume that employers show a constant distaste for foreign workers irrelevant to their unobservable characteristics (Becker 1971). Therefore, the implementation of the monitoring system might affect statistical discrimination but not taste-based discrimination (Becker 2010; Fang and Moro 2010). If statistic discrimination is at work, we may observe a significant decrease in the level of home bias. Therefore, we proposed the following predictions (Table 6):

Table 6. Types of Stereotyping Discrimination and Predictions

Forms of Discrimination	Dynamic Predictions about the Change in Home Bias
Statistical discrimination	After the implementation of the monitoring system, employers' home bias decreases in the treatment group, as compared to the control group
Taste-based discrimination	After the implementation of the monitoring system, employers' home bias remains unchanged in the treatment group, as compared to the control group

5.2. Coarsened Exact Matching (CEM)

To balance the distribution of observables between the treatment and control group, we conduct coarsened exact matching (CEM) to generate a comparable sample (King et al. 2010; Iacus et al. 2012). By using CEM, we explicitly match the fixed-price projects with time-based projects based on all the observables which might affect employers' selection of project types, such as the length of project description, the length of title, the number of bids, the size of project, employers' experience and reputation, the exact submit month of the project. CEM allow us to match two types of projects posted within the same month and of similar size. The refined matching empowered by CEM improves the robustness of our findings.

5.3. Empirical Result Regarding the Mechanism of Home Bias

To measure the decrease in employers' home bias after the implementation of the monitoring system, we construct the Differences-in-Differences estimation in both the Conditional Logit Model and the Linear Probability Model with the project-specific fixed-effects. Taking the Logit model as an example, the DID specification is given by:

$$U(Project_{i_award_bidder_j}) = \alpha_i + \beta_1 Homecountry_{ij} + \beta_2 Homecountry_{ij} \times Time_based_i + \beta_3 After_i \times Homecountry_{ij} + \beta_4 After_i \times Homecountry_{ij} \times Time_based_i + controls(Bidder_j) + \varepsilon_{ij} \quad (3)$$

A significantly positive effect of $Homecountry_{ij}$ prior to the implementation of monitoring systems (captured by $\hat{\beta}_1 + \hat{\beta}_2$) suggests that employers hold home bias previously. Moreover, based on our previous discussions, if $\hat{\beta}_4$ is significantly negative, it is likely that employers adjust their home bias according to available information through monitoring systems, which is known as statistical discrimination (Rubineau and Kang 2011).

As expected, the coefficient of the $After_i \times Homecountry_{ij} \times Time_based_i$ ($\hat{\beta}_4$) is significantly negative, which suggests that, for time-based projects, employers' additional preference for bidders from their home countries decreases as more ex post individual-specific information is accessible through the monitoring system. The decrease in employers' home bias due to the implementation of the monitoring system suggests that employers' home bias cannot be attributed to taste-based discrimination. This lends support to the role of the statistical discrimination mechanism in shaping employers' home bias. To better understand the strength and the economic value of home bias, next we examine the sizes of related coefficients based on the full sample. Specifically, we focus on the coefficients in the Logit model due to the nature of the decision process. Before the implementation of the monitoring system, the total effect of $Homecountry_{ij}$ is 0.953 ($\hat{\beta}_1 + \hat{\beta}_2 = 0.218 + 0.735 = 0.953$) while the coefficient of log (bid price) is -1.690. In this sense, the change in the bid price required to reach parity in workers' likelihood of winning projects from foreign employers to domestic employers is 1.865 ($\exp(0.953/1.690)=1.779$). Given that the average hourly wage of winners in time-based projects is 26.23 dollars, the effect of home bias translates to a premium of 46.10 dollars for domestic

workers. However, after the deployment of the monitoring system, the effect of $Homecountry_{ij}$ reduces to 0.063, implying that domestic workers can only charge a lower price premium after the implementation of monitoring system, all else equal. In other words, the economic value of $Homecountry_{ij}$ decreases to 27.23 dollars²¹. Since only the level of statistical discrimination may decrease due to the availability of ex post individual-specific information, our finding demonstrates that roughly 40.93%²² of home bias is driven by statistical discrimination. Given that monitoring is very likely to be imperfect and it could not help to alleviate the ex ante information asymmetry, the statistical discrimination is not likely to be completely gone after the implementation of the monitoring system. Therefore, this number is a conservative estimate.

