Home Bias in Online Employment

Completed Research Paper

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Abstract

We study the nature of home bias in online employment, wherein the employer prefers workers from his/her own home country. Using a unique large-scale dataset from one of the major online labor platforms, we identify employers' home bias in their online employment decisions. Moreover, we investigate the cause 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, we employ the difference-in-difference model to show that the home bias does exist in online employment, and at least 54.0% of home bias is driven by statistical discrimination.

Keywords: Home bias, Employment, Statistical discrimination, Taste-based discrimination, Quasi-natural experiment, Gig economy

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 help 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 single-directional 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.[1] 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 such discrimination as "home bias," which is a preference for parties with shorter geographic distance (Hortaçsu et al. 2009). 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. For one thing, home bias tends to lower the diversity of the employees (Åslund et al. 2014), which in turn lowers the creativity (Richard 2000). For another, home bias also 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 the offline employment relationship. In this paper, we seek to fill this gap and investigate the discrimination based on the similarity of home country 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 literature has offered explanations for the home bias, in particular, for investment portfolios and international trade (Obstfeld and Rogoff 2000). Generally, these explanations could be classified as two forms of bias, namely, statistical/rational discrimination (Cooper and Kaplanis 1994; Helliwell 2000) and taste-based discrimination (Lewis 1999; Lin and Viswanathan 2015). Specifically, 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, the home bias in investment portfolios might be driven by 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 well-established platform arbitration 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 its information distribution characteristics. To be specific, unlike the financing or trade decision, the employment decision is plagued with both the salient ex ante and ex post information asymmetry. On the one hand, in such a highly risky context, decision makers tend 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 heuristics, especially when the number of worker candidates is high and most of them are similar in some aspects. 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 literature in home bias by examining employment decisions in online labor markets (Gefen and Carmel 2008; Ghani et al. 2014), and specifically, we address the following two research questions:

- *Q1 (existence): Is there home bias towards workers based on nationality in online labor markets?*
- *Q2 (mechanism): If so, 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

[1] http://fortune.com/2017/01/18/labor-department-oracle/

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 the prevalent online labor markets, we document the existence of home bias towards workers in the employment setting. Further, our result suggests that at least 54.0% 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. 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 and 3, we introduce the theoretical background and proposed hypotheses. In the research methodology section, the identification strategy, data description, and empirical models are presented. Finally, we conclude the findings and implications.

Theoretical Background

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 afore-mentioned 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). Specially, 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).

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 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.

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 US.[2]

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 (Zhao 2008). By tracking and verifying workers' behaviors, monitoring could provide more procedural progress information and alleviate employers' uncertainty about workers' shirking (Pierce et al. 2015).

Hypotheses Development

Employers' Home Bias

When monitoring systems are not available, employers bear a high moral hazard risk. Specially, given that the spatial and temporal separation between employers and workers, it is costly for employers to overcome the difference in time zones and collect the information to infer workers' efforts. Moreover, even when employers are willing to spend enough time and effort to manually monitor workers' work flows, it is unlikely that employers could monitor workers' performance precisely. As such, relational contracting or "process-based trust" (Zucker 1986) might serve a more cost-efficient way to lower the moral hazard risk. Here, trust is defined as one decision maker's specific level of subjective probability with which another party will implement a desirable action before the actual action is monitored or verified (Gambetta 1988; Gulati 1995). According to Gulati (1995), perceived familiarity could breed the cognitive and emotional base of trust, which helps to alleviate the moral hazard concern and leads to a preference in the employment choice. Given that employers tend to feel more familiar with domestic workers, they will be more likely to develop a higher level of initial trust in domestic workers. Therefore, assuming that employers are rational and trying to maximizing their profits from the employment relationship, perceived familiarity and trust might be employed by them to lower the risk and uncertainty. Additionally, the preference for domestic workers might be subliminal. According to the "mere exposure theory" (Zajonc 1968), people tend to show a stronger liking for something that is familiar to them without notice. As such, it is possible that employers would prefer domestic workers, even when foreign workers have the comparable productivity. Since the risk is mainly allocated on employers who are faced with both hidden information issues and hidden action (moral hazard) issues (Mani et al. 2012), employers may more rely on trust or familiarity to lower their uncertainty or risk. Therefore, based on the

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

rational tradeoff or subliminal preference, employers would prefer hiring domestic workers, especially in time-based projects.

H1: Ceteris paribus, employers prefer workers from their home countries in online employment (time-based projects) relative to the sale contracts of outsourcing service (fixed-price projects).

