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https://pubsonline.informs.org/journal/isre

INFORMATION SYSTEMS RESEARCH
Vol. 36, No. 2, June 2025, pp. 736–760
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Monitoring and Home Bias in Global Hiring: Evidence from an Online Labor Platform

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Received: October 12, 2021
Revised: May 1, 2023; March 16, 2024
Accepted: May 4, 2024
Published Online in Articles in Advance: June 12, 2024

https://doi.org/10.1287/isre.2021.0526

Abstract. The increasing prevalence of remote work has accelerated the adoption of monitoring systems to keep track of worker behavior, especially on online labor platforms. In contrast to the existing literature that predominantly focuses on the effect of monitoring on productivity, this study investigates the impact of monitoring from the perspective of contractual governance. In principle, by enabling the detailed real-time observation of worker progress, the deployment of monitoring systems has the potential to improve contractual control and coordination, thereby reducing employers' preferences for domestic workers (home bias). Leveraging the exogenous introduction of a monitoring system for time-based projects on a leading online labor platform, we employ a difference-in-differences model to estimate the impact of monitoring systems in reducing home bias. Our findings reveal that following the monitoring system's introduction, the bias against foreign workers becomes substantially weaker and statistically insignificant, highlighting the overlooked role of monitoring systems in fostering a more level playing field for global workers. Our further analysis indicates that monitoring leads to a notable 15% increase in the hiring of foreign workers. Moreover, the decrease in home bias is more pronounced in high-routine projects or when employers lack prior positive experiences with foreign workers, two scenarios characterized by low external uncertainty and high internal uncertainty, respectively. Additionally, employers no longer exhibit a stronger home bias when workers have higher ratings, where the expected moral hazard risk is lower, nor when workers reside in the same time zone, where expected coordination costs are lower. These findings lend support to the effectiveness of monitoring systems in mitigating employers' home bias through enhancing contractual control and coordination. Our findings provide important managerial implications for the design of online labor platforms.

History: Deepa Mani, Senior Editor; Tianshu Sun, Associate Editor.
Funding: This work was supported by an NET Institute Grant and the Robert Wood Johnson Foundation (RWJF) [Grant 74503].
Supplemental Material: The online appendix is available at https://doi.org/10.1287/isre.2021.0526.

Keywords: monitoring • home bias • online labor market • task routineness • hiring experience

1. Introduction

Monitoring systems are becoming ubiquitous in the workplace. According to Gartner research, 60% of large companies used some type of monitoring since 2020, and the percentage was expected to rise to 70% in the next three years.[1] This trend was further accelerated by the massive shift toward remote work in recent years. For instance, TransparentBusiness, a tool for monitoring remote workers, has seen a 500% increase in the number of users month to month in 2020.[2]

Consistent with the increasing prevalence of monitoring systems, the extant literature has shown the significant benefits of monitoring in mitigating moral hazard and streamlining coordination with workers. For example, monitoring leads to an increase in workers' effort and productivity in various contexts (e.g., restaurants (Pierce et al. 2015), transportation (Kelley et al. 2023), and retail stores (Deng et al. 2023)) without changes in the incentive scheme. Meanwhile, monitoring can reduce other opportunistic behaviors as well, such as absenteeism (Duflo et al. 2012), hand hygiene noncompliance (Staats et al. 2017), and employee theft (Pierce et al. 2015). In addition, by automatically reporting workers' working hours and computer activities to employers in real time, monitoring systems can reduce the need for interactions between employers and workers (Aiello 1993) and depersonalize the work environment (Alder and Ambrose 2005). Despite the empirical evidence supporting the positive effects of monitoring on enhancing labor outcomes post-hiring, it remains unclear whether monitoring can also influence the upstream outcomes pertaining to how employers select and hire workers, which can have significant implications for enhancing labor market efficiency and shaping the future landscape of online employment.

In the absence of monitoring, employers who are looking to hire remote workers may resort to intuitive cues (such as shared country, language, and time zone) when making hiring decisions. This intuition is often motivated by the belief that familiarity and common backgrounds can foster greater trust and cooperation, thereby mitigating moral hazard risks and lowering coordination costs. This phenomenon is akin to the "home bias" effect documented in the finance literature, where investors exhibit a preference for domestic investments in their investment and trading decisions (e.g., French and Poterba 1991, Gefen 2000, Huberman 2001, Hortaçsu et al. 2009, Leblang 2010, Lin and Viswanathan 2016). Extant studies on home bias in investment generally suggest that individuals tend to exhibit home bias as a result of using familiarity (e.g., French and Poterba 1991, Huberman 2001, Leblang 2010) or common background characteristics (e.g., Anderson et al. 2011, Burtch et al. 2014, Kim et al. 2015) to mitigate transaction risks. More relatedly, in the online employment context, Gefen and Carmel (2008) find evidence of home bias: that is, the bias against foreign workers. However, the extent literature does not delve into the underlying mechanisms driving this bias, nor does it suggest potential remedies for addressing it.

With the rise of remote work, bolstered by the growing prevalence of online labor platforms, workers hailing from different countries vie for global job opportunities, leading to global trade of services and labor specialization (Grossman and Rossi-Hansberg 2008, Tambe and Hitt 2012) and contributing to economic growth and a flatter global labor market (Friedman 2005, p. 110). However, home bias can impede the flow of global talent, which is estimated to account for 5%–30% of the overall value of global trade (Lund et al. 2019), and it can give rise to hiring practices that discriminatorily impact certain groups of workers (Leamer 2007). Therefore, understanding home bias in online labor platforms and how it can be reduced are important questions, particularly as home bias poses a significant impediment to the development of frictionless global online labor platforms.

Notably, despite the increasing importance, both the finance literature and the online platforms literature are silent on how home bias can be reduced. To fill this gap, we draw on the literature on monitoring (e.g., Alder and Ambrose 2005, Pierce et al. 2015) and home bias (e.g., French and Poterba 1991, Gefen 2000) to posit that monitoring systems can play an important role in reducing employers' home bias. According to the prior literature on transaction governance (e.g., Lumineau and Henderson 2012, Lumineau 2017, Schilke and Lumineau 2018), *control* and *coordination* are two main contractual functions that help employers to establish clear expectations and guidelines for the performance and behavior of contract workers. However, the hiring of foreign workers presents unique challenges because of the complexities of exerting control and coordination over them.

In response to these challenges, monitoring systems, as automated tools, have emerged as a promising solution. For one thing, monitoring systems can automatically track workers' real-time progress, which restricts their ability to overreport working hours and enforces expectations for behavior and performance. This enables employers to effectively observe and possibly manage remote workers' effort level and mitigate moral hazard. For another, monitoring systems can generate real-time reports on remote workers' status and provide comprehensive information on their work processes, which in turn, facilitate employers in coordinating with workers to ensure that their efforts align with the intended trajectory. As monitoring systems can improve the effectiveness of contractual control and coordination with remote workers, they have the potential to increase employers' willingness to hire foreign workers.

Furthermore, the extent to which monitoring systems can effectively enable employers to exercise such control and coordination to reduce their home bias may be moderated by two sources of uncertainty, namely *external uncertainty* and *internal uncertainty* (Lumineau and Henderson 2012, Lumineau 2017). External uncertainty arises from the unpredictability of tasks or work environment, such as unexpected technological disruptions or exceptions, which are primarily associated with the nonroutineness of tasks (Lumineau and Henderson 2012). Conversely, internal uncertainty, also known as behavioral uncertainty, refers to the uncertainty about the behavior of the other party because of difficulties in accurately understanding or predicting partners' behavior. Internal uncertainty usually stems from a lack of common grounds or prior interactions (Abdi and Aulakh 2017).

Both external and internal uncertainty can affect the effectiveness of monitoring systems to manage remote workers. For one thing, in situations of high external uncertainty, such as low-routine projects, monitoring systems are less effective in revealing workers' effort (Davidson and Henderson 2000, Ranganathan and Benson 2016) and facilitating precise coordination with workers. This is because such projects are less standardized and require more complex communication to facilitate mutual understanding, making it challenging for employers to utilize monitoring systems to control and coordinate with foreign workers. Consequently, monitoring systems may result in a smaller reduction in home bias for employers in low-routine projects. For another, as employers acquire more positive experiences with foreign workers, their familiarity with foreign workers tends to increase as well as their confidence in foreign workers' effort, suggesting low internal uncertainty. As a result, employers' prior positive experiences with foreign workers can enable effective control and coordination with foreign workers, which in turn, lead to a lower level of home bias and potentially, reduce the need for monitoring systems. Consequently, we expect the effect of monitoring in reducing home bias to be attenuated when employers had prior positive hiring experiences with foreign workers and were less uncertain about their behavior. Therefore, to fill the literature gap on the role of monitoring in reducing home bias, we seek to (a) *investigate whether and how monitoring reduces home bias in the online labor platform context* and (b) *examine the moderating effect of external uncertainty (proxied by project nonroutineness) and that of internal uncertainty (proxied by the lack of employers' prior positive experiences with foreign workers).*

We obtained a unique, large-scale data set from a leading online employment market, in which we reliably observe both employers' and workers' countries, employers' consideration sets (job applicants), and their ultimate hiring decisions. After confirming the existence of employers' home bias, we examine the impact of monitoring systems on home bias by leveraging a quasinatural experiment (i.e., the introduction of a platform-provided monitoring system). Our econometric identification hinges on the fact that the monitoring system is made available only to time-based projects and not to fixed-price projects, which allows us to use a difference-in-differences (DID) framework along with coarsened exact matching (CEM) for causal inference. In our empirical models, we further control for project fixed effects (which subsume employer fixed effects), worker country dummies, and various measures regarding the similarity between the employer and the worker (i.e., same language, same time zone, and same currency). We further conduct the parallel trend test and a series of additional analyses (including placebo tests, instrumental variable, and sensitivity analysis) to demonstrate the robustness of our results.

Our econometric analyses first reveal that the monitoring system significantly reduces employers' home bias. In fact, after the introduction of the monitoring system, employers' home bias is no longer significant in the treatment group (i.e., time-based projects), whereas home bias persists in the control group (i.e., fixed-price projects). Our back-of-the-envelope estimation reveals that the introduction of the monitoring system leads to a notable 15.07% increase in the hiring of foreign workers compared with the counterfactual scenario, in which the monitoring system was not introduced. Moreover, the effect of the monitoring system on home bias varies across projects and employers depending on project routineness and employers' prior positive experiences with foreign workers. Specifically, the decrease in employers' home bias is larger in high-routine projects than in low-routine ones; the latter involves higher external uncertainty and is considered less amenable to effective control and coordination. Additionally, the decrease in employers' home bias is larger for employers who have no positive prior hiring experiences with foreign workers and tend to have higher internal uncertainty regarding their behavior. In addition, we present evidence indicating that both contractual control and coordination mechanisms contribute to explaining the mitigation effect of monitoring systems on employers' home bias.

Our paper contributes to three related streams of literature. First, our study contributes to the literature on home bias. Although prior studies have predominantly examined home bias in the context of financial markets (Sorenson and Stuart 2001, Lin and Viswanathan 2016) and commodity transactions (Hortaçsu et al. 2009), our research focuses on online employment, an area in which buyers (employers) seek to coordinate with sellers (workers) while also attempting to control their behavior to mitigate potential moral hazard risks. Our study not only confirms the presence of home bias on online labor platforms, but also identifies potential mechanisms that can help mitigate it. By providing evidence for both the contractual control and coordination mechanisms, our study showcases that platforms can adopt platform design strategies to protect employers' interests in cases of moral hazard while facilitating virtual collaboration across borders and cultures.

Second, our study advances the emerging literature on online platforms. Although previous research has highlighted the existence of various types of biases on online platforms (Chan and Wang 2018, Cui et al. 2020, Li et al. 2021, Sun et al. 2021), there has been a dearth of literature on effective strategies for mitigating those biases. Our research addresses this gap by demonstrating that monitoring systems can effectively reduce employers' bias against foreign workers. Our results suggest that monitoring systems can play a vital role in transforming online labor platforms populated with localized transactions into frictionless global labor platforms. This finding has important implications for online platform design aimed at fostering a more inclusive and equitable global employment landscape.