Table 7. DID Estimation of Employers' Home Bias

Sample Model	Full sample		Matched sample	
	Logit	LPM	Logit	LPM
Homecountry	0.218***(0.077)	0.016***(0.006)	0.294** (0.141)	0.041** (0.016)
Time-based*Homecountry	0.735***(0.176)	0.088***(0.020)	0.680*** (0.224)	0.077*** (0.027)
After*Homecountry	0.230*** (0.084)	0.021*** (0.007)	0.170 (0.154)	0.016 (0.018)
Time-based*After*Homecountry	-1.120*** (0.232)	-0.119*** (0.025)	-1.062*** (0.290)	-0.126*** (0.034)
Same language	0.366*** (0.027)	0.015*** (0.001)	0.329*** (0.044)	0.022*** (0.003)
Same currency	0.043** (0.022)	0.003*** (0.001)	0.059* (0.036)	0.006** (0.003)
Same time zone	0.222*** (0.057)	0.024*** (0.005)	0.374*** (0.092)	0.049*** (0.010)
Log bid price	-1.690*** (0.018)	-0.087*** (0.001)	-1.811*** (0.032)	-0.134*** (0.002)
Log milestone percentage	-0.113*** (0.016)	-0.005*** (0.001)	-0.227*** (0.027)	-0.017*** (0.002)
Log count rating	0.382*** (0.007)	0.018*** (0.000)	0.391*** (0.011)	0.029*** (0.001)
Log avg rating	-0.146*** (0.012)	-0.006*** (0.001)	-0.130*** (0.021)	-0.007*** (0.002)
Log bid order rank	0.202*** (0.019)	0.013*** (0.001)	0.150*** (0.033)	0.016*** (0.003)
Preferred freelancer	0.366*** (0.027)	0.015*** (0.001)	0.329*** (0.044)	0.022*** (0.003)
Bidder country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	86,840	86,840
R-squared		0.048		0.079
Number of projects	23,943	23,943	9,028	9,028

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

²¹ $26.23 * [\exp(0.063/1.690)] = 27.23$

²² $(46.10 - 27.23) / 46.10 * 100\% = 40.93\%$

6. IV Estimation

Given that the exogenous implementation of the monitoring system enables us to explore the mechanism of home bias with a quasi-natural experiment, there are two potential endogeneity concerns when unobserved characteristics might be correlated with employers' hiring decisions: 1) there might be potential unobserved variables that affect both employers' hiring preference and contract preference; 2) bidders may infer employers' preference and choose their bid prices accordingly²³. To alleviate these concerns, we employ both the 2SLS and control function method to estimate the local average treatment effect (LATE) (Angrist and Imbens 1995; Angrist 2004), i.e., the causal effect of the monitoring system on the margin of home bias.

First, regarding the potential endogenous contract type, we need instruments that are associated with the contract type but not with ε_{ij} in employers' hiring decision (Equation 3). Since employers' time-invariant preference for time-based contracts is nested within the project-specific fixed-effects, we only need to instrument employers' time-varying preference for time-based contracts. Specifically, we employ both the "residual" type IV (Dobbie et al. 2017) and the "BLP" type IV (Berry et al. 1995): a residualized, leave-out employers' tendency to use time-based contracts that accounts for selection bias (Dahl et al. 2014; Dobbie et al. 2017). Since the employers' tendency to use time-based contracts that might be related to employers' characteristics, the simple leave-out mean of employers' contract types or and the lagged term of employers' contract types (his/her last contract type) might still be influenced by the selection concern. Therefore, we predict employers' contract type choices with employer-specific fixed-effect, observable project characteristics, time dummies and calculate the residuals. Here, the residual might capture the specific unobserved project characteristics or the match between the employers' monitoring cost function and the specific project characteristics. Since these residuals capture the idiosyncratic features of the specific project, they are unlikely to correlate with the hiring decision of a different project in the LPM with project-specific fixed effects or the Conditional Logit setting. Therefore, we use the leave-out mean of residuals as the instrument for contract type. Moreover, following the previous literature, we use the percentage of time-based contract types in other rivals'

²³ Since employers' hiring preference is estimated given the bid prices submitted by workers, this will not be a concern if we are only interested in to what extent the statistical discrimination mechanism could explain employers' home bias. We instrument for it to better estimate the monetary value of employers' home bias.

projects which are submitted in the same week of the focal project as the instrument for employers' contract type choice (Ghose et al. 2012). Similar to Hausman's (1996) approach, we assume that controlling for the project-specific fixed effect, worker characteristics and bid characteristics, employer-specific utility from hiring worker j for project i is uncorrelated with other employers' contract type choice (exogeneity). However, the contract type choice of employer i is correlated with other employers' contract type choices within the same week owing to the common platform environment or the preference of contract type from the common labor supply force (relevance).

With regard to the second potential endogenous variable, workers' bid price, we take advantage of the exogenous "cost-shifter" from the supply side (the exogenous variation in the exchange rate of different currencies relative to the U.S. dollar) as the instrumental variable (Nevo 2000; Hong and Pavlou 2017). Since the exchange rate of local currencies²⁴ against U.S. dollar is negatively correlated with the actual purchasing power of the final payment and workers' reservation wage, we will expect the exogenous variation of normalized exchange rates of various currencies to be negatively related to workers' bid prices. Then, the first stage

$$Time_based_{ki} = \zeta_k + Time_dummies_i + \beta_1 residual_leaveout_timebased_i + \beta_2 perc_timebased_week_i + Controls(Project_i, Employer_k) + \eta_{ki} \quad (4)$$

$$Bidprice_{ij} = \alpha_i + Time_dummies_{ij} + \beta_1 Exchange_rate_{ij} + Controls(Bidder_{ij}) + \epsilon_{ij} \quad (5)$$

where ζ_k denotes employer k 's fixed-effect and α_i represents the project i 's fixed-effects.