The Impact of Information Change on Home Bias

With the implementation of the monitoring system, employers can reduce their uncertainty by monitoring, rely less on the trust-based relational contracting (Williamson 1985), and reduce their home bias. First, the monitoring system helps to alleviate hidden action issues and decrease workers' probability to shirk. When the monitoring system could automatically take screenshots and keep the log files of the project progress for employers to check anytime, both the shirking probability of foreign workers and that of domestic workers are reduced to a similarly low level. As such, the monitoring system serves as a prime example of process control mechanism and substitutes for relational contracting (Srivastava et al. 2012). Moreover, owing to the precise monitoring records, employers could provide more timely and specific instructions for workers to help them perform more efficiently. Specifically, regardless of workers' home countries and their trustworthiness, employers could keep their cost uncertainty low and ensure their own profit from the projects. In other words, when employers try to lower their cost uncertainty in a platform with the monitoring system already available, they could more tend to rely on monitoring instead of signal exaction from both the group-specific and the individual-specific signals (Belman and Heywood 1991). In other words, the implementation of the monitoring system serves as an exogenous information change by lowing the ex post information asymmetry and reducing the shirking risk, which is expected to decrease statistical discrimination (if there is any). Therefore, we propose the following hypothesis:

H2: The implementation of the monitoring system can mitigate employers' preference towards workers from their home countries in online employment (time-based projects) relative to the sale contracts of outsourcing service (fixed-price projects).

Research Methodology

Data

We obtained a dataset from www.freelancer.com (Freelancer), one of the largest online labor market platforms. On this platform, the employer can post a project, including its description, the budget and required skills, among others. In particular, the employer may specify the project as a fixed-price project by outsourcing it at a flat price (Figure 1-a), or a time-based project (an employment contract) by paying hourly wages to the hired worker (Figure 1-b). Workers could browse all the active or ongoing projects on the website and selectively bid for some of them. Due to the limit on the number of bids one can submit each month[3], workers may select projects that maximize their expected total rewards on the projects they are likely to win. Finally, a contract is reached if the employer assigns the project to one or more workers[4] and the contractor accepts the offer.

To rule out the effect of the auction format on employers' choices, we limit our analysis to projects using the most common public auction form[5]. Further, to construct a homogenous project sample, we focus on the most popular project category, i.e., "IT, software & website". The descriptive statistics of our final dataset are shown in Tables 1 and 2. The dataset includes the following attributes: 1) user-level characteristics (e.g., the number of reviews, the nationality, and the tenure of a user measured in months); project-level characteristics (the description, the budget, the type of contract, the number of bidders and the average bid price, who was awarded and so on).

[3] 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%.
[4] All these projects with more than one winners are dropped from our sample.
[5] 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.

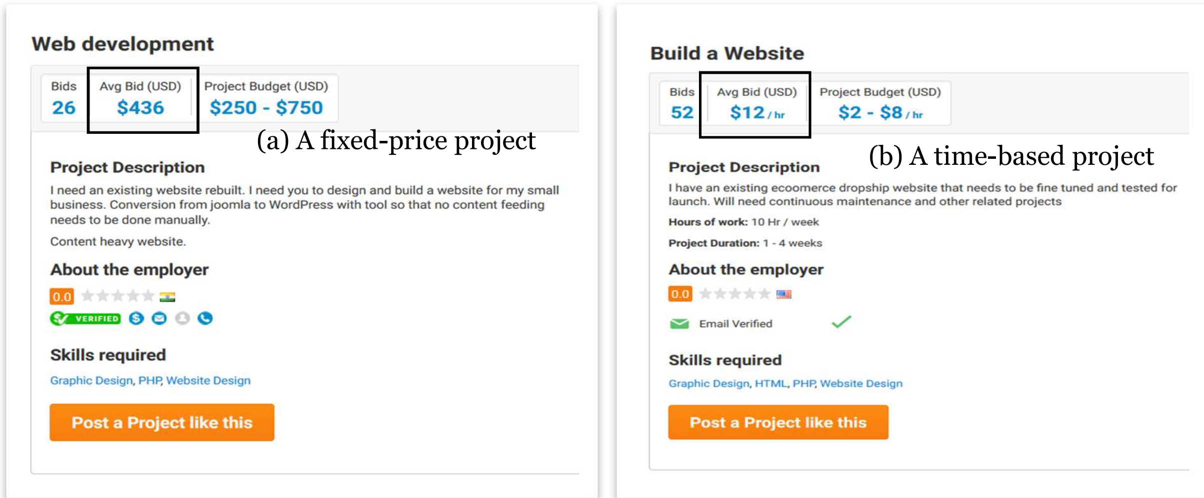

Figure 1. Two Screenshots from Freelancer (a Fixed-price Project vs. a Time-based Project)