Third, our study also adds to the existing literature on monitoring systems and technology adoption. Extending the growing literature on the effect of monitoring systems on workers' productivity (e.g., Boly 2011, Pierce et al. 2015, Deng et al. 2023) and the impact of technology adoption on transaction costs

(Subramani 2004, Kim and Son 2009), our study reveals that the effectiveness of monitoring systems in reducing home bias decreases with external uncertainty but increases with internal uncertainty. External uncertainty limits the effectiveness of monitoring systems, as they are less amenable to the control of workers' behavior, while requiring more complex communication to facilitate coordination. Internal uncertainty increases the need for such systems to better control and coordinate with remote workers, thus making monitoring more valuable. Our findings offer actionable implications for the design and implementation of monitoring systems and policies, suggesting that platforms can enhance the effectiveness of monitoring systems by providing a wider range of monitoring functions and by allowing employers to tailor monitoring strategies to the specific job characteristics and shared common grounds with workers.

2. Literature Review

2.1. Monitoring Systems

Monitoring systems refer to IT systems that collect, store, and report information regarding work activities and productivity of individuals during the production process (Stanton and Julian 2002, Alder and Ambrose 2005, Liang et al. 2024). In general, prior studies suggest that monitoring systems can mitigate moral hazard risks by enhancing employers' control over workers' opportunistic behavior (e.g., shirking and misconduct) and by reducing coordination costs (e.g., Clemons et al. 1993). There is a growing literature documenting the effect of monitoring systems on workers' productivity. In line with the agency theory, Boly (2011) finds that monitoring can increase workers' effort. Similarly, Hubbard (2003) finds that monitoring technologies that automatically record information on drivers' idle time and driving speed can increase truck drivers' productivity. Apart from the positive impact on effort and productivity, monitoring systems are also found to encourage good practice and reduce misconduct among workers. For instance, Pierce et al. (2015) show that monitoring systems do not only increase workers' productivity but also reduce their theft behavior. Moreover, Duflo et al. (2012) find that camera monitoring can increase teachers' attendance and thus, lead to higher student test scores. Staats et al. (2017) conclude that monitoring systems significantly improve process compliance in the healthcare industry. In addition, Clemons et al. (1993) conceptually argue that information technology (IT) investment can reduce the costs associated with information exchange and processing, thereby lowering interfirm coordination costs, as illustrated by several industrial examples.

Nevertheless, monitoring is not a panacea. Ranganathan and Benson (2016) show that monitoring only increases worker productivity in simple tasks but not in complex tasks. In addition, notwithstanding the benefits of monitoring systems in reducing worker misconduct, there are growing concerns that monitoring systems may raise serious privacy concerns among workers (Townsend and Bennett 2003) and lower work morale (Frey 1993) in the long run.

As monitoring systems can mitigate moral hazard risks (e.g., Clemons et al. 1993, Hitt 1999) and reduce interactions between employers and workers (e.g., Aiello 1993, Alder and Ambrose 2005), they have the potential to reduce employers' bias against workers who were perceived to have higher moral hazard risks or higher coordination costs, such as foreign workers. However, to the best of our knowledge, there is a void in the literature regarding the potential impact of monitoring systems on hiring biases. Specifically, most prior studies focus on the impact of monitoring systems on the effort and productivity of the same group of workers *after* employers made the hiring decisions (e.g., Duflo et al. 2012, Pierce et al. 2015, Staats et al. 2017) and have no information regarding employers' consideration sets when making hiring decisions. Such research design and data limitation preclude the possibility of investigating the impact of the monitoring system on employers' hiring biases (e.g., home bias), which requires observing employers' consideration sets and hiring decisions both *before* and *after* the introduction of the monitoring system. With the unique data from a major global online labor platform that allows us to observe employers' consideration sets and hiring decisions free of measurement error, we seek to fill this gap by empirically analyzing whether and how the introduction of a monitoring system can reduce employers' home bias in the hiring process.

2.2. Home Bias

The home bias is a long-standing phenomenon observed in financial markets (French and Poterba 1991, Grinblatt and Keloharju 2001, Huberman 2001, Leblang 2010) and international trade (Wolf 2000, Hortaçsu et al. 2009). Early studies on home bias have primarily focused on offline contexts (e.g., Obstfeld and Rogoff 2000). As online trade and online financial markets emerge, recent work has started to explore home bias in online settings (e.g., Hortaçsu et al. 2009, Lin and Viswanathan 2016).

These related studies suggest that owing to risk aversion, individuals have home bias because they lean on familiarity or common background characteristics to reduce transaction risk (e.g., French and Poterba 1991, Gefen 2000). Further, some studies argue that home bias stems from individuals perceiving higher familiarity with companies or assets in their home countries, thereby reducing perceived risk (e.g., French and Poterba 1991, Gefen 2000, Huberman 2001, Leblang

2010). For instance, French and Poterba (1991) propose a "familiarity effect" (that is, investors tend to be more optimistic about the domestic market with which they are familiar and fear foreign markets, which are perceived as riskier). Huberman (2001) also finds home bias among individual investors and reveals a consistent pattern that people tend to invest in the familiar. On the other hand, there is an emerging literature arguing that home bias may not be because of familiarity but rather, because of "cultural affinity" (e.g., Gefen 2000, Anderson et al. 2011, Burtch et al. 2014, Hong and Pavlou 2017) or other common background characteristics (e.g., economic environment or legal and regulatory background) (Kim et al. 2015). For instance, Grinblatt and Keloharju (2001) find that investors are more likely to make transactions on stocks of firms whose investors speak the same language and have the same cultural background as them. However, despite the long-standing interest in home bias, approaches to reduce home bias are underexamined. We, therefore, seek to contribute to the stream of literature by examining whether monitoring systems can reduce employers' home bias and the moderating roles of uncertainty factors, such as project routineness and prior positive hiring experiences with foreign workers.

3. Theoretical Framework and Hypotheses Development

We first introduce the theoretical framework of contractual control and coordination that originated from the transaction governance literature in Section 3.1. Building on these two contractual functions, in Section 3.2, we propose hypotheses regarding how the introduction of monitoring systems can influence employers' control and coordination with remote workers and thus, mitigate their home bias. In addition, we discuss the potential differential mitigation effect of monitoring contingent on external and internal uncertainty in Sections 3.3 and 3.4.

3.1. Theoretical Underpinning—Contractual Control and Coordination

According to the literature on transaction governance, two primary contractual functions exist for managing transactions between two parties: control and coordination (e.g., Lumineau and Henderson 2012, Lumineau 2017, Schilke and Lumineau 2018). Contractual control focuses on the governance of rights and obligations of both parties involved in transactions, mitigating potential concerns, such as moral hazard. By constraining one party's capacity to gain profits at the expense of the other, the control function can promote adherence to the agreed-upon collaboration between parties (Gulati and Singh 1998). Conversely, contractual coordination supports transactions by fostering the mutual understanding of the desires and priorities of both parties, leading to a mutually agreeable consensus concerning expectations and responsibilities (Mooi and Ghosh 2010, Schilke and Lumineau 2018). By directing structured communication and reporting, the coordination function can facilitate the alignment of expectations and enhance the likelihood of achieving the desired ultimate outcomes. In addition, the mechanisms and effectiveness of contractual functions vary considerably depending on the degrees of uncertainty (Lumineau and Henderson 2012, Lumineau 2017), including external uncertainty related to tasks per se (e.g., unpredictability or nonroutineness) and internal uncertainty stemming from uncertainty about the behavior of the other party because of the lack of common grounds or prior interactions (Abdi and Aulakh 2017).

In our research context, employers delegate specific IT development projects to remote nonemployee workers through contractual agreements, which highlights the need for effective transaction governance mechanisms. Specifically, compared with hiring domestic workers, employing foreign workers is more challenging because of the complexities in exerting control and coordination over them, which may lead to home bias. However, the introduction of monitoring systems, as automated tools, can potentially alter this situation and mitigate their home bias. In the following sections, we will discuss how monitoring systems can bring about this change.

3.2. Effect of Monitoring on Home Bias

The home bias phenomenon has been shown to exist in various contexts, such as financial markets and international trades (e.g., French and Poterba 1991, Hortaçsu et al. 2009). Although Gefen and Carmel (2008) find supporting evidence of home bias in the online employment context, the specific mechanisms that drive this bias are not explored. Drawing on the theoretical framework of contractual control and coordination, we argue that people tend to perceive individuals in their home countries as associated with lower transaction risks and costs because of the higher expected effectiveness in control and coordination with them as compared with foreign ones. For one thing, people, in general, are more familiar with individuals in their home countries, and they tend to expect that these workers are more trustworthy and easier to control. Consequently, this can result in less expected moral hazard risk in comparison with foreign workers (e.g., French and Poterba 1991, Huberman 2001, Leblang 2010). For another, because people in the same country share a common background in terms of culture, economic environment, and regulation, it is easier for them to understand each other, predict each other's behavior, and solve problems together in the event of unpredicted obstacles, which implies lower coordination costs (e.g., Gefen 2000, Anderson et al. 2011, Burtch et al. 2014).

With the advances in digital technologies, monitoring systems that automatically track workers' working hours and computer activities are increasingly deployed to help employers manage remote workers (Griffith 1993, Laker et al. 2020, Parker et al. 2020). We propose that when the monitoring system is in place, employers' home bias will be reduced for the following two reasons.

First, the monitoring system mitigates the information asymmetry associated with workers' effort, which restricts their ability to overreport working hours, thereby enabling employers to more effectively control worker behavior and mitigate moral hazard. As discussed, before the introduction of the monitoring system, employers' home bias is partly because they face higher moral hazard risks in their transactions with foreign workers. The introduction of the monitoring system reduces employers' concern about foreign workers' shirking behavior as the monitoring system would allow employers to observe such shirking behavior, thus incentivizing workers to expend adequate effort in accomplishing projects (e.g., Pierce et al. 2015, Staats et al. 2017). Further, employers are now able to better evaluate foreign workers' effort by examining how they perform in each milestone based on their computer activities documented in the monitoring logs (e.g., screenshots of their work processes and tracked working hours) (Griffith 1993, Boly 2011, Liang et al. 2023). Even with minimal familiarity, the access to detailed and objective records of workers' work processes over time can effectively enable employers to ensure that workers comply with agreed-upon project responsibilities and thereby, curtail moral hazard risks.

Second, as an automatic tool to share information on project progress, the monitoring system reduces the need for communication (Alder and Ambrose 2005), thus assisting employers in coordinating with foreign workers to ensure that their effort aligns with the intended trajectory. Because employers face higher coordination costs with foreign workers when they rely on unstructured communication (rather than formal monitoring records) to assess project progress (Espinosa et al. 2007), the monitoring system should have a stronger effect in reducing coordination costs with foreign workers than domestic workers. Specifically, because of the difference in background, it is more difficult for employers to communicate with foreign workers as well as to react to unpredicted changes or obstacles while working with foreign workers. As an information-sharing tool, the monitoring system can generate formal progress reports and facilitate coordination with foreign workers. As noted by Aiello (1993), unlike direct communication that is heavily affected by personal relationships, the monitoring system tends to depersonalize the work environment and automate the progress report. By automatically informing employers of foreign workers' activities on the project, the monitoring system lowers the need for verbal communication (Alder and Ambrose 2005) and improves employers' understanding of foreign workers' work processes. Moreover, the timely information regarding foreign workers' work processes enables employers to follow up on project progress and require foreign workers to make adjustments if any problems are observed. This can help reduce the risk of project failure and avoid serious setbacks to schedules because of inadequate coordination, which in turn, make employers more comfortable hiring foreign workers who used to be considered risky hires. Therefore, we formally propose the following hypothesis.

Hypothesis 1. *Monitoring systems can reduce employers' home bias.*

As discussed, contractual control and coordination with hired workers are essential for employers to achieve project goals efficiently. However, uncertainty can affect the effectiveness of contractual control and coordination (Lumineau and Henderson 2012), thus influencing project outcomes. In particular, external and internal uncertainty can play a moderating role in shaping employers' contractual control and coordination practices with hired workers, thus impacting their home bias. We propose hypotheses regarding the moderating roles of external and internal uncertainty, respectively.

3.3. Moderating Effect of External Uncertainty

External uncertainty refers to uncertainty or unpredictability in tasks or the work environment (Tushman and Nadler 1978, Schilke and Lumineau 2018). Prior research suggests that task predictability or routineness is an important contextual factor that has a negative impact on the effectiveness of contractual control and coordination (Basco and Mestieri 2018).