To estimate the treatment effect in both the Linear Probability Model and the Conditional Logit Model, we employ the 2SLS and control function method respectively. First, in the linear probability setting, there are three endogenous variables in the LPM, including $Homecountry_{ij} \times Time_based_i$, $After_i \times Homecountry_{ij} \times Time_based_i$ and bidders' bid price $Bidprice_{ij}$. Since bidder j 's bidding decision ($Homecountry_{ij}$) and the platform's decision to implement monitoring systems ($After_i$) are exogenous factors, we can have four instrumental variables by assuming that the error term in predicting project i 's contract type (η_{ki}) is uncorrelated with the error term in employers' hiring decision equation (ϵ_{ij}), including $Homecountry_{ij} \times residual_leaveout_timebased_i$, $Homecountry_{ij} \times perc_timebased_week_i$, $After_i \times$

²⁴ The final contract price is measured in the currency set by the employer. To rule out the unobserved workers' preference for currencies, we rule out those projects whose currencies are not U.S. dollar.

$Homecountry_{ij} \times residual_leaveout_timebased_i$ and $After_i \times Homecountry_{ij} \times perc_timebased_week_i$. In the Logit model estimation scenario, we employ the control function to estimate the treatment effect. Specifically, following the previous literature (Petrin and Train 2009; Polyakova 2016), we assume the linearity and additive separability of the unobservables, include the residuals of the first stage of 2SLS into the Conditional Logit Model.

Based on the first-stage of 2SLS, we find that all the four instrument variables related to contract types are significantly correlated with time-based contract dummy. Specifically, when there are more time-based projects posted by other employers within this week, it is less likely that employers could choose time-based projects. Moreover, the high residualized, leave-out employers' tendency to use time-based contracts implies that employers will be more likely to choose time-based projects. Additionally, when the short-term interest rate again U.S. dollar is higher, workers tend to bid a lower price. We also conduct the weak identification test and find that Cragg-Donald Wald F statistic is 78.97 and Kleibergen-Paap Wald rk F statistic is 65.48, which suggests that the week instrument issue is not a concern in our study. Our identification test result (Hansen J statistic is 0.552, Chi-sq(2) P-value = 0.7589; Sargan-Hansen statistic is 0.552 Chi-sq(2) P-value = 0.7589) suggests that at least one instruments may be exogenous.

Additionally, we adjust the standard error for the conditional logit model with the control function by calculating the bootstrap error clustering at the project level. As Table 8 suggests, employers reduce their home bias after the implementation of the monitoring system. The result is highly consistent if we employ the IV estimation on the matched sample.

Table 8. IV Estimation of Employers' Home Bias in the Quasi-natural Experiment

Sample Model	Full sample		Full sample	
	2SLS		Logit with the control function	
Homecountry	0.108***	(0.029)	0.114	(0.096)
Time-based*Homecountry	-0.156***	(0.037)	0.231**	(0.106)
After*Homecountry	0.010	(0.008)	0.924***	(0.222)
Time-based*After*Homecountry	0.016*	(0.009)	-1.374***	(0.295)
Same language	-0.123***	(0.033)	0.307***	(0.085)
Same currency	0.030***	(0.006)	0.050*	(0.029)
Same time zone	0.005**	(0.002)	0.240***	(0.069)
Log bid price	0.024***	(0.006)	-1.737***	(0.025)
Log milestone percentage	-0.005***	(0.002)	-0.090***	(0.019)
Log count rating	0.005***	(0.000)	0.103***	(0.008)
Log avg rating	0.003***	(0.001)	0.098***	(0.011)
Log bid order rank	-0.020***	(0.005)	-0.310***	(0.016)
Preferred freelancer	0.027***	(0.002)	0.464***	(0.021)
Bidder country dummy	yes		yes	

Project fixed effects	yes	yes
Observations	263,752 ²⁵	234,736
R-squared	0.041	
Number of projects	20,255	17,903

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (country rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (country rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (name as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7. Robustness Check

7.1 More Controls: Controlling for the Competition among Bidders from the Same Country

Though we control for worker countries dummies in all the main analysis by reducing the potential existing difference of worker competitiveness across countries, there might still exist time-varying or project-specific contingent factors influencing the estimate of home bias. To control for the potential different time-varying worker competitiveness across countries, we control for the country-month two-way fixed effect and reexamine our analysis. We find that all the analysis including the existence of home bias, the heterogeneity of home bias and the mechanism of home bias is highly consistent after adding the control of two-way fixed effect. Additionally, we also consider the potential time-varying variation in levels of competitiveness and "market tightness"²⁶ from a worker's fellow countrymen in different projects as potential confounders. Therefore, we also calculate the number of workers and the average rating of workers from each country within the employer's specific consideration set. Again, we still find the result is highly consistent.