Table 1. Definitions and Summary Statistics of Workers' Characteristics

Variable	Variable definition	Mean	SD	Min	Max
Bid Price	The bid price posted by the worker	277.95	464.73	2.00	5000.00
Milestone percentage	A feature provided by Freelancer, it denotes the percentage of controlled payments paid to the worker during the project	72.94	33.35	0.00	120.00
Bidder tenure month	the worker's tenure at Freelancer measured in months	31.13	28.48	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	18.33	19.19	1.00	263.00
Preferred freelancer	A dummy variable (0,1), =1 if the worker won the "Preferred Freelancer Badge"	0.18	0.38	0.00	1.00
Bidder developed	A dummy variable (0,1), =1 if the worker comes from a developed country	0.08	0.28	0.00	1.00
Count rating	The number of reviews entered by previous employers	247.67	0.00	4202.00	247.67

Table 2. Definitions and Summary Statistics of Project Characteristics

Variable	Variable definition	Mean	SD	Min	Max
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 contractor-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

Identification: 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. As a result, workers couldn't shirk or intentionally finish the time-based projects in a low demanding way. Specifically, 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 and the time-based projects as the treatment group.

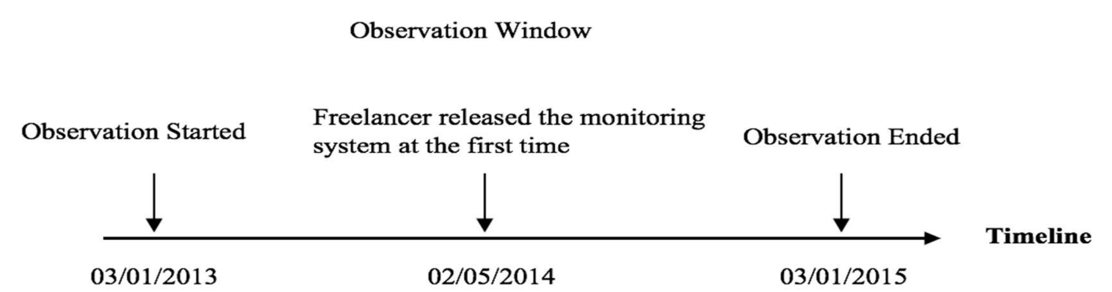

Figure 2. A Timeline of the whole Observation Window

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. For one thing, 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. For another, taste-based discrimination is merely based on preference, which is irrelevant to the availability of information and the expected productivity (Becker 1971). Therefore, the implementation of the monitoring system might affect statistical discrimination but not taste-based discrimination. 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 3):

Table 3. 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

Empirical Model and Results

Propensity Score Matching

To generate a more comparable sample, we deploy the propensity score matching method to match fixed-price projects with time-based projects (Xue et al. 2010; Hong et al. 2015; Lin et al. 2016; Xu et al. 2016). Specifically, we identify project characteristics and employer characteristics which might be associated with the contract type (Banerjee and Duflo 2000; Gopal and Sivaramakrishnan 2008; Lin et al. 2016; Roels et al. 2010). Then, we match fixed-price projects with time-based projects according to the estimated propensity score. Further, we conduct a balance check of all the observed covariates (Xu et al. 2016) and find that the mean values of these covariates are not significantly different between the two groups. Our final sample includes 5,223 fixed-price projects and 5,223 time-based projects.

Table 4. Balance Check for Propensity Score Matching

Covariates	Variables	Mean		%bias	t-test		V(T)/V(C)
		Treated	Control		t	p>t	
Project description (Lin et al. 2016)	Description length	16.33	16.40	-1.70	-0.87	0.38	1.19*
	Title length	5.77	5.81	-1.20	-0.63	0.53	1.09*
Project size (Lin et al. 2016)	Paid amount	250.25	286.15	-1.00	-1.42	0.16	1.04
Environment change (Banerjee and Duflo 2000)	Month dummies[6]	0.04	0.04	0.00	0.00	1.00	-
Client's knowledge (Lin et al. 2016)	Employer tenure month	729.31	728.75	0.10	0.03	0.97	0.94*
	Employer overall rating	4.89	4.90	-1.00	-0.46	0.65	0.83*