Task routineness measures how easily the task can be codified and automated by computers (Autor et al. 2003, Dorn 2009), serving as an indicator of high project predictability. High-routine projects are usually standardized tasks with well-defined procedures, such as HTML coding. In contrast, low-routine projects are frequently unstructured or poorly understood, and they tend to involve a substantial number of unpredictable exceptions (Beekun and Glick 2001), such as algorithm design. Because of the external uncertainty, characterized by project unpredictability, employers face challenges in leveraging monitoring systems to improve their control and coordination with workers (particularly foreign workers), suggesting a smaller decrease in home bias in low-routine projects.

Compared with high-routine projects that follow explicit rules, low-routine projects are less standardized and thus, more difficult to monitor (Davidson and Henderson 2000, Ranganathan and Benson 2016). For instance, foreign workers in low-routine projects (e.g., algorithm design or academic writing) may spend a lot of time thinking without many computer activities, indicating that monitoring records cannot well capture foreign workers' effort. Accordingly, in low-routine projects, the monitoring system is less effective in overseeing foreign workers' effort and controlling their conduct toward the intended direction, thus restricting its ability to reduce the moral hazard risks of hiring foreign workers in such projects as compared with high-routine ones.

Furthermore, given that low-routine projects tend to involve more unpredictable obstacles than high-routine projects, they also need more complex communication to facilitate mutual understanding and exchange of tacit knowledge (Chung and Jackson 2013). Even with the monitoring system, employers may still need to frequently interact with foreign workers. In such a case, communication with domestic workers is still likely to be easier and more efficient than that with foreign workers because the common background is especially beneficial for such communication involving tacit and complex knowledge (Ahammad et al. 2016, Sun and Taylor 2020). Therefore, the monitoring system is less effective in facilitating communication and coordination with foreign workers in low-routine projects than in high-routine ones. In summary, we expect that the monitoring system leads to a smaller decrease in home bias in low-routine projects than in high-routine projects.

Hypothesis 2. *The effect of monitoring systems in reducing home bias is stronger for projects with low external uncertainty (proxied by high project routineness).*

3.4. Moderating Effect of Internal Uncertainty

In addition to proposing the moderating effect of project routineness as external uncertainty (Hypothesis 2), we expect that the effect of monitoring systems will also vary by internal uncertainty. Internal uncertainty pertains to the uncertainty concerning the other party's behavior because of inadequate common ground and shared frameworks, leading to divergent understandings and expectations between both parties (Abdi and Aulakh 2017). Although domestic workers are often perceived as familiar and predictable for most employers, employers' uncertainty regarding the behavior of foreign workers can vary greatly based on their prior positive experiences with crossborder hiring. Therefore, we propose that prior positive hiring experiences with foreign workers can serve as a proxy for low internal uncertainty. This internal uncertainty proxy can moderate the effectiveness of monitoring systems in contractual control and coordination with foreign workers, and subsequently, it impacts employers' home bias.

The literature has suggested that prior hiring experience is an important avenue for employers to learn what types of workers can perform well on projects and adjust their hiring strategy over time to reduce transaction risk (e.g., Kokkodis 2018, Leung 2018). As such, even without monitoring systems, employers' home bias may be reduced after they have prior positive experiences hiring foreign workers. Prior positive hiring experiences with foreign workers boost employers' confidence in foreign workers' effort and familiarity with foreign workers, making it easier for employers to enforce their compliance with agreed-upon project responsibilities. Such effective contractual control facilitated by prior positive experiences can reduce the perceived moral hazard risks of hiring foreign workers (Kim and Krishnan 2015, Leung 2018), leading to a lower level of home bias.

Furthermore, as employers accumulate more positive experiences with foreign workers, they become more adept at interacting with workers from a foreign culture, resulting in increased coordination effectiveness. For instance, employers with such positive experiences are more aware of potential cultural differences when describing project requirements and know better how to securely share large files with foreign workers and how to effectively check their progress without the monitoring system in place.

This suggests that prior positive experiences improve the effectiveness of contractual control and coordination when dealing with foreign workers, therefore reducing the necessity for monitoring systems. Therefore, the bias reduction effect of monitoring is expected to be smaller in such cases. Formally, we hypothesize the following.

Hypothesis 3. *The effect of monitoring systems in reducing home bias is weaker for projects with lower internal uncertainty (proxied by the employer's prior positive hiring experiences with foreign workers).*

4. Research Context and Data

4.1. Research Setting

Most online labor platforms follow a reverse, employer-determined hiring mechanism (Hong and Pavlou 2017). To recruit remote workers, an employer first posts a project on an online platform (e.g., Upwork, Freelancer, or Guru). Detailed information about the project, such as requirements and budget, is provided on the dedicated web page for the project. Workers who are interested in the job opportunity then bid on the project. Upon evaluating the bids, the employer makes a hiring decision based on the bid prices and workers' characteristics (e.g., reputation and country) (Kokkodis and Ipeirotis 2016).[3]

In this study, to assess the impact of monitoring systems on employers' home bias, we leverage a data set from a leading online labor platform. On this platform, employers may specify a project as either fixed-price or time-based, wherein they compensate the hired worker with either a fixed amount or hourly wages, respectively. Workers can browse active projects on the website and selectively bid on them.

On February 5, 2014, the platform officially introduced a desktop app that enables employers to conveniently monitor workers' time spent and computer activities in time-based projects. Specifically, this monitoring system automatically takes a screenshot of workers' desktops every few minutes and keeps track of workers' working hours (Figure 1). It can potentially affect employers in the following two ways. (1) It can deter workers from shirking and promote the production of high-quality work because workers will be penalized if caught shirking by the monitoring system. (2) Instead of relying on workers' self-reports, it enables employers to objectively monitor the real-time progress of projects and keep projects on the right track.

More importantly, according to the platform announcement, the monitoring system is a mandatory tool for time-based projects, whereas it is not made available for fixed-price projects. Given that there is an exogenous change in the availability of the monitoring system among time-based projects alone, we use time-based projects and fixed-price projects as the treatment and control groups, respectively, to investigate whether monitoring can mitigate employers' home bias.

Our observation window is from March 1, 2013 to March 1, 2015. Note that the platform only released a Windows-based desktop app in the beginning.[4] However, considering the dominating market share of Windows (i.e., over 90%) in 2014[5] and that most workers are coming from developing countries (e.g., India, Pakistan, and Bangladesh), where the share of Windows users is even higher,[6] suggests that the monitoring feature is available to almost all platform workers. Moreover, we expect most workers in time-based projects to use this monitoring feature as the platform advertised it as mandatory in announcements. Although the platform did make a few exceptions, workers without the app installation are significantly disadvantaged as the platform declared that the milestone payment of time-based projects will not be automatically releasable, and such workers' ranking on the website will also suffer.[7]

4.2. Data

To construct our sample, we focus on projects in the most popular category (i.e., "IT, Software & Website"),[8] in which technologies are standardized globally and foreign workers are comparable with domestic workers in technical skills and experience. In addition, we focus on employers from larger countries as employers from small countries may not have bids from their home countries, thus making home bias a moot issue for these employers. Specifically, we restrict our sample to projects posted by employers from the top 25 employer countries, which account for 83.8% of total projects on the platform. The definition and summary statistics of the key variables in our final sample are provided in Table 1.[9] As Table 1 shows, on average, roughly 5% of bids are submitted from workers from the employer's home country. Moreover, workers vary significantly in terms of project experience and rating. Additionally, the percentage of workers whose self-reported primary language is the same as the employer's primary language is as high as 77%, which is probably because of the dominance of English on the platform. Meanwhile, the percentages of workers who reside in the same time

Figure 1. (Color online) Screenshots of the Monitoring System

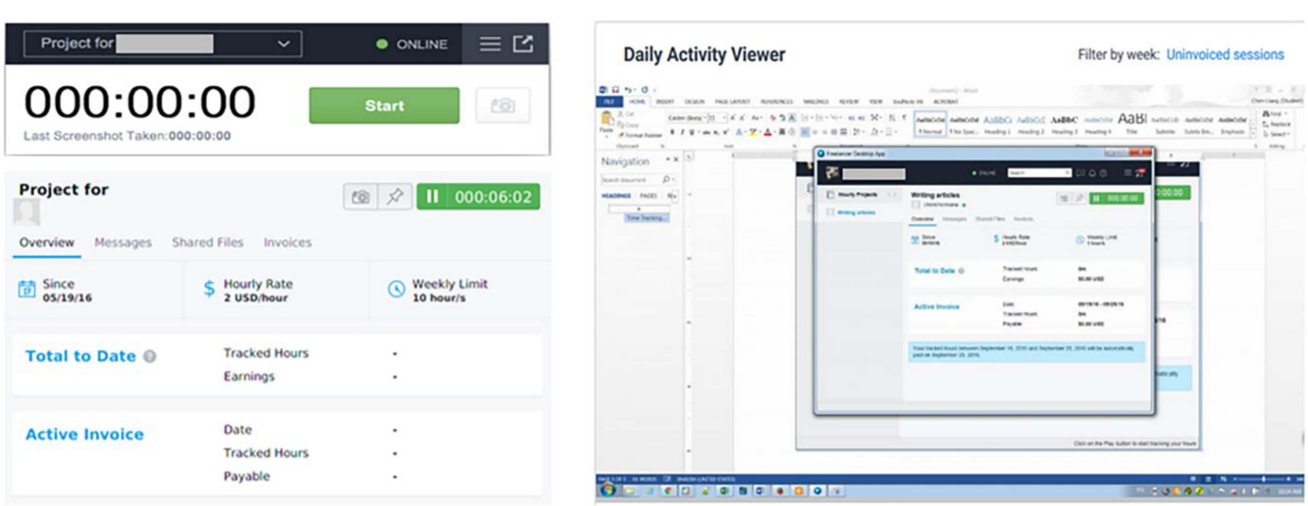


Table 1. Definitions and Summary Statistics of Key Variables

Variable	Variable definition	Mean	Standard deviation	Min	Max
	Panel A. Bid characteristics				
Bid price	The bid price posted by the worker	300.87	485.52	2.00	5,000.00
Milestone pct	A feature provided by the platform that denotes the percentage of controlled payments paid to the worker before the project ends	73.24	33.33	0.00	120.00[a]
Home	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 shown on the project page	19.50	19.88	1.00	263.00
Preferred worker	A dummy variable (0, 1), =1 if the worker won the preferred worker badge	0.20	0.40	0.00	1.00
Review count	The number of reviews entered by previous employers	78.07	171.04	0.00	3,937.00
Avg rating	The average overall employer-entered ratings for the worker	3.91	1.70	0.00	5.00
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	0.77	0.42	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 the platform	0.45	0.50	0.00	1.00
Same time zone	A dummy variable (0, 1), =1 if the time zone in which the employer lives is the same as that of the worker	0.02	0.15	0.00	1.00
	Panel 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	0.28	0.00	1.00
Employer overall rating	The average overall worker-entered ratings for the employer	4.91	0.47	0.00	5.00
Employer tenure day	Employer's tenure measured in days	853.89	945.06	0.00	5,072.00
Title length	Number of words in the project title	5.83	3.12	1.00	44.00
Desc length	Number of words in the project description posted by the employer	88.24	93.30	1.00	1,504.00
Project size	Project size bin classified based on the total amount paid by the employer	188.02	970.06	0.00	20,000.00
Bid count	Number of bids received by the project	16.37	16.41	1.00	254.00

Notes. In total, 7% of workers did not have country information available. For them, we use their time zone names (generated from the internet protocol address) to infer their countries. Project size bin is defined by referring to the platform's project size cutoffs (e.g., 100 U.S. dollars (USD), 250 USD, 750 USD, etc.). The minimum project size bin is 0 USD because the total amount paid by the employer could be zero. Because the minimums of review count, employer tenure, and project size are zero, we add a small positive constant (0.01) to them when performing the log transformation.

[a]There are a few cases in which workers requested a milestone percentage larger than 100.

zone and use the same currency as the employers are 2% and 45%, respectively.