Table 9. Estimation Results of Linear Probability Model and Conditional Logit Model

Sample Model	Full sample				Matched sample			
	Logit		LPM		Logit		LPM	
Homecountry	0.226***	(0.076)	0.015**	(0.006)	0.226***	(0.076)	0.015**	(0.006)
Time-based*Homecountry	0.743***	(0.174)	0.088***	(0.020)	0.743***	(0.174)	0.088***	(0.020)
After*Homecountry	0.218***	(0.083)	0.019***	(0.007)	0.218***	(0.083)	0.019***	(0.007)

²⁵ Because we obtain the monthly short-term interest rate of each worker country from the OECD data website: <https://data.oecd.org/interest/short-term-interest-rates.htm>, those workers whose home countries' interest rate information is not provided by this website are ruled out from the IV estimation.

²⁶ We assume that as the number of bidders increase, the market competition becomes more fierce and the market tightness increases.

Time-based*After *Homecountry	-1.103*** (0.230)	-0.120*** (0.025)	-1.103*** (0.230)	-0.120*** (0.025)
Same language	0.412*** (0.026)	0.017*** (0.001)	0.412*** (0.026)	0.017*** (0.001)
Same currency	0.065*** (0.021)	0.004*** (0.001)	0.065*** (0.021)	0.004*** (0.001)
Same time zone	0.250*** (0.057)	0.025*** (0.005)	0.250*** (0.057)	0.025*** (0.005)
Log bid price	-1.735*** (0.018)	-0.090*** (0.001)	-1.735*** (0.018)	-0.090*** (0.001)
Log milestone percentage	-0.067*** (0.016)	-0.003*** (0.001)	-0.067*** (0.016)	-0.003*** (0.001)
Log count rating	0.097*** (0.007)	0.005*** (0.000)	0.097*** (0.007)	0.005*** (0.000)
Log avg rating	0.102*** (0.010)	0.001*** (0.000)	0.102*** (0.010)	0.001*** (0.000)
Log bid order rank	-0.312*** (0.013)	-0.016*** (0.001)	-0.312*** (0.013)	-0.016*** (0.001)
Preferred freelancer	0.474*** (0.018)	0.026*** (0.001)	0.474*** (0.018)	0.026*** (0.001)
log avg country rating	0.001 (0.011)	0.009*** (0.001)	0.001 (0.011)	0.009*** (0.001)
log country bidder	-0.093*** (0.015)	-0.002 (0.001)	-0.093*** (0.015)	-0.002 (0.001)
Bidder country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	86,840	86,840
R-squared		0.045		0.045
Number of projects	23,943	23,943	9,028	9,028

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7.2 Parallel Trends Assumption

Following the previous literature (Autor 2003), we explicitly test the parallel trend assumption of the DID model (Angrist and Pischke 2008) by checking whether the control group (fixed-price projects) has the same trend as the treatment group (time-based projects). Accordingly, we estimate the time-varying change in employers' home bias for time-based projects based on the following equation:

$$U(Project_{i_award_bidder_j}) = \alpha_i + \beta_1 Homecountry_{ij} + \beta_2 Homecountry_{ij} \times Time_based_i + \rho \tau_t \times Homecountry_{ij} + \mu(\tau_t \times Time_based_j \times Homecountry_{ij}) + controls(Bidder_j) + \varepsilon_{ij} \quad (4)$$

where τ_t represents a vector of time dummies and $\{\mu\}$ denotes the matrix of relative time parameters of employer i ' home bias for bidder j estimated at time t . Estimating the treatment effect at different time periods enables us to examine the potential pre-treatment trend. Specifically, given that the monitoring system was implemented on February 5th, 2014, we use the month prior to the actual treatment (January 2014) as the baseline (Autor 2003). According to Table 10, all the relative time parameters are insignificantly positive prior to the implementation while most of the

relative time parameters in both the Conditional Logit Model and the Linear Probability Model turn to be negative. To sum up, the result of the relative time model lends support to the causality of our findings.