Measures and Models

Employers' Decision

We estimate the coefficients of the dummy variable $Home\text{country}_{ij}$ on the decision of employers before and after the implementation of the monitoring system based on a linear probability model (LPM) with project-level fixed-effects and a conditional logit model. Taking the Logit model as an example, the probability of the employer of project i assigns a project to bidder j is $\Pr(Project_i\_award\_bidder_j)$ and the utility that the employer of project i obtains from hiring bidder j is constructed as follows:

$$\mathrm{U}(Project_i\_award\_bidder_j) = \alpha_i + \beta_1 Home\text{country}_{ij} + \beta_2 Home\text{country}_{ij} \times Time\_based_i + \beta_3 After_i \times Home\text{country}_{ij} + \beta_4 After_i \times Home\text{country}_{ij} \times Time\_based_i + controls(Bidder_j) + \varepsilon_{ij} \quad (1)$$

where α_i means the project-level fixed effect. Specifically, the employer-level fixed effects are nested within the project-level fixed effects. $Home\text{country}_{ij}$ denotes whether the employer of project i and bidder

[6] Since we employ one-to-one matching without replacement, all the means of month dummies are equal. Because of the limitation of length, the complete list of the t-test of month dummies is suppressed for brevity.

j are from the same country. $controls(Bidder_j)$ include various bidders' related characteristics[7]. ε_{ij} is assumed to follow the type-I extreme value distribution (Train 2009). A significantly positive effect of $Home\text{country}_{ij}$ prior to the implementation of monitoring systems (captured by $\hat{\beta}_1 + \hat{\beta}_2$) suggests that employers hold home bias. Moreover, based on our previous discussions, if $\hat{\beta}_4$ is significantly negative, we could conclude that employers adjust their home bias according to the information change and there exists statistical discrimination (Rubineau and Kang 2011).

Empirical Results

Based on the results of LPM and the Logit model, both the coefficients of $Home\text{country}_{ij}$ ($\hat{\beta}_1$) and $Home\text{country}_{ij} \times Time\_based_i$ ($\hat{\beta}_2$) are significantly positive, which indicates that employers are more willing to hire workers from their home countries, especially for time-based contracts. Hence, Hypothesis 1 is supported. Moreover, the coefficient of $After_i \times Homecountry_{ij}$ ($\hat{\beta}_3$) is not significant, which suggests that we don't have a weak control problem. As expected, the coefficient of the $After_i \times Home\text{country}_{ij} \times Time\_based_i$ ($\hat{\beta}_4$) 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. This lends support to Hypothesis 2.

To better understand the strength and the economic value of home bias, next we examine the sizes of related coefficients. 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 $Home\text{country}_{ij}$ is 0.801 ($\hat{\beta}_1 + \hat{\beta}_2 = 0.323 + 0.478 = 0.801$) while the coefficient of log (bid price) is -1.592. In this sense, employers are willing to pay 65.4% (exp(0.801/1.592)-1= 1.654-1=0.654) more to domestic workers than to foreign workers, all else equal. 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 17.15 dollars for domestic workers. However, after the deployment of the monitoring system, the effect of $Home\text{country}_{ij}$ reduces to 0.419, implying that domestic workers can still charge 30.1% [8] more as compared to foreign workers, all else equal. In other words, the economic value of $Home\text{country}_{ij}$ decreases to 7.90 dollars[9]. Since only the level of statistical discrimination may decrease due to the availability of ex post individual-specific information, our finding demonstrates that roughly 54.0%[10] 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, employers may still, to some extent, perform statistical discrimination after the implementation of the monitoring system. Therefore, our estimate of the percentage of home bias driven by statistical discrimination is probably relatively conservative. To sum up, both Hypotheses 1 and 2 are supported in the data.

Table 5. Estimation Results of Linear Probability Model and Conditional Logit Model

Sample	Full sample		Matched sample	
Model	LPM	Logit	LPM	Logit
DV: whether the bidder is awarded				
Homecountry	0.023***	0.368***	0.022***	0.323***
	(0.005)	(0.064)	(0.008)	(0.107)
Time_based×Homecountry	0.061***	0.458***	0.061***	0.478***
	(0.016)	(0.152)	(0.018)	(0.175)
After×Homecountry	0.008	0.102	0.009	0.127
	(0.006)	(0.076)	(0.010)	(0.131)
Time_based ×After ×Homecountry	-0.052***	-0.443**	-0.047**	-0.382*

[7] Within data, a contractor's average rating is almost constant during our observational period. Therefore, we didn't treat the contractor rating as a time-variant variable here.
[8] exp(0.419/1.592)-1= 1.301-1=0.301
[9] 26.23*30.1%=7.90
[10] (0.654-0.301)/0.654*100%=54.0%