5. Empirical Analysis

5.1. Coarsened Exact Matching

To balance the distribution of observables between the treatment and control groups, we conduct coarsened exact matching to generate a comparable sample (Blackwell et al. 2009, Iacus et al. 2012). CEM is a matching approach based on the monotonic imbalance bounding method, which prunes observables to increase the balance of sample distribution between the treatment and control groups (Stuart 2010). Moreover, unlike the propensity score matching (PSM) approach, which matches samples merely based on the expected probability of being treated, CEM is designed to balance the distribution of multiple covariates that are related to the treatment assignment (Iacus et al. 2012). As such, CEM has two advantages—that is, a lower model dependence and a better balance among various coarsened levels of covariates (Iacus et al. 2012). Specifically, by using CEM, we explicitly match fixed-price projects with time-based projects based on a set of observable project characteristics, including the length of project description, the length of project title, the number of bids, the size of the project, the employer's experience and reputation, and the exact project submission month. CEM allows us to match two types of IT projects posted within the exact same month, of similar sizes, and with a similar length of title and description and a similar number of bids received. By matching these two groups from a multivariate perspective, CEM enhances the robustness of our findings within a balanced sample. The detailed results of balance checks are reported in Online Appendix B. Furthermore, we also enhance our matching process in two ways. First, we include skill requirement dummies as additional matching criteria and report highly consistent results based on the new matched sample, which are shown in Online Appendix C.[10] Second, we apply an alternative matching method, PSM, to both groups. All results are highly consistent as detailed in Online Appendix D.

5.2. Difference-in-Differences Models

To examine whether the deployment of the monitoring system mitigates employers' home bias in hiring, we construct the DID estimation using both a conditional logit model and a linear probability model (LPM) with project-level fixed effects, and we apply this to both the full sample and the matched sample. Using the logit model as an example, the DID specification is given by

$$\begin{aligned} &\mathrm{U}\,(Project_i\_award\_worker_j)\\ &= \boldsymbol{\alpha_i} + \beta_1\, Home_{ij} + \beta_2\, Time\text{-}based_i \times Home_{ij} + \beta_3\, After_i\\ &\quad \times Home_{ij} + \beta_4\, Time\text{-}based_i \times After_i \times Home_{ij}\\ &\quad + \boldsymbol{\gamma}\, \boldsymbol{Controls}(\boldsymbol{Worker_j}) + \varepsilon_{ij}, \end{aligned} \tag{1}$$

where projects are indexed by i and workers (bids) are indexed by j. The dependent variable, $Project_i\_award\_worker_j$, equals one if project i is awarded to worker j. $\boldsymbol{\alpha_i}$ represents project-level fixed effects. $Home_{ij}$ indicates whether the employer of project i and worker j reside in the same country. $Time\text{-}based_i$ specifies whether project i is time based or not, and $After_i$ denotes whether project i is posted after the introduction of the monitoring system. In addition, $\boldsymbol{Controls}(\boldsymbol{Worker_j})$ includes various characteristics related to worker j and their bid—such as review count, cumulative average rating, bid order rank, bid price, milestone payment request, "preferred worker" badge, whether worker j shares the same language as the employer, whether worker j uses the same currency as the employer, and whether worker j is located in the same time zone as the employer as well as worker country dummies. The error term ε_{ij} is assumed to follow the type 1 extreme value distribution (Train 2009).

Notably, our model incorporates project-level fixed effects $\boldsymbol{\alpha_i}$, which nest employer-level fixed effects and time fixed effects, as every project has only one employer and can only be posted in a specific month. As such, project-level fixed effects enable us to account for the impact of time-invariant employer-level heterogeneity (e.g., country and personality) and time-varying factors (e.g., seasonality and exogenous temporal shocks). Additionally, the main effects of $After_i$ and $Time\_based_i$ are subsumed by project-level fixed effects $\boldsymbol{\alpha_i}$.

A significantly positive effect of $Home_{ij}$ (captured by $\hat{\beta}_1$ and $\hat{\beta}_1 + \hat{\beta}_2$ for the treatment and control groups, respectively) suggests that employers previously have home bias before the introduction of the monitoring system. The effect of the monitoring system on the treatment group (i.e., time-based projects) is captured by $\hat{\beta}_4$. A significantly negative coefficient would confirm Hypothesis 1.

It is worth noting that the DID model does not require employers to have the same level of home bias in the treatment group and the control group (Wang et al. 2022). Instead, it only relies on the parallel trend assumption (Angrist and Krueger 1999, Abadie 2005); that is, in the absence of the treatment (i.e., the introduction of the monitoring system), employers' home bias in the treatment group (i.e., time-based projects) should experience parallel trends to that in the control group (i.e., fixed-price projects). To validate this assumption, we perform a parallel trend test in Section 7.

5.3. Main Results

We report the result of the DID model based on the full sample and the matched sample in Table 2. As expected, *Home* is significantly positive, suggesting that employers exhibit home bias before the introduction of the monitoring system.

The coefficient of *Time-based* × *After* × *Home* ($\hat{\beta}_4$) is significantly negative, which suggests that for the treatment group (i.e., time-based projects), employers' preference for domestic workers decreases after the introduction of the monitoring system. This is consistent with Hypothesis 1: that employers' home bias decreases likely because they can use the monitoring system to control and coordinate with foreign workers, leading to lower moral hazard risks and coordination costs with these workers. Therefore, Hypothesis 1 is supported.

We visualize the change in employers' home bias in the treatment and control groups in Figure 2. As shown in Figure 2, employers' home bias still manifests in the control group (i.e., fixed-price projects) as the platform-provided monitoring system was not made available to it (effect size = 0.062, $p = 0.000$). In contrast, employers' home bias in the treatment group (i.e., time-based projects) decreases significantly after the introduction of the monitoring system and becomes insignificant (effect size = 0.018, $p = 0.314$). This implies that in the treatment group, foreign workers are no longer in a disadvantaged position compared with domestic workers after the monitoring system is introduced, all else being equal.

To present direct and meaningful policy implications, based on the estimated relationship between different worker/bid characteristics and employers' utility in the treatment and control groups, we conduct a back-of-the-envelope calculation to quantify to what extent monitoring systems lead to a redistribution of employment to the disadvantaged group (foreign workers). To achieve this, we estimate the counterfactual employer utility by assuming that employer preferences remained unchanged after the introduction of

Table 2. DID Estimation of the Mitigation Effect of Monitoring on Employers' Home Bias

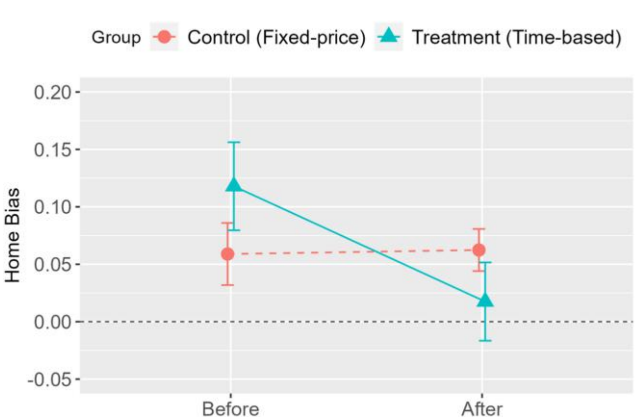
Sample	Full sample		Matched sample	
Model	(1) Logit	(2) LPM	(3) Logit	(4) LPM
Home	0.369*** (0.069)	0.028*** (0.005)	0.482*** (0.124)	0.059*** (0.014)
Time-based × *Home*	0.608*** (0.163)	0.069*** (0.017)	0.579*** (0.206)	0.059** (0.023)
After × *Home*	0.134* (0.078)	0.012* (0.006)	0.057 (0.140)	0.003 (0.016)
Time-based × *After* × *Home*	−0.945*** (0.221)	−0.096*** (0.022)	−0.913*** (0.274)	−0.104*** (0.030)
Same language	0.358*** (0.026)	0.015*** (0.001)	0.330*** (0.043)	0.021*** (0.003)
Same currency	0.069*** (0.021)	0.004*** (0.001)	0.089*** (0.034)	0.008*** (0.003)
Same time zone	0.156*** (0.050)	0.014*** (0.004)	0.259*** (0.077)	0.029*** (0.008)
Log *bid price*	−1.737*** (0.018)	−0.087*** (0.001)	−1.842*** (0.031)	−0.133*** (0.002)
Log *milestone pct*	−0.046*** (0.016)	−0.002** (0.001)	−0.175*** (0.026)	−0.013*** (0.002)
Log *review count*	0.052*** (0.006)	0.001*** (0.000)	0.055*** (0.010)	0.003*** (0.001)
Avg rating	0.260*** (0.010)	0.011*** (0.000)	0.210*** (0.015)	0.013*** (0.001)
Log *bid order rank*	−0.360*** (0.013)	−0.019*** (0.001)	−0.370*** (0.023)	−0.030*** (0.002)
Preferred worker	0.469*** (0.018)	0.025*** (0.001)	0.453*** (0.031)	0.040*** (0.003)
Worker country dummy	Yes	Yes	Yes	Yes
Project fixed effects	Yes	Yes	Yes	Yes
Observations	402,543	402,543	94,749	94,749
R^2		0.045		0.071
LogLik	−49,974		−15,690	
AIC	100,022		31,454	
BIC	100,426		31,804	
Number of projects	24,978	24,978	9,428	9,428

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

monitoring systems, and we subsequently predict the counterfactual winning bids in such a scenario. Our counterfactual analysis reveals that the introduction of monitoring systems leads to a notable 15.07% increase in the hiring of foreign workers.

The results are consistent when we use a series of alternative empirical specifications, as shown in Section 7. Next, we test Hypotheses 2 and 3 regarding the potential heterogeneity in the treatment effect of monitoring by project routineness and employers' prior

Figure 2. (Color online) Employers' Home Bias Before vs. After the Introduction of the Monitoring System



Notes. This plot illustrates the marginal effect of the *Home* dummy based on LPM (Model (4)). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

positive experiences with foreign workers. We also conduct additional analyses to investigate whether contractual control and coordination mechanisms underlie the effect of monitoring on employers' home bias in Section 6.

5.4. Moderating Effects

5.4.1. Moderating Effect of External Uncertainty. We further examine whether the impact of monitoring on employers' home bias varies in a predictable way across projects with different levels of external uncertainty as predicted by Hypothesis 2. Specifically, we expect that when projects are more routine and involve less external uncertainty, monitoring systems can remarkably enhance the effectiveness of contractual control and coordination, leading to a more pronounced decrease in employers' home bias (Hypothesis 2).

Following Autor et al. (2003), we employ routine task intensity (RTI) as a comprehensive proxy of the measure of project routineness. RTI refers to the ratio of routine task inputs to nonroutine task inputs in each occupation. Nonroutine task inputs include those manual tasks that involve physical and/or interpersonal activities and are mostly concentrated in service jobs and those abstract tasks that are creative and require certain managerial capabilities or professional skills (Dorn 2009, Autor and Dorn 2013). We calculate it based on Equation (2). A higher RTI value implies that the project is more routine. To calculate the RTI of the project, we first match the project subcategory list to the standard occupational classification (SOC) system[11] based on the definitions of project subcategories, and then, we find the corresponding routine, manual, and abstract task inputs for each project:

$$\mathrm{RTI}_i = \ln\left(Task_i^{Routine}\right) - \ln\left(Task_i^{Manual}\right) - \ln\left(Task_i^{Abstract}\right). \tag{2}$$

To test Hypothesis 2, we rerun the DID model separately for both high-routine and low-routine projects. Here, "high-routine projects" mean that the RTI of the project is higher than the mean RTI of the overall IT category, and "low routine" indicates the opposite scenario. As Models (1) and (2) of Table 3 show, both coefficients of *After* × *Home* and *Time-based* × *After* × *Home* are insignificant. This implies that for those low-routine projects, the introduction of the monitoring system does not significantly affect employers' home bias. Specifically, based on Model (2) of Table 3, employers have home bias in low-routine time-based projects both before (effect size = $0.060 + 0.079 = 0.139$, $p = 0.012$) and after the introduction of the monitoring system (effect size = $0.060 + 0.079 - 0.011 - 0.023 = 0.105$, $p = 0.021$).