Table 10. Estimation Results of the Relative Time Model

Sample Model	Full sample Logit		Full sample LPM	
Homecountry	0.325	(0.204)	0.035*	(0.019)
Time_based×Homecountry	0.408	(0.465)	0.053	(0.052)
201303×Homecountry	-0.308	(0.340)	-0.035	(0.025)
201304×Homecountry	0.100	(0.321)	0.002	(0.030)
201305×Homecountry	0.128	(0.328)	-0.003	(0.029)
201306×Homecountry	-0.664**	(0.336)	-0.064**	(0.026)
201307×Homecountry	-0.401	(0.343)	-0.046*	(0.023)
201308×Homecountry	-0.089	(0.311)	-0.029	(0.025)
201309×Homecountry	0.090	(0.310)	-0.001	(0.027)
201310×Homecountry	0.083	(0.291)	0.013	(0.029)
201311×Homecountry	-0.525*	(0.309)	-0.053**	(0.025)
201312×Homecountry	0.134	(0.291)	-0.000	(0.027)
201401×Homecountry	Omitted baseline			
201402×Homecountry	0.406	(0.285)	0.050	(0.031)
201403×Homecountry	-0.104	(0.286)	-0.015	(0.026)
201404×Homecountry	-0.359	(0.290)	-0.024	(0.028)
201405×Homecountry	-0.081	(0.278)	-0.010	(0.027)
201406×Homecountry	-0.500*	(0.294)	-0.041*	(0.025)
201407×Homecountry	0.111	(0.279)	0.007	(0.026)
201408×Homecountry	0.358	(0.255)	0.026	(0.024)
201409×Homecountry	0.253	(0.251)	0.010	(0.023)
201410×Homecountry	0.251	(0.247)	0.009	(0.022)
201411×Homecountry	0.427*	(0.247)	0.019	(0.023)
201412×Homecountry	0.018	(0.251)	-0.017	(0.021)
201501×Homecountry	-0.028	(0.247)	-0.015	(0.022)
201502×Homecountry	0.213	(0.243)	0.007	(0.022)
201303×Time_based×Homecountry	0.318	(0.749)	-0.007	(0.076)
201304×Time_based×Homecountry	-0.542	(0.828)	-0.025	(0.106)
201305×Time_based×Homecountry	-0.708	(0.751)	-0.028	(0.097)
201306×Time_based×Homecountry	0.649	(0.765)	0.026	(0.073)
201307×Time_based×Homecountry	1.654**	(0.731)	0.172**	(0.086)
201308×Time_based×Homecountry	0.663	(0.790)	0.078	(0.089)
201309×Time_based×Homecountry	0.413	(0.699)	0.041	(0.070)
201310×Time_based×Homecountry	-0.915	(0.791)	-0.082	(0.082)
201311×Time_based×Homecountry	0.917	(0.833)	0.150	(0.101)
201312×Time_based×Homecountry	1.947**	(0.802)	0.194*	(0.104)
201401×Time_based×Homecountry	Omitted baseline			
201402×Time_based×Homecountry	-0.847	(0.767)	-0.127	(0.079)
201403×Time_based×Homecountry	-0.438	(0.812)	-0.069	(0.096)
201404×Time_based×Homecountry	-0.066	(0.777)	-0.038	(0.088)
201405×Time_based×Homecountry	-1.283	(0.869)	-0.138	(0.101)
201406×Time_based×Homecountry	0.063	(0.901)	0.002	(0.081)
201407×Time_based×Homecountry	-0.791	(0.991)	-0.123	(0.107)
201408×Time_based×Homecountry	-0.708	(0.618)	-0.071	(0.073)
201409×Time_based×Homecountry	-0.365	(0.602)	-0.062	(0.063)
201410×Time_based×Homecountry	-1.179*	(0.656)	-0.113*	(0.066)
201411×Time_based×Homecountry	-2.056***	(0.694)	-0.175**	(0.073)
201412×Time_based×Homecountry	-1.096	(0.718)	-0.096	(0.066)
201501×Time_based×Homecountry	0.376	(0.701)	0.014	(0.084)
201502×Time_based×Homecountry	-1.525**	(0.707)	-0.120*	(0.063)
Same language	0.413***	(0.026)	0.018***	(0.001)
Same currency	0.062***	(0.021)	0.004***	(0.001)
Same time zone	0.258***	(0.057)	0.025***	(0.005)
Log bid price	-1.738***	(0.018)	-0.090***	(0.001)
Log milestone percentage	-0.065***	(0.016)	-0.003***	(0.001)
Log count rating	0.096***	(0.007)	0.005***	(0.000)
Log avg rating	0.103***	(0.009)	0.003***	(0.000)
Log bid order rank	-0.313***	(0.014)	-0.016***	(0.001)

Preferred freelancer	0.472***	(0.018)	0.026***	(0.001)
Country dummy	yes		yes	
Project fixed effects	yes		yes	
Observations	371,968		371,968	
Number of project_id	23,943		23,943	
R-squared			0.044	

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker's fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as "dual-typed workers") (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4. Coefficients of the Monthly DID Estimates of the Treatment Effect

Note: The dash vertical line denotes when *Freelancer* first implemented the monitoring system (February 2014).

7.3 Placebo Tests

To reinforce the credibility of our main finding, we conduct two additional placebo tests. First, we assign a placebo intervention to the middle of our pre-treatment period (August 1st, 2013) and check whether there exists a pre-treatment tendency prior to the actual implementation of the monitoring system. As Table 11 shows, the interaction between the “pseudo” *After* dummy and the *Time_based* dummy is insignificant. Second, following Abadie et al. (2015), we randomly

reassign the treatment to the projects and run the same model with the placebo treatment assignment. We replicate the analysis for 100 times²⁷ and generate the distribution of placebo treatment effects based on the “pseudo” treatments of monitoring intervention (Greenwood and Wattal 2015). By comparing the actual estimated coefficient of three key covariates to the whole distribution of “placebo” treatment effects, we find that it is very unlikely to observe a similar size of treatment effect by chance, which lends support to the causal relationship between monitoring and the drop in home bias.