	(0.019)	(0.192)	(0.021)	(0.221)
Log bid price	-0.082***	-1.707***	-0.080***	-1.592***
	(0.001)	(0.016)	(0.001)	(0.025)
Bidder developed	0.029***	0.477***	0.029***	0.475***
	(0.001)	(0.022)	(0.002)	(0.036)
Log milestone percentage	-0.005***	-0.107***	-0.012***	-0.243***
	(0.001)	(0.014)	(0.001)	(0.020)
Log count rating	0.016***	0.374***	0.018***	0.378***
	(0.000)	(0.006)	(0.000)	(0.009)
Log_bid_order_rank	-0.008***	-0.186***	-0.006***	-0.148***
	(0.001)	(0.010)	(0.001)	(0.016)
Preferred freelancer	0.007***	0.113***	0.007***	0.108***
	(0.001)	(0.016)	(0.002)	(0.026)
Project fixed effects	yes	yes	yes	yes
Observations	530,229	530,229	199,604	199,604
R-squared	0.041		0.040	
Number of projects	31,926	31,926	12,378	12,378

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 month) 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 month) 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.

Heterogeneous Treatment Effects in Different Sub-categories

In our main analysis, we found that employers hold home bias and the bias becomes weaker after the implementation of the monitoring system. In line with this finding, we expect that the magnitude of such a change should be contingent on the observability of the project performance and the effectiveness of the monitoring system. As such, we should observe a more significant effect of the implementation of the monitoring system in projects whose outcomes are easier to be tracked by the monitoring system. For projects relying on creative thinking or background operations, the impact of monitoring might be very limited. Therefore, we explore the heterogeneous treatment effects in top 5 subcategories ranked by the number of projects. Among these five subcategories, two subcategories are expected to be easier to monitor (html and html5) based on our interviews with programmers. Overall, we find that the implementation of the monitoring system effectively reduces employers' home bias in these two subcategories (html and html5) but not in the other three ones. Therefore, the result supports the causal relationship between monitoring and the weakened home bias.

Table 6. Estimation Results of Heterogeneous Treatment Effects

Subcategory	HTML	Wordpress	MySQL	jQuery / Prototype	HTML5
Model	LPM	LPM	LPM	LPM	LPM
DV: whether the bidder is awarded					
Homecountry	0.027***	0.012	0.029*	0.023	-0.006
	(0.005)	(0.014)	(0.016)	(0.023)	(0.018)
Time_based×Homecountry	0.048**	0.001	0.092	0.040	0.177***
	(0.019)	(0.040)	(0.066)	(0.064)	(0.060)
After×Homecountry	0.008	0.008	0.008	0.008	0.053**
	(0.006)	(0.017)	(0.021)	(0.028)	(0.022)

Time_based × Homecountry ×After	-0.040*	-0.032	-0.018	-0.018	-0.193**
	(0.023)	(0.056)	(0.079)	(0.087)	(0.076)
Bidder developed	0.021***	0.028***	0.020***	0.029***	0.039***
	(0.002)	(0.005)	(0.005)	(0.007)	(0.008)
Log (bid price)	-0.060***	-0.072***	-0.085***	-0.086***	-0.061***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Log (milestone percentage)	-0.002**	-0.006***	-0.006**	0.004	-0.007**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Log (count rating)	0.013***	0.011***	0.023***	0.018***	0.012***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Log (bid order rank)	-0.002***	-0.017***	-0.005**	-0.011***	-0.010***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Preferred freelancer	0.009***	0.015***	-0.002	0.008	0.019***
	(0.001)	(0.003)	(0.004)	(0.005)	(0.005)
Project fixed effects	yes	yes	yes	yes	yes
Observations	339,899	46,986	39,271	22,890	21,696
R-squared	0.032	0.038	0.048	0.040	0.032
Number of projects	15,503	2,482	2,904	1,728	1,239

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 month) 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 month) 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 projects (the "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.