By comparison, *Time-based* × *After* × *Home* is significantly negative in Models (3) and (4) of Table 3, suggesting that the introduction of the monitoring system significantly decreases employers' home bias in those high-routine projects within the treatment group (i.e., high-routine time-based projects). Therefore, Hypothesis 2 is supported. In particular, based on Model (4) of Table 3, employers' home bias in high-routine time-based projects is significant before the introduction of the monitoring system (effect size = $0.058 + 0.056 = 0.114$, $p = 0.000$) but becomes insignificant after the system introduction (effect size = $0.058 + 0.056 + 0.006 - 0.122 = -0.002$, $p = 0.917$). This suggests that monitoring systems can effectively mitigate employers' home bias for projects with low external uncertainty.

We further visualize the change in employers' home bias for high-routine projects in Figure 3. As shown in Figure 3, employers' home bias still manifests in high-routine fixed-price projects as the monitoring system was never made available to fixed-price projects (effect size = 0.064, $p = 0.000$). In contrast, employers' home bias in high-routine time-based projects decreases significantly after the introduction of the monitoring system and becomes insignificant (effect size = −0.002, $p = 0.917$). Combined with the insignificant change in employers' home bias for low-routine projects, we find

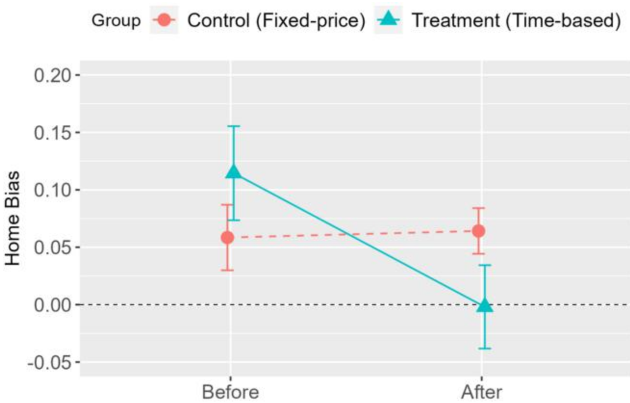
Table 3. Employers' Home Bias in Low-Routine vs. High-Routine Projects

Sample	Low-routine projects		High-routine projects	
Model	(1) Logit	(2) LPM	(3) Logit	(4) LPM
Home	0.429 (0.274)	0.060 (0.039)	0.481*** (0.140)	0.058*** (0.015)
Time-based × *Home*	0.606 (0.467)	0.079 (0.067)	0.582** (0.230)	0.056** (0.025)
After × *Home*	−0.066 (0.312)	−0.011 (0.044)	0.105 (0.157)	0.006 (0.017)
Time-based × *After* × *Home*	−0.053 (0.600)	−0.023 (0.084)	−1.177*** (0.308)	−0.122*** (0.032)
Same language	0.326*** (0.093)	0.028*** (0.008)	0.326*** (0.048)	0.020*** (0.003)
Same currency	0.061 (0.075)	0.008 (0.007)	0.092** (0.038)	0.007** (0.003)
Same time zone	0.192 (0.175)	0.019 (0.020)	0.271*** (0.085)	0.030*** (0.009)
Log *bid price*	−1.854*** (0.071)	−0.161*** (0.006)	−1.839*** (0.035)	−0.126*** (0.002)
Log *milestone pct*	−0.192*** (0.057)	−0.018*** (0.005)	−0.173*** (0.029)	−0.012*** (0.002)
Log *review count*	0.085*** (0.022)	0.008*** (0.002)	0.044*** (0.011)	0.001 (0.001)
Avg rating	0.203*** (0.033)	0.012*** (0.003)	0.212*** (0.017)	0.014*** (0.001)
Log *bid order rank*	−0.406*** (0.050)	−0.040*** (0.005)	−0.364*** (0.026)	−0.028*** (0.002)
Preferred worker	0.461*** (0.072)	0.048*** (0.009)	0.457*** (0.035)	0.039*** (0.003)
Worker country dummy	Yes	Yes	Yes	Yes
Project fixed effects	Yes	Yes	Yes	Yes
Observations	16,677	16,677	78,072	78,072
R^2		0.103		0.066
LogLik	−3,056		−12,598	
AIC	6,185		25,269	
BIC	6,471		25,612	
Number of projects	2,160	2,160	7,268	7,268

Notes. The results are estimated based on the matched sample with the CEM approach. The results are highly consistent if we estimate the model based on the full sample. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.

**$p < 0.05$; ***$p < 0.01$.

Figure 3. (Color online) Employers' Home Bias Before vs. After the Introduction of the Monitoring System for High-Routine Projects



Notes. This plot illustrates the marginal effect of the *Home* dummy in high-routine projects based on LPM (Model (4)). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

that the mitigation effect of the monitoring systems on home bias is mainly concentrated in high-routine projects, where external uncertainty is relatively low.

5.4.2. Moderating Effect of Internal Uncertainty. To further examine whether a project's internal uncertainty (proxied by the lack of the employer's prior positive experiences with foreign workers) moderates the mitigation effect of monitoring systems on home bias, we compute a measure, *Foreign Prior*, based on employers' hiring experiences. *Foreign Prior*, is defined as whether the employer had positive hiring experiences with foreign workers before the introduction of the monitoring system. Here, the positive hiring experience means that the employer gave a five-star rating and confirmed that the project was completed within the budget and time frame. Specifically, to test Hypothesis 3, we investigate whether the decrease in home bias after the introduction of the monitoring system is smaller for employers with prior positive hiring experiences with foreign workers (*Foreign Prior* = 1) than those without (*Foreign Prior* = 0) as the former group likely has a better understanding and more accurate expectations of foreign workers' behavior, resulting in lower internal uncertainty when hiring them.

Based on Models (2) and (4) of Table 4, before the introduction of the monitoring system, employers exhibit a significant preference for domestic workers, regardless of whether they have had prior positive experiences with foreign workers. In particular, employers who did not have positive hiring experiences with foreign workers tended to have a stronger home bias than those who had such experiences (effect size difference = 0.083, $p = 0.009$).

Moreover, the coefficient of *After* × *Home* is insignificant, which indicates that employers' home bias in the control group (i.e., fixed-price projects) does not significantly change over time. By comparison, employers' home bias in the treatment group (i.e., time-based projects) remarkably decreases after the introduction of the monitoring system. Notably, the decrease in employers' home bias is significantly more pronounced among those without prior positive experiences hiring foreign workers (effect size difference = 0.136, $p = 0.009$). Specifically, after the system is introduced, the extent of home bias among employers with and without prior positive hiring experiences is not significantly different (effect size difference = 0.053, $p = 0.391$), and neither one is significantly different from zero. Additionally, given that monitoring can reduce employers' home bias even when they did not have positive hiring experiences with foreign workers, it is worthy to highlight the beneficial role of information systems in mitigating hiring bias among a broad range of users. Overall, this indicates that monitoring systems can lead to a larger reduction in employers' home bias in scenarios with high internal uncertainty compared with those with low internal uncertainty.

In Figure 4, we further visualize the marginal effect of the *Home* dummy (i.e., home bias) for employers with prior positive experiences hiring foreign workers and those without such experiences before and after the introduction of the monitoring system, respectively, displaying a pattern that closely aligns with the aforementioned description.

6. Exploration of Underlying Mechanisms

As outlined in the theoretical sections, the monitoring system may reduce employers' home bias by improving the effectiveness of contractual control and/or coordination. To empirically investigate the underlying mechanisms of our findings, we examine the heterogeneity in employers' preference across different types of workers, characterized by varying degrees of moral hazard risks and coordination costs.

First, to test the contractual control mechanism, given that high ratings are commonly viewed as an indicator of low moral hazard risks (e.g., Dellarocas 2006, Hui et al. 2016), we classify domestic workers into two groups, those with high ratings (denoted as *Home High Rating*) and those with low ratings (denoted as *Home Low Rating*), using the mean rating of all awarded workers as the dividing threshold. As shown in Figure 5 and Table 5, we find that prior to the introduction of monitoring systems, employers have a significant preference for domestic workers. Moreover, this preference is significantly stronger for domestic workers with high ratings compared with those with low ratings (effect size difference = 0.063, $p = 0.007$). Nonetheless, after the introduction of monitoring

Table 4. Moderating Effect of the Prior Positive Experiences with Foreign Workers on Home Bias

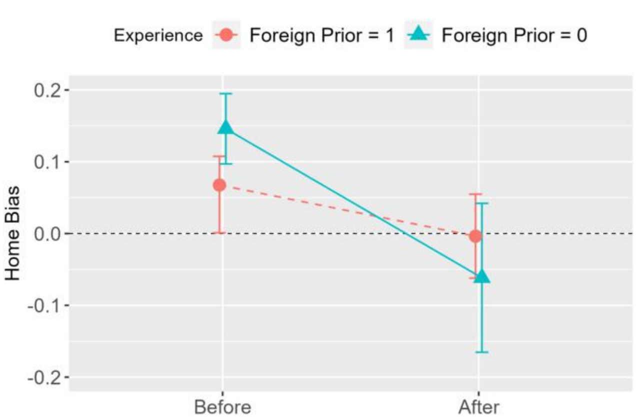
Sample	Employers with positive foreign hires				Employers without positive foreign hires			
Model	(1) Logit	Standard error	(2) LPM	Standard error	(3) Logit	Standard error	(4) LPM	Standard error
Home	0.150	(0.094)	0.011	(0.007)	0.873***	(0.133)	0.061***	(0.010)
Time-based × *Home*	0.512**	(0.208)	0.057***	(0.021)	0.871***	(0.289)	0.084***	(0.026)
After × *Home*	0.133	(0.143)	0.015	(0.013)	−0.477	(0.330)	−0.037	(0.025)
Time-based × *After* × *Home*	−0.804*	(0.447)	−0.087**	(0.038)	−1.839**	(0.844)	−0.171***	(0.064)
Same language	0.294***	(0.044)	0.012***	(0.002)	0.377***	(0.079)	0.014***	(0.003)
Same currency	0.066*	(0.035)	0.005***	(0.002)	0.065	(0.063)	0.003	(0.003)
Same time zone	0.095	(0.089)	0.007	(0.006)	0.318**	(0.129)	0.029***	(0.010)
Log *bid price*	−1.893***	(0.031)	−0.098***	(0.002)	−1.821***	(0.054)	−0.093***	(0.003)
Log *milestone pct*	0.013	(0.026)	0.001	(0.001)	−0.134***	(0.042)	−0.007***	(0.002)
Log *review count*	0.063***	(0.010)	0.001**	(0.001)	0.058***	(0.018)	0.001	(0.001)
Avg rating	0.305***	(0.016)	0.012***	(0.001)	0.275***	(0.028)	0.012***	(0.001)
Log *bid order rank*	−0.412***	(0.021)	−0.025***	(0.001)	−0.402***	(0.037)	−0.022***	(0.002)
Preferred worker	0.546***	(0.029)	0.035***	(0.002)	0.310***	(0.057)	0.015***	(0.004)
Worker country dummy	Yes		Yes		Yes		Yes	
Project fixed effects	Yes		Yes		Yes		Yes	
Observations	137,710		137,710		45,734		45,734	
R^2			0.054				0.052	
LogLik	−17,830				−5,541			
AIC	35,734				11,156			
BIC	36,098				11,479			
Number of projects	9,552		9,552		2,822		2,822	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. In this analysis, we limit our sample to those employers who at least posted one project during our pretreatment period. Therefore, the sample size here is smaller than that in the main analysis. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

systems, employers' preference for domestic workers becomes statistically insignificant, regardless of whether those workers have high or low ratings. This observation implies that the intensity of employers' previous home bias is also dependent on worker rating, which serves as an indicator of moral hazard risk. This finding lends support to the contractual control mechanism as a plausible explanation for the observed mitigation effect of monitoring on home bias.

