Discrimination in Science: Salaries of Foreign and US Born Land-Grant University Scientists

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Abstract

The dominance of the US innovation and academic system relies heavily on foreign-born labor for its success. Recent literature has shown evidence of wage gaps in academia based on gender and race; however, little is known about whether a wage gap might exist for foreign-born faculty. This paper studies the wage gap between the US and foreign-born agricultural and life science faculty at 52 US Land Grant Universities (LGU) using a survey of over 1,400 scientists conducted in 2005 and 2015. We develop a framework to categorize the sources of a potential wage gap into testable categories that capture *direct* discrimination as well as indirect (*systemic*) discrimination. We find that among the tenure-track faculty, foreign-born earn about 4% or $5,200 lower annual wages even though, on average, foreign-born scientists work more hours per week and produce about 52% more journal articles than US-born scientists. The estimated wage gap is robust to a range of alternative empirical specifications. The decomposition analysis suggests that about one-third of the wage gap is due to direct discrimination, and about two-thirds is due to various types of systemic discrimination. Using our framework, we then rule in and rule out some important types of systemic discrimination. Estimates from this paper are crucial for understanding potential policies that could improve diversity, equity, and inclusion in US academia.

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1 Introduction

Close to 43 percent of US labor force growth in the last two decades is due to immigrants (Basso and Peri, 2020) and the foreign-born population in the US reached a record number of 44.8 million in 2018 (Budiman, 2020). These foreign-born workers constitute about 17% of the total US labor force (US Bureau of Labor Statistics (BLS), 2019).[1] Research shows that foreign-born workers make large contributions to the US enterprise through innovation, science, and productivity and have positive spillover to their native-born counterparts. Agarwal *et al.* (2023), for example, shows that immigration to the US is very important both for the US and the advancement of global science and demonstrates that policies to incentivize foreign-born scholars could increase global scientific output by up to 42 percent. Akcigit *et al.* (2017) use historical data to show that, in the US, immigrant inventors are more productive than US-born during their life cycle. Similarly, in medical sciences, patients treated by international graduates had lower mortality than those treated by US graduates (Tsugawa *et al.*, 2017). Despite their importance and potential productivity advantage, foreign-born earn lower wages than US-born in many sectors of the economy (Espenshade *et al.*, 2001).

Immigrants constitute 26 percent of the science, technology, engineering, and mathematics (STEM) workforce, own 28 percent of higher-quality patents, and hold 31 percent of all PhDs (Shambaugh *et al.* (2017)). Stephan and Levin (2003) suggest that the US benefits from immigration as it 'displaces' US-born scientists to seek better opportunities and high-paying positions elsewhere in the economy. In academia, where universities employ a large number of foreign-born scientists, research shows that foreign-born faculty produce more scholarly work than US-born faculty (Webber, 2012). It is, however, unknown whether foreign-born academic scientists are appropriately compensated for this productivity compared to US-born scientists.

Do foreign-born faculty earn the same wages as US-born faculty? The available evidence in the existing literature suggests the wage gap could be either positive or negative. Universities have complex and relatively well-regulated structures that might make them less likely to discriminate compared to other employers (Keohane, 1996). Under guidance from the Equal

[1] The BLS report also suggests that in 2018-19 the labor force participation rate for foreign-born was 67% for workers in the 25 years and older category and 63.6% for the native-born workers in that category.

Pay Act and Title VII, universities have numerous policies in place to achieve equality in wages among different under-representative groups, and one may expect universities to have more equalized wages based on merit. The main study on foreign-born faculty suggests that foreign-born earn about \$6,000 less compared to the US-born scientists, but that work is based on recent PhDs rather than capturing the full work cycle of professors (Corley and Sabharwal, 2007).[2] In contrast to that study in academia, the Bureau of Labor Statistics reports that foreign-born holders of a bachelor's degree or higher earn about 4% higher than US-born in median weekly earnings in the *bachelor's degree and higher* category.[3]

This work provides empirical estimates of the wage gap between foreign-born and US-born scientists by using novel survey data on agricultural and life science faculty in 52 Land-Grant Universities (LGUs) in the US. We use survey data on more than 1,400 randomly selected tenure track faculty from LGUs collected in 2005 and 2015 in agricultural and life science departments. The goal of this paper is to identify if there exists a wage gap between US and foreign-born academic scientists and to understand the underlying reasons for such a potential wage gap between foreign and US-born scientists. In particular, we test to what extent wage differentials are affected by the level of observable factors like output and effort (*direct* discrimination), and to what extent the wage gap arises because of labor market discrimination against foreign-born scientists (*systemic* discrimination).