Table 11. Estimation Results based on the “Placebo” Treatment Time

Sample Model	Full sample				Matched sample			
	Logit		LPM		Logit		LPM	
Homecountry	0.196	(0.135)	0.010	(0.009)	0.197	(0.255)	0.024	(0.024)
Time-based*Homecountry	0.734**	(0.287)	0.078**	(0.031)	0.786**	(0.367)	0.078*	(0.043)
Afterplacebo*Homecountry	0.183	(0.152)	0.020*	(0.011)	0.338	(0.295)	0.042	(0.031)
Time-based* Afterplacebo *Homecountry	0.111	(0.377)	0.023	(0.041)	-0.161	(0.483)	-0.006	(0.057)
Same language	0.349***	(0.049)	0.014***	(0.002)	0.328***	(0.086)	0.020***	(0.007)
Same currency	0.045	(0.040)	0.005**	(0.002)	0.077	(0.069)	0.010	(0.006)
Same time zone	0.240**	(0.107)	0.024***	(0.009)	0.480***	(0.174)	0.065***	(0.021)
Log bid price	-1.938***	(0.035)	-0.108***	(0.002)	-2.011***	(0.066)	-0.164***	(0.005)
Log milestone percentage	-0.034	(0.027)	-0.003*	(0.002)	-0.163***	(0.045)	-0.016***	(0.004)
Log count rating	0.089***	(0.013)	0.005***	(0.001)	0.081***	(0.022)	0.007***	(0.002)
Log avg rating	0.142***	(0.017)	0.004***	(0.001)	0.123***	(0.028)	0.006**	(0.002)
Log bid order rank	-0.414***	(0.024)	-0.024***	(0.001)	-0.379***	(0.046)	-0.035***	(0.004)
Preferred freelancer	0.507***	(0.033)	0.031***	(0.003)	0.559***	(0.061)	0.057***	(0.008)
log avg_country_rating	0.196	(0.135)	0.010	(0.009)	0.197	(0.255)	0.024	(0.024)
log country_bidder	0.734**	(0.287)	0.078**	(0.031)	0.786**	(0.367)	0.078*	(0.043)
Bidder country dummy	yes		yes		yes		yes	
Project fixed effects	yes		yes		yes		yes	
Observations	104,653		104,653		21,797		21,797	
R-squared			0.056				0.087	
Number of projects	7,602		7,602		2,625		2,625	

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included in our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we control for the country-month two-way fixed effect and the potential time-varying levels of competitiveness from a worker’s fellow countrymen. The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

²⁷ We employ both the LPM with project-specific fixed effects and the conditional logit model to estimate the placebo treatment effects and find highly consistent result.

Table 12. Placebo Effects of Random Implementation Model

Variables	Homecountry	Time_based×Homecountry	Time_based ×After ×Homecountry
Mean of placebo effects	0.340	-0.016	0.021
SD of placebo effects	0.022	0.217	0.265
Actual treatment effects	0.029***	0.082***	-0.112***
Models	Including project fixed effects and bidder country dummies	Including project fixed effects and bidder country dummies	Including project fixed effects and bidder country dummies
Replication	100	100	100
Z-score	-5.657	3.452	-4.298
P-value	0.000***	0.000***	0.000***

Notes : a) The result of the placebo test based on the full sample is reported. b) All the bids which are submitted by bidders having previous collaboration experience with the employ before are dropped. Moreover, our sample is only limited to projects with only one winner. c) Log (bidder tenure) is not included into our model because it is highly correlated with Log (count rating). d) Robust standard errors clustered by projects are reported in parentheses; e) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

7.4 Other Robustness Checks

To further check the robustness of our conclusions, we conduct additional analyses which are suppressed because of the limitation of length. First, we rerun the model with a shorter range of observational window (six months before and after) and still find a consistent result based on the full sample and matched sample. Second, to ensure the workers are comparable and similar between the treatment group and the control group, we limit our sample to the bids which are submitted by those workers who bid for both fixed-price and time-based projects. The result of the restricted sample is still highly consistent with our main findings. Overall, all the additional analyses lend support to our main conclusions. Third, in line with the previous literature suggesting that consumers also have home bias at the state and city levels (Hortaçsu et al. 2009; Lin and Viswanathan 2015), we check whether employers show additional bias towards domestic workers by leveraging the fact that Freelancer provides detailed users' location information. We find that employers have significantly positive preference for workers located in the same city with them. This city-level home bias also lends to support the existence of home bias.

8. Conclusion

8.1. Key Findings and Implications

Based on a quasi-natural experiment wherein the platform introduces a monitoring system for time-based projects, we explore the existence of employers' preference for workers from their home countries and the change in their preference after the implementation of the monitoring system. First, our estimation results suggest that there exists a home bias towards workers in online employment. Second, the implementation of the monitoring system reduces the ex post information asymmetry regarding hidden actions and lowers employers' home bias. Based on the different predictions from taste-based discrimination and statistical discrimination assumptions, we suggest that employers' home bias is more likely to be driven by statistical discrimination.