Robustness Check

Alternative Models

In the main analysis, we employ both the LPM and Logit models to explore employers' hiring decisions by balancing multiple workers' characteristics and bid prices, etc. To verify the robustness of our results, we follow the model in the previous discrimination literature by including the worker-specific fixed-effects (Åslund et al. 2014) and tracking the change in the effect of the $Homecountry_{ij}$ dummy. Specifically, based on the covariates listed in the Propensity Score Matching section (except for the month dummies), we match time-based projects posted prior to the implementation of the monitoring system with those time-based projects posted after its implementation. We compare the impact of $Homecountry_{ij}$ dummy on the probability of bidder j being hired by the employer of project i ($\Pr(Hire_{ijt})$) before and after within the full sample and the matched sample.

$$Pr(Hire_{ijt}) = \alpha_j + \beta_1 Homecountry_{ij} + \beta_2 After_i + \beta_3 After_i \times Homecountry_{ij} + controls\left(bidder_j\right) + \gamma_t + \varepsilon_{jt}$$

where α_j denotes bidder-specific fixed-effects. The notations of all the other covariates are similar to those in the main result. Additionally, we also control for the time fixed-effects and cluster the standard errors by workers instead of projects. Further, following Åslund et al. (2014), we estimate the change in workers' probability of being hired in the Linear Probability Model. As Table 6 shows, after the implementation of the monitoring system, the positive effect of the $Homecountry_{ij}$ dummy on the probability of being hired significantly decreases, which is highly consistent with our main result.

Table 7. Estimation Results of the Linear Probability Model

DV: whether the bidder j is awarded in project i ($Hire_{ijt}$)		
Sample	Full sample	Matched sample
Model	LPM	LPM
After	-0.028	-0.050
	(0.023)	(0.062)
Homecountry	0.041***	0.109***
	(0.010)	(0.024)
After×Homecountry	-0.026**	-0.076***
	(0.012)	(0.027)
Log (bid price)	-0.009***	-0.021***
	(0.002)	(0.004)
Log (milestone percentage)	-0.010***	-0.024***
	(0.002)	(0.005)
Log (bidder overall rating)	-0.012	-0.023
	(0.008)	(0.020)
Log (bid order rank)	-0.034***	-0.085***
	(0.002)	(0.005)
Preferred freelancer	-0.011	-0.032
	(0.022)	(0.026)
Observations	48,552	15,187
R-squared	0.029	0.071
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) Robust standard errors clustered by workers are reported in parentheses. c) the coefficients of month dummies are suppressed for brevity. d) * p<0.1, ** p<0.05, *** p<0.01.		

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 7 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 times[11] and generate the distribution of placebo treatment effects based on the "pseudo" treatments of monitoring intervention. By comparing the 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 8. Estimation Results based on the "Placebo" Treatment Time		
DV: whether the bidder is awarded		
Sample	Full sample	
Model	Logit	LPM
Homecountry	0.179	0.008
	(0.115)	(0.007)
Time_based×Homecountry	0.681***	0.071***
	(0.251)	(0.025)
After×Homecountry	0.377***	0.029***
	(0.137)	(0.009)
Time_based ×After ×Homecountry	-0.355	-0.017
	(0.320)	(0.032)

[11] To save the computation time, we employ the LPM to estimate the placebo treatment effects.

Bidder developed	0.443***	0.029***
	(0.038)	(0.002)
Log (bid price)	-1.864***	-0.095***
	(0.028)	(0.001)
Log (milestone percentage)	-0.137***	-0.006***
	(0.022)	(0.001)
Log (count rating)	0.443***	0.020***
	(0.010)	(0.000)
Log (bid order rank)	-0.242***	-0.013***
	(0.016)	(0.001)
Preferred freelancer	0.030	0.002
	(0.028)	(0.002)
Project fixed effects	yes	yes
Observations	173,034	1 73,034
R-squared		0.053
Number of project_id	11,550	11,550
Notes: a) All the bids which are submitted by bidders having prior collaboration experience with the employers are dropped. Moreover, our sample is only limited to projects with only one winner. b) Robust standard errors clustered by projects are reported in parentheses; c) * p<0.1, ** p<0.05, *** p<0.01.		

Table 9. Placebo Effects of Random Implementation Model			
Variables	Homecountry	Time_based×Homecountry	Time_based ×After ×Homecountry
Mean of placebo effects	0.031	0.000	0.000
SD of placebo effects	0.001	0.014	0.017
Actual treatment effects	0.023***	0.061***	-0.052***
Models	Including project fixed effects		
Replication	100	100	100
Z-score	-5.699	4.331	-3.035
P-value	0.000***	0.000***	0.002***

Other Analyses

To further check the robustness of our conclusions, we conduct additional analyses which are suppressed because of the limitation of length. First, to validate the existence of home bias and rule out alternative explanations, we add the dummies to denote whether the employer and the bidder use the same primary language, adopt the currency setting, and live in the same time zone, respectively. After controlling for the effect of language, currency, and time zone, we find that employers still show a significant preference towards domestic contractors. Second, we rerun the model with a shorter range of observational window (night months before and after; six months before and after) and still find a consistent result. Third, we conduct a falsification test based on employers' project experience. We expect that employers who have never posted a time-based project should not be affected by the implementation of the monitoring system. Hence, we rerun the model with employers with no time-based project experience and find their home bias doesn't decrease. Four, 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.