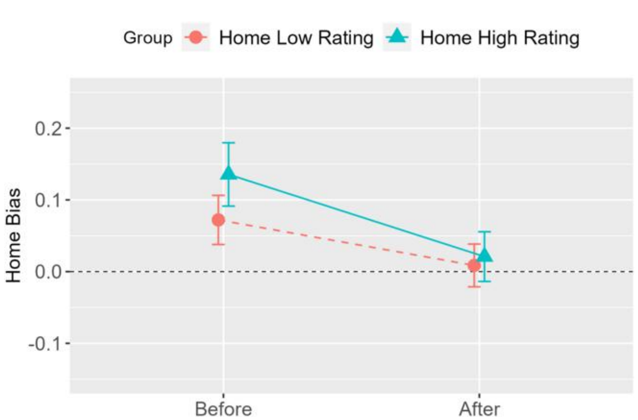
Similarly, to examine the contractual coordination mechanism, we posit that working with workers in the same time zone entails lower coordination costs (Sarker and Sahay 2004), and thus, we classify domestic workers into two groups: those in the same time zone as the

Figure 4. (Color online) Change in Home Bias of Employers with Positive Hiring Experiences vs. Without Positive Hiring Experiences with Foreign Workers for Time-Based Projects



Notes. This plot illustrates the marginal effect of the *Home* dummy in the treatment group based on LPM (Models (2) and (4)). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

Figure 5. (Color online) Change in Home Bias of Employers for Domestic Workers with High vs. Low Ratings



Notes. This plot illustrates the marginal effects of domestic worker dummies (i.e., *Home High Rating* and *Home Low Rating*) in the treatment group based on LPM (Model (2)). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

Table 5. Employers' Home Bias for Workers with High vs. Low Ratings

Model	(1) Logit	Standard error	(2) LPM	Standard error
	Dependent variable: Whether the worker is awarded			
Home High Rating	0.609***	(0.081)	0.069***	(0.009)
Time-based × *Home High Rating*	0.517***	(0.189)	0.067***	(0.024)
After × *Home High Rating*	0.079	(0.092)	0.001	(0.010)
Time-based × *After* × *Home High Rating*	−1.006***	(0.259)	−0.116***	(0.030)
Home Low Rating	0.072	(0.091)	−0.001	(0.006)
Time-based × *Home Low Rating*	0.763***	(0.196)	0.073***	(0.018)
After × *Home Low Rating*	0.210**	(0.106)	0.016**	(0.007)
Time-based × *After* × *Home Low Rating*	−0.885***	(0.262)	−0.079***	(0.024)
Same language	0.396***	(0.026)	0.016***	(0.001)
Same currency	0.049**	(0.021)	0.003***	(0.001)
Same time zone	0.140***	(0.050)	0.012***	(0.004)
Log *bid price*	−1.733***	(0.018)	−0.086***	(0.001)
Log *milestone pct*	−0.075***	(0.016)	−0.003***	(0.001)
Log *count rating*	0.171***	(0.004)	0.007***	(0.000)
Log *bid order rank*	−0.249***	(0.012)	−0.014***	(0.001)
Preferred worker	0.463***	(0.018)	0.025***	(0.001)
Worker country dummy	Yes		Yes	
Project fixed effects	Yes		Yes	
Observations	402,543		402,543	
R^2			0.044	
LogLik	−50,312			
AIC	100,704			
BIC	101,141			
Number of projects	24,978		24,978	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^{**}p < 0.05$; $^{***}p < 0.01$.

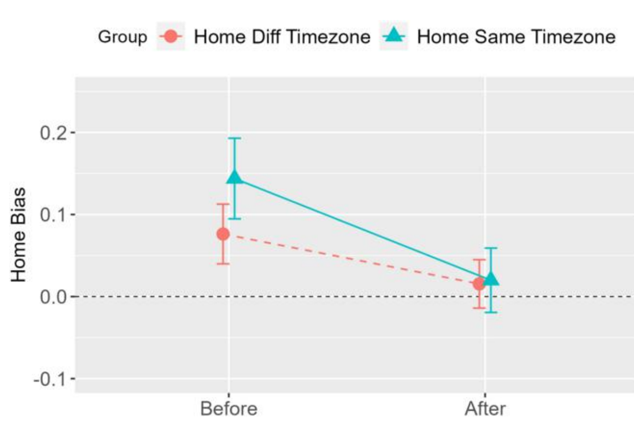
employer (denoted as *Home Same Timezone*) and those in a different time zone (denoted as *Home Diff Timezone*). As demonstrated in Figure 6 and Table 6, we find that prior to the introduction of the monitoring system, employers exhibit a significant preference for domestic workers, and this preference is stronger for domestic workers in the same time zone compared with those in a different time zone (effect size difference = 0.068, p = 0.018). However, after the introduction of monitoring systems, employers' preference for domestic workers becomes statistically insignificant, regardless of whether those workers are in the same time zone or not. This result suggests that the intensity of employers' home bias is also dependent on the coordination costs associated with time zone differences, providing supporting evidence for the contractual coordination mechanism.

On the whole, we find evidence that both contractual control and coordination mechanisms are at play. Monitoring systems reduce employers' home bias by improving the effectiveness of controlling remote workers' behavior to mitigate moral hazard, and the effectiveness of coordinating with remote workers to ensure their effort align with the intended project objectives.

7. Robustness Checks

We now perform robustness checks to assess the sensitivity of our findings to alternative empirical specifications. Specifically, Section 7.1 tests the parallel trend assumption. Section 7.2 incorporates two placebo tests to rule out the possibility that our findings are driven by a spurious relationship. Next, instead of relying on the parallel trend assumption, Section 7.3 uses

Figure 6. (Color online) Change in Home Bias of Employers for Domestic Workers Within vs. Outside the Same Time Zone



Notes. This plot illustrates the marginal effects of domestic worker dummies (i.e., *Home Same Timezone* and *Home Diff Timezone*) in the treatment group based on LPM (Model (2)). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

Table 6. Employers' Home Bias for Workers Within vs. Outside the Same Time Zone

Model	(1) Logit	Standard error	(2) LPM	Standard error
	Dependent variable: Whether the worker is awarded			
Home Same Timezone	0.631***	(0.100)	0.056***	(0.009)
Time-based × *Home Same Timezone*	0.681***	(0.218)	0.088***	(0.027)
After × *Home Same Timezone*	0.122	(0.119)	0.009	(0.011)
Time-based × *After* × *Home Same Timezone*	−1.259***	(0.303)	−0.133***	(0.034)
Home Diff Timezone	0.303***	(0.078)	0.021***	(0.006)
Time-based × *Home Diff Timezone*	0.540***	(0.190)	0.055***	(0.019)
After × *Home Diff Timezone*	0.138	(0.092)	0.013*	(0.007)
Time-based × *After* × *Home Diff Timezone*	−0.739***	(0.255)	−0.074***	(0.025)
Same language	0.358***	(0.026)	0.015***	(0.001)
Same currency	0.069***	(0.021)	0.004***	(0.001)
Log *bid price*	−1.738***	(0.018)	−0.087***	(0.001)
Log *milestone pct*	−0.046***	(0.016)	−0.002**	(0.001)
Log *count rating*	0.052***	(0.006)	0.001***	(0.000)
Avg rating	0.259***	(0.010)	0.011***	(0.000)
Log *bid order rank*	−0.360***	(0.013)	−0.019***	(0.001)
Preferred worker	0.468***	(0.018)	0.025***	(0.001)
Worker country dummy	Yes		Yes	
Project fixed effects	Yes		Yes	
Observations	402,543		402,543	
R^2			0.045	
LogLik	−49,965			
AIC	100,009			
BIC	100,454			
Number of projects	24,978		24,978	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

an alternative identification strategy, instrumental variable, to address the concern regarding the selection on unobservables. Then, Section 7.4 assesses the sensitivity of our results to the potential omitted variable bias, and Section 7.5 reports estimates with additional controls on worker fixed effects. All these robustness checks lend support to our main finding that the introduction of the monitoring system reduces employers' home bias.

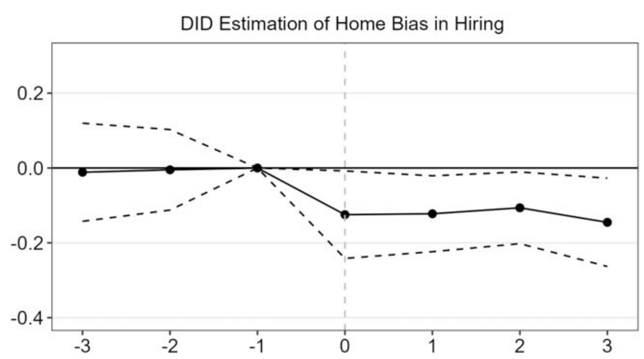
7.1. Parallel Trend

In line with the previous literature (Autor 2003, Angrist and Pischke 2008, Chen et al. 2011, Cheng et al. 2020, Wang et al. 2022), we test the parallel trend assumption of the DID model by checking whether the control group (i.e., fixed-price projects) has the same trend as the treatment group (i.e., time-based projects) prior to the treatment. Specifically, we estimate the time-varying change in employers' home bias for time-based projects based on the following equation:

$$\begin{aligned} &U(Project_i\_award\_worker_j) \\ &= \boldsymbol{\alpha_i} + \beta_1 Home_{ij} + \beta_2 Home_{ij} \times Time\text{-}based_i \\ &\quad + \boldsymbol{\rho\tau_t} \times Home_{ij} + \boldsymbol{\mu}(\boldsymbol{\tau_t} \times Time\text{-}based_i \times Home_{ij}) \\ &\quad + \boldsymbol{\gamma Controls(Worker_j)} + \varepsilon_{ij}, \end{aligned} \tag{3}$$

where $\boldsymbol{\tau_t}$ represents a vector of relative time dummies and $\{\boldsymbol{\mu}\}$ denotes the vector of relative time parameters of employer i's home bias for domestic worker j estimated at time t. Estimating the treatment effect at different time periods enables us to examine the potential pretreatment trend. Specifically, given that the monitoring system was implemented on February 5, 2014, we use the quarter prior to the actual treatment (from

Figure 7. Relative Time DID Estimates of the Treatment Effect



Notes. This graph illustrates quarter-level relative time parameters. The dashed vertical line denotes the quarter when the platform officially introduced the monitoring system (from February 2014 to May 2014). Error bars denote the 95% confidence intervals calculated based on clustered standard errors.

Table 7. Estimation Results of the Relative Time Model

Sample	Matched sample		Matched sample	
Model	(1) Logit	Standard error	(2) LPM	Standard error
Home	0.405**	(0.190)	0.059***	(0.022)
Time-based × *Home*	0.757**	(0.345)	0.074*	(0.039)
$Quarter_{-3}$ × *Home*	−0.042	(0.352)	−0.024	(0.037)
$Quarter_{-2}$ × *Home*	0.080	(0.288)	−0.000	(0.031)
$Quarter_{-1}$ × *Home*	Omitted baseline			
$Quarter_{+0}$ × *Home*	−0.048	(0.244)	−0.008	(0.030)
$Quarter_{+1}$ × *Home*	0.383*	(0.231)	0.037	(0.027)
$Quarter_{+2}$ × *Home*	0.104	(0.222)	−0.011	(0.025)
$Quarter_{+3}$ × *Home*	0.128	(0.284)	0.004	(0.033)
$Quarter_{-3}$ × *Time-based* × *Home*	−0.368	(0.572)	−0.011	(0.067)
$Quarter_{-2}$ × *Time-based* × *Home*	0.013	(0.502)	−0.005	(0.055)
$Quarter_{-1}$ × *Time-based* × *Home*	Omitted baseline			
$Quarter_{+0}$ × *Time-based* × *Home*	−1.036**	(0.507)	−0.125**	(0.060)
$Quarter_{+1}$ × *Time-based* × *Home*	−0.909**	(0.452)	−0.122**	(0.052)
$Quarter_{+2}$ × *Time-based* × *Home*	−1.171**	(0.463)	−0.106**	(0.049)
$Quarter_{+3}$ × *Time-based* × *Home*	−1.665**	(0.657)	−0.145**	(0.060)
Same language	0.328***	(0.043)	0.021***	(0.003)
Same currency	0.090***	(0.034)	0.008***	(0.003)
Same time zone	0.245***	(0.077)	0.028***	(0.008)
Log *bid price*	−1.842***	(0.031)	−0.133***	(0.002)
Log *milestone percentage*	−0.176***	(0.026)	−0.013***	(0.002)
Log *review count*	0.055***	(0.010)	0.003***	(0.001)
Avg rating	0.210***	(0.015)	0.013***	(0.001)
Log *bid order rank*	−0.370***	(0.023)	−0.030***	(0.002)
Preferred worker	0.452***	(0.031)	0.040***	(0.003)
Country dummy	Yes		Yes	
Project fixed effects	Yes		Yes	
Observations	94,749		94,749	
R^2			0.071	
LogLik	−15,685			
AIC	31,464			
BIC	31,909			
Number of projects	9,428		9,428	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. The results are highly consistent for the full sample. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

October 2013 to January 2014) as the baseline (Autor 2003). According to Figure 7 and Table 7, all the relative time parameters (captured by *Quarter* × *Time-based* × *Home*) are insignificant prior to the introduction of the monitoring system. However, after the monitoring system is introduced, all the relative time parameters in both the conditional logit model and LPM become significantly negative. In summary, the results of such an event study design suggest that a pre-existing downward trend is unlikely to exist in our data set. In addition, we observe that $Quarter_{t+3}$ × *Time-based* × *Home* remains significantly negative, suggesting that the negative effect of monitoring systems on home bias is long standing and can persist for over one year.