This paper made important contributions to several streams of literature. First, this is the first study that confirms the existence of home bias in online employment. Despite the rich literature on home bias in equity and trade, the existence of home bias in online employment remains an open question. Åslund et al.'s (2014) study might be the most relevant paper to ours. They found that immigrant managers show less discrimination against immigrant applicants in Sweden. However, given that their limited data from only one country, they could not disentangle the impact of the similar immigrant identity on hiring decisions from that of home bias. Moreover, they also failed to control for the informational difference between immigrant managers and native managers. Second, we also contribute to the emerging stream of research on the discrimination studies based on dynamic predictions and quasi-experiments (Goldin and Rouse 1997; Rubineau and Kang 2011). By now, the most popular method applied in discrimination studies is audit test (Bertrand and Duflo 2017). However, as listed by Heckman and Siegelman (1993) and Heckman (1998), the audit studies suffer from the fact that the differences between the auditors in a pair are not well controlled or perfectly manipulated, and the non-double-blind research setting (Bertrand and Duflo 2017). As Rubineau and Kang (2011) stated, "*The key to identifying statistical discrimination lies in scrutinizing its dynamic rather than static predictions.*" By checking the consistency between the predictions based on statistical discrimination assumption and the actual observed result, we could build a more robust causal relationship between the information change and the dynamic change in discrimination, and subsequently identify the mechanism of

discrimination. Third, our paper also contributes to the recent research on the discrimination phenomenon in the “Gig” economy. It has been found that there exists racial discrimination in on-demand short-term accommodation service (Edelman et al. 2017) and on-demand E-hailing service (Ge et al. 2016). We contribute to this stream of discrimination literature by showing that the discrimination based on the similarity of the home country is also one prevalent discrimination in the “Gig” economy. Our study suggests that by improving some platform-level information policies, we could increase the fairness of the “Gig” economy without reducing the market efficiency.

8.2. Concluding Remark

Using a unique large-scale data set from one of the prevalent online labor platforms, we document the existence of home bias in the online employment setting for the first time. Moreover, owing to the quasi-natural experiment design, we conclude that the implementation of the monitoring system lowers employers’ home bias by 54.0%. Our result suggests that when information is limited, employers might employ statistical discrimination and prefer to hire workers from their home countries. This kind of discrimination could be alleviated without the loss of market efficiency if the platform makes some changes to its information policies and reduces the ex ante or ex post information asymmetry. Overall, our study provides support for the existence of statistical home bias in the context of online employment.

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Appendix

A) Robustness Check with A Different Observational Windows

We rerun the model with a shorter observational window (six months before and after) and still find a consistent result within the full sample panel and the matched sample panel.

Table A1. Estimation Results Based on a Different Observational Windows

Sample Model	Full sample (Six months before and after)		Matched sample (Six months before and after)	
	Logit	LPM	Logit	LPM
	DV: whether the bidder is awarded			
Homecountry	0.279*** (0.101)	0.021** (0.009)	0.351* (0.181)	0.051** (0.023)
Time_based×Homecountry	0.773*** (0.237)	0.094*** (0.026)	0.647** (0.300)	0.067* (0.036)
After×Homecountry	-0.007 (0.121)	0.006 (0.011)	-0.098 (0.217)	-0.011 (0.030)
Time_based × After × Homecountry	-0.857** (0.357)	-0.112*** (0.041)	-0.922** (0.451)	-0.123** (0.055)
Same language	0.406*** (0.041)	0.016*** (0.002)	0.440*** (0.071)	0.028*** (0.005)
Same currency	0.057* (0.033)	0.005*** (0.002)	0.067 (0.055)	0.007 (0.005)
Same time zone	0.249*** (0.088)	0.025*** (0.008)	0.523*** (0.145)	0.075*** (0.019)
Log bid price	-1.862*** (0.028)	-0.105*** (0.002)	-2.013*** (0.051)	-0.161*** (0.004)
Log milestone percentage	-0.058*** (0.022)	-0.003*** (0.001)	-0.136*** (0.037)	-0.011*** (0.003)
Log count rating	0.091*** (0.011)	0.005*** (0.001)	0.100*** (0.018)	0.008*** (0.002)
Log avg rating	0.077*** (0.014)	0.002*** (0.001)	0.049** (0.023)	0.002 (0.002)
Log_bid_order_rank	-0.350*** (0.020)	-0.020*** (0.001)	-0.328*** (0.037)	-0.028*** (0.003)
Preferred freelancer	0.508*** (0.027)	0.031*** (0.002)	0.469*** (0.047)	0.045*** (0.005)
Country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	155,471	155,471	35,110	35,110
R-squared		0.049		0.079
Number of projects	10,925	10,925	4,003	4,003

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included into our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B) Robustness Check regarding Dual-typed Workers

Further, to ensure the workers are comparable and similar between the treatment group and the control group, we limit our sample to the bids which are submitted by those workers who bid for both fixed-price and time-based projects. The result of the restricted sample is still highly consistent with our main findings. Overall, all the additional analyses lend support to our main conclusions.