Discussion

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.

We add to the previous literature in three ways. 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. For one thing, "Gig" economy platforms could provide more IT-enabled tools to help to lower the information asymmetry and mitigate the discrimination issues. For another, high-quality sellers or workers from the minority group could also self-signal themselves by providing more individual information or choose to join those platforms with less information asymmetry.

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.

References

Abadie, A., Diamond, A. and Hainmueller, J., 2015. Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), pp.495-510.

Aigner, D.J. and Cain, G.G., 1977. Statistical theories of discrimination in labor markets. *ILR Review*, *30*(2), pp.175-187.

Arrow, K.J., 1973. The theory of discrimination.

Åslund, O., Hensvik, L., & Skans, O. N. 2014. Seeking similarity: How immigrants and natives manage in the labor market. *Journal of Labor Economics*, *32*(3), 405-441.

Banerjee, A. V., and Duflo, E. 2000. Reputation effects and the limits of contracting: A study of the Indian software industry. *The Quarterly Journal of Economics*. 115(3): 989-1017.

Becker, G. S. 2010. *The economics of discrimination*. University of Chicago press.

Belman, D., & Heywood, J. S. 1991. Sheepskin effects in the returns to education: An examination of women and minorities. *The Review of Economics and Statistics*, 720-724.

Belzer, A. and Leong, N., 2016. The New Public Accommodations

Bergstrand J 1985. The gravity equation in international trade: Some microeconomic foundations and empirical evidence. *Rev. Econom. Statist.* 67(3):474–481.

Bertrand, M., Chugh, D., & Mullainathan, S. 2005. Implicit discrimination. *American Economic Review*, 94-98.

Bertrand, M., & Duflo, E. 2017. Field experiments on discrimination. *Handbook of Economic Field Experiments*, *1*, 309-393.

Bertrand, M., & Mullainathan, S. 2004. Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *The American Economic Review*, *94*(4), 991-1013.

Brunetti, A., Kisunko, G., & Weder, B. 1997. *Institutional Obstacles to Doing Business: Region-by-region Results from a Worldwide Survey of the Private Sector* (Vol. 1759). World Bank Publications.

Burtch, G., Ghose, A., & Wattal, S. 2013. Cultural differences and geography as determinants of online pro-social lending.

Cooper, I., & Kaplanis, E. 1994. Home bias in equity portfolios, inflation hedging, and international capital market equilibrium. *Review of Financial Studies*, *7*(1), 45-60.

Coval, J. D., & Moskowitz, T. J. 1999. Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, *54*(6), 2045-2073.

Doleac, J. L., & Hansen, B. 2016. *Does "ban the box" help or hurt low-skilled workers? Statistical discrimination and employment outcomes when criminal histories are hidden* (No. w22469). National Bureau of Economic Research.

Edelman, B., Luca, M. and Svirsky, D., 2017. Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics*, *9*(2), pp.1-22.

Forman, C., Ghose, A. and Goldfarb, A., 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management science*, *55*(1), pp.47-57.

Forman, C., Goldfarb, A. and Greenstein, S., 2012. The Internet and local wages: A puzzle. *The American Economic Review*, *102*(1), pp.556-575.Obstfeld, M. and Rogoff, K., 2000. The six major puzzles in international macroeconomics: is there a common cause?. *NBER macroeconomics annual*, *15*, pp.339-390.

French, K. R., & Poterba, J. M. 1991. *Investor diversification and international equity markets* (No. w3609). National Bureau of Economic Research.

Fryer, R. and Jackson, M.O., 2008. A categorical model of cognition and biased decision-making. *The BE Journal of Theoretical Economics*, *8*(1), pp.1935-1704.

Gambetta, D. 1988. Trust: Making and breaking cooperative relations.

Ge, Y., Knittel, C.R., MacKenzie, D. and Zoepf, S., 2016. *Racial and gender discrimination in transportation network companies* (No. w22776). National Bureau of Economic Research.

Gefen, D. and Carmel, E., 2008. Is the world really flat? A look at offshoring at an online programming marketplace. *MIS quarterly*, pp.367-384.

Ghani, E., Kerr, W. R., & Stanton, C. 2014. Diasporas and outsourcing: evidence from oDesk and India. *Management Science*, *60*(7), 1677-1697.