7.2. Placebo Tests

To further assess the credibility of our main findings, we conduct two placebo tests. First, we assign a placebo intervention to the middle of our pretreatment period (August 1, 2013) and check whether a pretreatment tendency existed before the actual introduction of the monitoring system. As Table 8 shows, the coefficient of *Time-based* × *Afterplacebo* × *Home* is insignificant.

Second, following Abadie et al. (2015), we randomly reassign the monitoring treatment to projects and run the same model with the placebo treatment assignment. We replicate the analysis 1,000 times and generate the distribution of the placebo treatment effects based on the pseudotreatment of the monitoring intervention (Ranganathan and Benson 2016). By comparing the actual estimated coefficient of two key covariates with the whole distribution of placebo treatment effects (Table 9), we find that it would be very unlikely to observe a similar size of home bias or treatment effect by chance, which implies that our findings are robust to alternative variance-covariance specifications.

Table 8. Estimation Results Based on the "Placebo" Treatment Time

Sample	Full sample				Matched sample			
Model	(1) Logit	Standard error	(2) LPM	Standard error	(3) Logit	Standard error	(4) LPM	Standard error
Home	0.315**	(0.127)	0.018**	(0.008)	0.416*	(0.238)	0.046**	(0.022)
Time-based × *Home*	0.634**	(0.276)	0.067**	(0.029)	0.637*	(0.354)	0.064	(0.040)
Afterplacebo × *Home*	0.213	(0.145)	0.021**	(0.010)	0.241	(0.280)	0.032	(0.028)
Time-based × *Afterplacebo* × *Home*	0.086	(0.362)	0.011	(0.037)	−0.020	(0.464)	−0.006	(0.051)
Same language	0.280***	(0.048)	0.011***	(0.002)	0.247***	(0.084)	0.013**	(0.006)
Same currency	0.060	(0.039)	0.005**	(0.002)	0.098	(0.067)	0.011*	(0.006)
Same time zone	0.081	(0.091)	0.009	(0.006)	0.226	(0.142)	0.023	(0.015)
Log *bid price*	−1.938***	(0.034)	−0.101***	(0.002)	−2.015***	(0.064)	−0.155***	(0.005)
Log *milestone percentage*	−0.004	(0.026)	−0.000	(0.001)	−0.134***	(0.044)	−0.012***	(0.004)
Log *review count*	0.053***	(0.011)	0.001	(0.001)	0.049**	(0.019)	0.001	(0.002)
Avg rating	0.313***	(0.018)	0.012***	(0.001)	0.270***	(0.029)	0.018***	(0.002)
Log *bid order rank*	−0.446***	(0.022)	−0.027***	(0.001)	−0.408***	(0.043)	−0.039***	(0.004)
Preferred worker	0.508***	(0.033)	0.031***	(0.003)	0.583***	(0.060)	0.059***	(0.007)
Worker country dummy	Yes		Yes		Yes		Yes	
Project fixed effects	Yes		Yes		Yes		Yes	
Observations	118,003		118,003		24,602		24,602	
R^2			0.057				0.088	
LogLik	−14,916				−4,218			
AIC	29,905				8,510			
BIC	30,263				8,811			
Number of projects	8,031		8,031		2,774		2,774	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

7.3. Instrumental Variable

With the introduction of the monitoring system that enables us to test whether monitoring systems can reduce employers' home bias through a quasi-natural experiment, there are two potential endogeneity concerns when unobserved characteristics might be correlated with employers' hiring decisions. (1) There may be potential unobserved variables that affect both employers' preference for compensation model (time-based or fixed-price) and hiring preference.[12] Additionally, (2) workers may infer employers' preferences and determine their bid prices accordingly.[13] To alleviate these concerns, we employ both the two-stage least squares (2SLS) model and the conditional logit model with the control function method to estimate the local average treatment effect (Angrist et al. 1996, Ray et al. 2013) of the monitoring system on the margin of home bias.

Table 9. Placebo Effects of the Random Treatment Assignment Model

Variables	*Home*	*Time-based* × *After* × *Home*
μ of placebo β	0.037	0.001
σ of placebo β	0.001	0.021
Estimated β	0.028	−0.096
Replication	1,000	1,000
Z-score	−5.992	−4.687
p-value	0.001	0.001

Notes. The result of the placebo test based on the full sample is reported. All the bids that are submitted by workers having previous collaboration experience with the employer before are dropped. Moreover, our sample is only limited to projects with only one winner. A linear probability model with project fixed effects and worker country dummies is included in the model; the conditional logit model provides consistent results. Robust standard errors clustered by projects are reported in parentheses.

First, regarding the potential endogenous compensation model choice, we need instruments that are associated with the compensation model but not with the error term (ε_{ij}) for employers' hiring decisions. Because employers' time-invariant preference for time-based contracts is nested within the project-level fixed effects, we only need to instrument employers' time-varying preference for time-based contracts. Specifically, we employ two instruments: (1) the "residual" type instrumental variable (IV) (Arnold et al. 2018, Dobbie et al. 2018): a residualized, leave out employers' tendency to use time-based compensation model that accounts for selection bias (Arnold et al. 2018, Dobbie et al. 2018) and (2) the "Hausman" type IV (Hausman et al. 1994, Schneider 2010, Ghose et al. 2012). Here, the residuals may capture the specific unobserved project characteristics or the match between the employer's monitoring cost function and the specific project characteristics. Because these residuals capture the idiosyncratic features of the specific project, they are unlikely to correlate with the hiring decision of a different project in

Table 10. IV Estimation of Employers' Home Bias

Sample	Full sample		Full sample	
Model	(1) 2SLS	Standard error	(2) Logit control function	Standard error
Home	0.003	(0.013)	0.156	(0.126)
Time-based × *Home*	0.142***	(0.053)	0.546*	(0.314)
After × *Home*	0.026*	(0.015)	0.101	(0.149)
Time-based × *After* × *Home*	−0.266***	(0.072)	−1.073**	(0.478)
Same language	0.036***	(0.008)	0.368***	(0.130)
Same currency	0.004*	(0.002)	0.047	(0.039)
Same time zone	0.031***	(0.008)	0.278***	(0.093)
Log *bid price*	−0.112***	(0.002)	−1.720***	(0.040)
Log *milestone percentage*	−0.002*	(0.002)	−0.047*	(0.026)
Log *review count*	0.002***	(0.001)	0.062***	(0.009)
Avg rating	0.012***	(0.001)	0.243***	(0.016)
Log *bid order rank*	−0.024***	(0.001)	−0.354***	(0.020)
Preferred worker	0.031***	(0.002)	0.450***	(0.030)
Worker country dummy	Yes		Yes	
Project fixed effects	Yes		Yes	
Observations	137,815[a]		137,815	
R^2	0.053			
LogLik			−20,364	
AIC			40,809	
BIC			41,202	
Number of projects	11,349		11,349	

Notes. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. For LPMs, robust standard errors clustered by projects are reported in parentheses. The significance levels and standard errors of all the coefficients in the control function are calculated after 1,000 bootstrap cycles. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.

[a]Given that we obtain the monthly short-term interest rate of each worker country from the Organisation for Economic Co-operation and Development 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 excluded in the IV estimation.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

models with project-level fixed effects. Therefore, we use the leave-out mean of residuals as the instrument for the compensation model. Moreover, following the previous literature (Hausman et al. 1994, Schneider 2010, Ghose et al. 2012), we use the percentage of time-based compensation models in other rivals' projects, which are submitted in the same week of the focal project as the instrument for employers' compensation model choice (Ghose et al. 2012).

Regarding 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). Because the exchange rate of local currencies against the U.S. dollar is negatively correlated with the actual purchasing power of the final payment and workers' reservation wage,[14] we expect that the exogenous variation of normalized exchange rates of various currencies would be negatively related to workers' bid prices.

Further, we conduct the weak identification test and find that the Kleibergen–Paap rk Wald F-statistic is 24.620, which is above the cutoff values suggested by Stock and Yogo (2005). Therefore, the weak instrument issue is not a concern in our study. Our overidentification test statistic (the Hansen J-statistic is 5.210, and the chi square (2) p-value is 0.157) suggests that we cannot reject the null hypothesis that the instruments used are exogenous.

Additionally, we adjust the standard error for the conditional logit model with the control function (Petrin and Train 2010) by calculating the bootstrapped standard error clustered at the project level. As Table 10 suggests, employers reduce their home bias remarkably after the introduction of the monitoring system. The results are highly consistent after employing the IV estimation on the matched sample.

Table 11. Sensitivity Analysis Using the Method of Selection on Unobservables

θ_{Home}	Home bias	$\theta_{Time-Based \times Home \times After}$	Treatment effect
$\lvert\delta_1\rvert$ when $\theta_{Home}=0$	$\lvert\delta_1\rvert = 3.790$	$\lvert\delta_2\rvert$ when $\theta_{Time-Based \times After \times Home}=0$	$\lvert\delta_2\rvert = 2.106$
Lower bound	0.032	Lower bound	−0.296
Upper bound	0.037	Upper bound	−0.102

7.4. Sensitivity Analysis

In order to assess whether our findings are robust to potential omitted variable bias, we further employ another method to alleviate the endogeneity concern—that is, *selection on unobservables* (Altonji et al. 2005, Oster 2019). This method assesses the sensitivity of our findings to the omitted variable bias and generates the lower/upper bounds of reported home bias and the treatment effect of monitoring.

First, we evaluate the possibility that the estimated home bias and treatment effect of monitoring (i.e., the decrease in home bias because of monitoring) may be driven by the selection on unobservables. Following the previous literature (Dale and Krueger 2002, Altonji et al. 2005, Oster 2019), we assess the minimum selection on unobservables that can explain the home bias and treatment effect found in the main analysis. Specifically, we use parameter δ to denote the ratio of selection on unobservables to selection on observables. As Table 11 shows, we find that the selection on unobservables needs to be at least twice as strong as the selection of observables ($|\delta_1| \geq 3.790$ for the reported home bias; $|\delta_2| \geq 2.106$ for the estimated treatment effect) in order for the selection bias to completely explain the observed home bias and treatment effect of monitoring. Further, as the previous literature (Dale and Krueger 2002, Altonji et al. 2005, Oster 2019) suggests that, at most, an equal selection on unobservables and observables ($|\delta| \leq 1$) is a well-accepted assumption, our results ($|\delta_1| \geq 3.790$ and $|\delta_2| \geq 2.106$) imply that it is very unlikely that the estimated home bias and the treatment effect of monitoring are driven by the omitted variable bias.

Second, as suggested by Oster (2019), we construct the lower bound and the upper bound of the estimated home bias and treatment effect using $\delta = 0$ (when there is no selection on unobservables) and $\delta = 1$ (when the amount of selection on unobservables is equal to that of selection on observables) as the boundaries. As shown in Table 11, we find that both the upper bound and the lower bound of the coefficient of the *Home* dummy are positive and that both bounds of the estimated coefficient of *Time-based* × *After* × *Home* are negative. This result lends support to our finding that employers have home bias, but their home bias decreases significantly after the introduction of the monitoring system.

7.5. Other Robustness Checks

To further check the robustness of our findings, we perform an additional analysis with the control of worker-level fixed effects along with project-level fixed effects (which nest employer-level fixed effects). As Table 12 shows, after controlling the unobserved heterogeneity of projects (as well as employers) and workers with fixed effects, we consistently find that the introduction of the monitoring system reduces employers' home bias significantly.