Table A2 Estimation of Employers' Home Bias Based on Dual-typed Workers

Sample	Dual-typed sample	
Model	Logit	LPM
	DV: whether the bidder is awarded	
Homecountry	0.387*** (0.054)	0.036*** (0.005)
Log bid price	0.407*** (0.029)	0.019*** (0.001)
Log milestone percentage	0.051** (0.023)	0.004*** (0.001)
Log count rating	0.240*** (0.065)	0.025*** (0.006)
Log avg rating	-1.779*** (0.020)	-0.101*** (0.001)
Log_bid_order_rank	-0.096*** (0.017)	-0.006*** (0.001)
Preferred freelancer	0.085*** (0.008)	0.005*** (0.000)
Country dummy	yes	yes
Project fixed effects	yes	yes
Observations	297,724	297,724
R-squared		0.047
Number of projects	21,129	21,129

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included into our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 DID Estimation Results Based on Dual-typed Workers

Sample	Full sample		Matched sample	
Model	Logit	LPM	Logit	LPM
	DV: whether the bidder is awarded			
Homecountry	0.240*** (0.089)	0.022*** (0.008)	0.405*** (0.157)	0.060*** (0.021)
Time_based×Homecountry	0.739*** (0.181)	0.084*** (0.021)	0.607*** (0.235)	0.063** (0.031)
After×Homecountry	0.188* (0.099)	0.019** (0.009)	0.059 (0.176)	0.003 (0.024)
Time_based × After×Homecountry	-1.069*** (0.239)	-0.118*** (0.026)	-0.947*** (0.303)	-0.115*** (0.038)
Log bid price	0.406*** (0.029)	0.019*** (0.001)	0.361*** (0.047)	0.027*** (0.003)
Log milestone percentage	0.052** (0.023)	0.004*** (0.001)	0.080** (0.038)	0.008** (0.003)
Log count rating	0.236*** (0.065)	0.025*** (0.006)	0.387*** (0.101)	0.053*** (0.012)
Log avg rating	-1.779*** (0.020)	-0.101*** (0.001)	-1.861*** (0.035)	-0.152*** (0.003)
Log_bid_order_rank	-0.095*** (0.017)	-0.006*** (0.001)	-0.244*** (0.028)	-0.020*** (0.002)
Preferred freelancer	0.085*** (0.008)	0.005*** (0.000)	0.087*** (0.013)	0.007*** (0.001)
Country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	297,724	297,724	71,400	71,400
R-squared		0.047		0.075
Number of projects	21,129	21,129	8,024	8,024

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included into our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we

include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C) Robustness Check with Home Bias at the City Level

In line with the previous literature suggesting that consumers also have home bias at the state and city levels (Hortaçsu et al. 2009; Lin and Viswanathan 2015), we reexamine whether employers show additional bias towards domestic workers by leveraging the fact that Freelancer provides detailed users' location information. As Table x shows, after controlling for the difference in language, currency, time zone, and country, employers have significantly positive preference for workers located in the same city with them. This city-level home bias may be mainly related to the statistical discrimination, as living in the same city opens up the possibility of direct contract enforcement (Hortaçsu et al. 2009).

Table A4 Estimation Results of City-level Home Bias

Sample Model	Full sample		Matched sample	
	Logit	LPM	Logit	LPM
DV: whether the bidder is awarded				
Same city	0.898***(0.142)	0.120***(0.022)	1.041***(0.195)	0.178***(0.035)
Homecountry	0.363***(0.047)	0.029***(0.004)	0.417***(0.075)	0.049***(0.008)
Same language	0.417***(0.026)	0.018***(0.001)	0.386***(0.043)	0.026***(0.003)
Same currency	0.062***(0.021)	0.004***(0.001)	0.082** (0.035)	0.008***(0.003)
Same time zone	0.239***(0.057)	0.024***(0.005)	0.394***(0.091)	0.051***(0.010)
Log bid price	-1.736***(0.018)	-0.090***(0.001)	-1.847***(0.032)	-0.139***(0.002)
Log milestone percentage	-0.066***(0.016)	-0.003***(0.001)	-0.200***(0.026)	-0.016***(0.002)
Log count rating	0.096***(0.007)	0.005***(0.000)	0.092***(0.012)	0.007***(0.001)
Log avg rating	0.104***(0.009)	0.003***(0.000)	0.081***(0.014)	0.003***(0.001)
Log bid order rank	-0.313***(0.014)	-0.016***(0.001)	-0.328***(0.024)	-0.025***(0.002)
Preferred freelancer	0.471***(0.018)	0.026***(0.001)	0.451***(0.032)	0.040***(0.003)
Country dummy	yes	yes	yes	yes
Project fixed effects	yes	yes	yes	yes
Observations	371,968	371,968	86,840	86,840
R-squared		0.044		0.071
Number of project id	23,943	23,943	9,028	9,028

Notes: a) All the bids which are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is only limited to projects with only one winner. b) Log (bidder tenure) is not included into our model because it is highly correlated with log (count rating). The results are highly consistent if we include Log (bidder tenure) instead of Log (count rating). c) The result is highly consistent if we limit our sample to bids submitted by workers who bided for both fixed-price and time-based projects (named as “dual-typed workers”) (Lin et al. 2016). The result is highly consistent if we include the original bid price instead of log-transformed bid price into the model. d) Robust standard errors clustered by projects are reported in parentheses; e) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.