Goldin, C., & Rouse, C. 1997. *Orchestrating impartiality: The impact of" blind" auditions on female musicians* (No. w5903). National bureau of economic research.

Gopal, A., and Sivaramakrishnan, K. 2008. Research note-On vendor preferences for contract types in offshore software projects: The case of fixed price vs. time and materials contracts. *Information Systems Research*. 19(2): 202-220.

Gulati, R. 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. *Academy of management journal*, *38*(1), 85-112.

Heckman, J. J., & Siegelman, P. 1993. The Urban Institute audit studies: Their methods and findings.

Heckman, J. J. 1998. Detecting discrimination. *The Journal of Economic Perspectives*, *12*(2), 101-116.

Helliwell, J. F. 2000. *How much do national borders matter?*. Brookings Institution Press.

Hendricks, W., DeBrock, L. and Koenker, R., 2003. Uncertainty, hiring, and subsequent performance: The NFL draft. *Journal of Labor Economics*, *21*(4), pp.857-886.

Hong, Yili, Chong Wang, and Paul A. Pavlou.2015. "Comparing Open and Sealed Bid Auctions: Evidence from Online Labor Markets." *Information Systems Research*, (27:1), pp.49-69.

Hong, Y., Pavlou, P. A. 2017. On Buyer Selection of Service Providers in Online Outsourcing Platforms. *Information Systems Research*, forthcoming.

Hortaçsu, A., Martínez-Jerez, F., & Douglas, J. 2009. The geography of trade in online transactions: Evidence from eBay and mercadolibre. *American Economic Journal: Microeconomics*, *1*(1), 53-74.

Kugler, A.D. and Saint-Paul, G., 2000. *Hiring and firing costs, adverse selection and long-term unemployment* (No. 134). IZA.

Lewis, K. K. 1999. Trying to explain home bias in equities and consumption. *Journal of economic literature*, *37*(2), 571-608.

Lin, M., & Viswanathan, S. 2015. Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, *62*(5), 1393-1414.

Lin, M., Liu, Y., & Viswanathan, S. 2016. Effectiveness of reputation in contracting for customized production: Evidence from online labor markets. *Management Science*.

Mani, D., Barua, A., and Whinston, A. B. 2012. "An empirical analysis of the contractual and information structures of business process outsourcing relationships," *Information Systems Research* (23:3-part-1), pp. 618-634.

Phelps, E.S., 1972. The statistical theory of racism and sexism. *The american economic review*, *62*(4), pp.659-661.

Pierce, L., Snow, D. C., and McAfee, A. 2015. Cleaning house: The impact of information technology monitoring on employee theft and productivity. *Management Science*. 61(10): 2299-2319.

Richard, O. C. 2000. Racial diversity, business strategy, and firm performance: A resource-based view. *Academy of management journal*, *43*(2), 164-177.

Roels, G., Karmarkar, U. S., and Carr, S. 2010. Contracting for collaborative services. *Management Science*. 56(5): 849-863.

Rubineau, B., & Kang, Y. 2012. Bias in white: A longitudinal natural experiment measuring changes in discrimination. *Management Science*, *58*(4), 660-677.

Schwab, S. 1986. Is statistical discrimination efficient?. *The American Economic Review*, *76*(1), 228-234.

Simon, H. A. 1951. A formal theory of the employment relationship. *Econometrica: Journal of the Econometric Society*, 293-305.

Sorenson, O. and Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments 1. *American journal of sociology*, *106*(6), pp.1546-1588.

Srivastava, S. C., & Teo, T. S. 2012. Contract performance in offshore systems development: Role of control mechanisms. *Journal of Management Information Systems*, *29*(1), 115-158.

Todisco, M., 2014. Share and Share Alike: Considering Racial Discrimination in the Nascent Room-Sharing Economy. *Stan. L. Rev. Online*, *67*, p.121.

Williamson, O. E. 1985. *The economic intstitutions of capitalism*.

Xu, K., Chan, J., Ghose, A. and Han, S.P. (2016) Battle of the channels: The impact of tablets on digital commerce. *Management Science* (forthcoming).

Xue, Mei, Lorin M. Hitt, and Pei-yu Chen. 2010. Determinants and outcomes of internet banking adoption. *Management science,* (57:2), pp. 291-307.

Zajonc, R. B. 1968. Attitudinal effects of mere exposure. *Journal of personality and social psychology*, *9*(2p2), 1.

Zhao, R.R. 2008. All-or-nothing monitoring. *The American Economic Review*. 98(4): 1619-1628.