Results of other robustness checks are reported in the Online Appendix. First, we employ an alternative matching algorithm, PSM, to regenerate a matched sample, and our results are highly consistent (Online Appendix D). Second, we rerun the model with a

Table 12. DID Estimation of the Mitigation Effect of Monitoring with Worker Fixed Effects

	Linear probability model			
Sample	Full sample	Standard error	Matched sample	Standard error
Model	Dependent variable: Whether the worker is awarded			
Home	0.021***	(0.005)	0.035**	(0.015)
Time-based × *Home*	0.069***	(0.013)	0.085***	(0.024)
After × *Home*	0.004	(0.006)	0.007	(0.017)
Time-based × *After* × *Home*	−0.089***	(0.016)	−0.113***	(0.030)
Same language	−0.005	(0.004)	−0.009	(0.009)
Same currency	0.004***	(0.001)	0.008**	(0.004)
Same time zone	0.013***	(0.003)	0.019**	(0.009)
Log *bid price*	−0.072***	(0.001)	−0.110***	(0.003)
Log *milestone pct*	−0.009***	(0.001)	−0.018***	(0.002)
Log *count rating*	−0.006***	(0.001)	−0.013***	(0.002)
Avg rating	0.004***	(0.001)	0.007***	(0.002)
Log *bid order rank*	−0.023***	(0.001)	−0.029***	(0.003)
Preferred worker	0.007	(0.010)	0.013	(0.026)
Worker fixed effects	Yes		Yes	
Project fixed effects	Yes		Yes	
Observations	402,543		94,749	
R^2	0.326		0.439	

Notes. Given the large number of workers and projects in our sample, we were only able to run the LPM with project and worker two-way fixed effects. All the bids that are submitted by workers having prior collaboration experience with the employer are dropped. Moreover, our sample is limited to projects with only one winner. Robust standard errors clustered by projects are reported in parentheses. The key coefficients are shaded in grey. AIC, Akaike information criterion; BIC, Bayesian information criterion; LogLik, log-likelihood.
$^{**}p < 0.05$; $^{***}p < 0.01$.

shorter observational window (six months before and after) and still find consistent results based on the full sample and the matched sample (Online Appendix E). Third, to ensure that the workers are comparable and similar between the treatment group and the control group, we limit our sample to the bids submitted by those workers bidding on both fixed-price and time-based projects. The results of the restricted sample are still highly consistent with our main findings (Online Appendix F). Fourth, to enhance the comparability between employers in fixed-price and time-based projects, we conduct a robustness check by limiting our sample to projects posted by dual-type employers (those who posted both fixed-price and time-based projects), and we find that the results remain consistent (Online Appendix G). Fifth, to rule out the potential effect of employer composition shift,[15] we employ an inverse probability of treatment weighting analysis (Rosenbaum and Rubin 1983, Zhang et al. 2021) by computing the propensity score for each project with a project-type selection model that is exclusively trained based on the pretreatment sample. We find that results are highly consistent (Online Appendix H). Overall, all our robustness checks are consistent with our main findings.

8. Discussion and Conclusion

Using a large-scale archival data set from a leading online labor platform, we investigate whether and how the introduction of the monitoring system can mitigate employers' home bias in hiring remote workers. Based on a DID model with a matched sample and the exogenous event of the introduction of a platform-provided monitoring system for time-based projects, our study provides strong evidence that the introduction of the monitoring system can reduce employers' home bias. Further, we find that the effect of the monitoring systems on home bias varies by external and internal uncertainty. In particular, the decrease in employers' home bias is stronger for projects with low external uncertainty (proxied by high routineness) and weaker for projects with lower internal uncertainty (proxied by the employer's prior positive hiring experiences with foreign workers). In addition, our results suggest that both contractual control and coordination mechanisms underlie the mitigation effect of monitoring systems on home bias.

This paper makes several notable contributions. First, our study advances our understanding of the beneficial role of monitoring systems in online labor platforms. Although there is extensive evidence regarding the effectiveness of monitoring systems in mitigating moral hazard and improving worker performance in restaurants (Pierce et al. 2015), transportation (Kelley et al. 2023), and retail stores (Deng et al. 2023), whether monitoring systems can reduce employment biases, particularly the home bias, is still an open question. As the first attempt to investigate the impact of monitoring systems on employers' home bias and related contingent factors (i.e., external and internal uncertainty), our study provides rigorous evidence for the mitigation effect of monitoring systems and actionable guidance on the design of online labor platforms for more equitable employment opportunities.

Second, our work extends the growing literature on various biases in online employment. The bias problem in online employment has received increasing attention in the press and academia. Recent studies on various online platforms suggest that people exhibit local bias (Sun et al. 2021), gender bias (Chan and Wang 2018), cultural bias (Li et al. 2021), and racial bias (Cui et al. 2020). However, studies on how to effectively reduce biases are very limited. Based on our review of the related literature, there are two potential remedies explored by prior studies: that is, learning from personal experience (Cain 1986, Rubineau and Kang 2012) and the removal of the proxy information associated with bias (Agan and Starr 2018). However, learning from personal experience suffers from the cold-start problem (i.e., it requires employers' willingness to hire foreign workers for the first time to acquire experience). Meanwhile, prior studies suggest that the removal approach does not diminish bias but only changes the way that people show bias (Agan and Starr 2018). In an effort to address these biases, we propose and validate another actionable approach for alleviating employers' bias: that is, monitoring, which is a popular platform-provided feature to assist employers in tracking project progress in real time, thereby facilitating the control and coordination process with remote workers. Moreover, compared with personal experience, monitoring has a remarkable advantage (i.e., it can be easily implemented via platform design).

Third, our study contributes to the research on home bias and labor globalization. Although several prior studies suggest that employers can get productivity gains and save on labor costs by offshoring projects to workers from low-cost countries (e.g., Grossman and Rossi-Hansberg 2008, Tambe and Hitt 2012), we find that conditional on price, employers still tend to favor domestic workers owing to the low effectiveness in contractual control and coordination with foreign workers. Our analysis finds that platforms can provide monitoring systems to help employers control and coordinate foreign workers more effectively and thus, mitigate their home bias. This suggests that monitoring systems can reduce employers' hesitation to offshore projects globally and lead to a redistribution of online hiring toward an increase in crossborder hiring, which subsequently paves the way for online labor platforms to become frictionless global marketplaces for talent.

Our study provides important managerial implications for operators of online labor platforms, employers, and workers. From a platform perspective, monitoring systems can empower platforms to attain a truly global reach. By facilitating employers' control and coordination with remote workers through monitoring systems, platforms can foster a more inclusive and level global employment landscape. From the employers' perspective, they can benefit from monitoring systems by gaining access to a global talent pool and tapping the best talent around the world, regardless of their locations. Consequently, monitoring systems not only help them save on labor costs but also, improve their competitiveness by providing access to a diverse talent pool with unique skills and training. From the worker's perspective, monitoring systems can provide them with better opportunities to connect with employers from around the world. This increased global access can lead to better job prospects and skill development, ultimately improving workers' career development and well-being.

This study also provides important political implications. By enabling businesses to efficiently control and coordinate with foreign workers, monitoring systems can enable them to leverage a broader, more varied pool of talent, enhancing the diversity and global composition of their workforce. This advantage is particularly pronounced for businesses operating in countries where labor costs are notably high. Meanwhile, for workers in countries characterized by lower socioeconomic statuses and an abundance of skilled labor, they are encouraged to leverage either platform-provided or third-party monitoring systems. The monitoring tools can enhance the transparency of work progress and improve coordination with employers, thereby boosting their competitiveness and reducing bias in the global labor market. More broadly, the combination of online platforms and monitoring systems has the potential to promote a more equitable distribution of job opportunities worldwide, thereby enhancing crossborder labor exchanges and contributing to a more efficient and inclusive employment landscape globally.

We acknowledge several limitations of our study, which open up avenues for follow-up studies. First, we note that our sample is limited to projects within the IT category. Monitoring systems may play a less important role in other creative tasks that may have a lower routineness than IT projects. Second, we conduct our study in the online labor platform setting, and our findings may not be directly generalizable to offline labor markets or other online platforms. In offline labor markets, for example, employment contracts for long-term collaboration may serve as an effective incentive mechanism to motivate workers' effort, thus lowering the moral hazard risk. Third, we acknowledge that our study cannot fully disentangle the mitigation effects of monitoring systems, whether through enhancing control effectiveness or through improving coordination effectiveness. Future research can employ a variety of randomly assigned monitoring treatments, including improvement in control effectiveness, coordination effectiveness, and a combination of both, to better separate and quantify the contribution of each mechanism to the overall mitigation effect of monitoring systems. In addition, future research can explore whether monitoring can alleviate other types of biases in online employment settings. Finally, we acknowledge the possibility that other factors, such as political preferences and rhetoric, may influence employers' home bias. Given that political preferences tend to be stable over time, their impact on the reduction of home bias observed in our DID estimation framework that leverages the exogenous change introduced by monitoring systems is likely minimal. Nonetheless, the extent to which time-varying political factors affect home bias remains an area for further investigation. Future research should consider exploring this avenue, especially in the event of significant exogenous shifts in political preferences and rhetoric, to better understand the broader political policy implications.

Endnotes

[1] See https://www.gartner.com/en/articles/the-right-way-to-monitor-your-employee-productivity.

[2] See https://www.cnbc.com/2020/06/17/employee-surveillance-software-is-seeing-a-spike-as-workers-stay-home.html.

[3] In rare cases, a project can have multiple winners. In our main analysis, projects with more than one winner are dropped. The results of our analysis are consistent if we keep the projects with more than one winner.

[4] The platform officially released the Mac OS version of the desktop app on October 8, 2014.

[5] In 2014, the market share of Windows was 91.5%, whereas that of Mac OS was about 7.3%. (See more at https://www.zdnet.com/article/windows-8-8-1-overtakes-xp-on-new-netmarketshare-numbers/.)

[6] For instance, the market shares of Windows in India and Pakistan are about 94.6% and 96.5%, respectively. (See more at https://gs.statcounter.com/os-market-share/desktop/india/2014 and https://gs.statcounter.com/os-market-share/desktop/pakistan/2014.)

[7] Note that the app installation is optional for employers because they can always check the monitoring records directly from the platform website.

[8] To rule out the effect of the auction format on employers' choices, we limit our analysis to projects using the most common public, open-bid auction format. As such, special projects, such as those with a Non-Disclosure Agreement (NDA), featured projects, and sealed bid projects, are dropped from our sample.

[9] Additional descriptive statistics for those projects posted before and after the introduction of the monitoring system, presented separately, can be found in Online Appendix A.

[10] Given that we require all dummy variables to be exactly matched in CEM, this significantly reduces the sample size within each stratum. Owing to the relatively small sample size of the CEM sample with additional matching criteria, we report related results in the Online Appendix only.

[11] To find the corresponding SOC code for each job subcategory, we put the subcategory name into the search field of the O*Net database (https://www.onetonline.org/find/quick?s=), and we search for related occupations within the "IT, software & website" area. Further, we manually verify whether the definition of the occupation is consistent with the definition of the job subcategory. Based on SOC codes, we further find the corresponding 2000 American Community Survey (ACS) Occupation Codes (OCC) and then, the 1990 ACS OCC. Next, based on the 1990 OCC codes, we find the corresponding occupational task data from Autor and Dorn (2013), which include the abstract, manual, and routine task inputs for each occupation (and each project category). We use the abstract, manual, and routine task inputs of each project primary subcategory to calculate the RTI of each project.

[12] It is worth noting that if employers' compensation model selection decisions are mostly related to their personality and traits (e.g., inclination toward controlling workers' behavior or risk aversion tendency), such time-invariant employer-level differences should be absorbed by project-level fixed effects (which nest employer-level fixed effects) and should not lead to the decrease in employers' home bias in the treatment group. Furthermore, the DID estimation used in our main analysis does not require strict exogeneity (Abadie 2005) and can produce consistent treatment effects as long as the parallel trend assumption holds (Angrist and Pischke 2008).

[13] Because employers' hiring bias is estimated given the bid prices submitted by workers, this will not be a concern if we are only interested in whether monitoring systems can reduce employers' home bias or not. That being said, we instrument for it to better estimate the monetary value of employers' home bias.

[14] 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. dollars.

[15] Notably, it appears that there has not been a significant shift in the composition of employers. As shown by the summary statistics regarding employer experience and reputation in Figure A1 in the Online Appendix, we do not find any systematic differences between employers in the two groups (time-based and fixed-price projects). Furthermore, we observe no significant shifts in the distribution of employer characteristics before and after the implementation of the monitoring system.

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