We develop a novel framework to disentangle *direct* and *systemic* types of discrimination building from the work of Bohren *et al.* (2022) while adding some novel parts and nuance relevant to our setting. From that framework, we divide *systemic* discrimination into *informational*, *technological*, and *cultural* and further divide into specific categories that we can estimate with our data to understand the mechanisms driving discrimination. This novel framework allows a better specification of the causes of discrimination that can help identify potential policy solutions.

Like all studies in the racial or gender wage gap literature, we do not have random assignment between two groups to casually interpret potential estimates of discrimination. As is

[2]They use data on the employment and salaries of recent Ph.D. graduates from the *Survey of Doctorate Recipients (SDR)*, conducted by the National Science Foundation (NSF).

[3]BLS Report 2018-19.

typically done in the literature, we use yearly wages as an outcome variable and control for the factors that measure the quality of individuals' work and their output, as well as employing the Kitagawa-Oaxaca-Blinder decomposition to test for types of discrimination. This strategy of comparing two groups and using decomposition methods has been used successfully in studies of the gender gap in academia (Blau and Kahn, 2017, Chen and Crown, 2019) as well as other labor market settings (Trejo, 1997). To our knowledge, this paper is among the first to study whether foreign-born scientists are rewarded equally, conditional on a rich set of controls that account for the scientists' quality and merit.

Our results show that foreign-born LGU scientists earn about 4% less ($5,000) in yearly wages than US-born scientists after controlling for a large set of controls. A Kitagawa-Oaxaca-Blinder decomposition then demonstrates that unobserved characteristics explain about 67% (60% in log salary) of this gap which is typically considered as evidence of labor market *systemic* discrimination (Kitagawa (1955), Oaxaca (1973), Blinder (1973)).[4] We find our results are robust to alternate specifications by controlling for the quality of publications, dropping weekly working hours to avoid reverse causality, and restricting the sample to scientists without any formal administrative appointments.

We then test various mechanisms for discrimination. In terms of *direct* discrimination, we find a larger salary gap for the faculty from Latin America & the Caribbean (8.8% or about $11,500) and Sub-Saharan Africa (12.7% or about $14,500), which is broadly consistent with patterns of the racial wage gap in the US. In terms of *systemic* discrimination, we find evidence of *technological* discrimination due to past opportunities to develop human capital. We, however, do not find evidence that a common type of informational discrimination, *signal inflation*, causes the wage gap, nor do we find that base salary or formal administrative appoints explain the wage gap. Finally, we also discuss partial correlational evidence on how cultural discrimination might play a role in the observed wage gap.

This paper contributes to at least three different literatures. First, we contribute to a wage discrimination literature focusing on indirect (*systemic*) discrimination (Kline *et al.*, 2022,

[4]Decomposition is used to provide a more comprehensive appropriation of the wage gap (Chen and Crown (2019)).

Bohren *et al.*, 2022, Kitagawa, 1955, Oaxaca, 1973, Blinder, 1973).[5] That literature shows that standard models of statistical or taste-based discrimination are poorly suited for describing such *systemic* discrimination (Bohren *et al.*, 2022). Importantly, the economic literature on group-based disparities mainly focuses on the *direct* discrimination, that is, explicit differential group-based treatment, while mostly ignoring *systemic* sources of discrimination. We contribute to the literature by developing a single framework to disentangle between *direct* and *systemic* parts and show how to estimate and test these parts with data. This framework expands and more clearly specifies the discussion in (Bohren *et al.*, 2022), which for example, does not consider multiple types of technological discrimination nor considers cultural discrimination.

Our framework has three main components of *systemic* discrimination. First, it can take the form of *informational* discrimination, e.g., a committee deciding wages may have prior biased beliefs that the quality of similar work from one group (US-born scientists) is better than another group (foreign-born scientists). Second is *technological* systemic discrimination that arises due to differences in opportunities for human capital development. For instance, foreign-born might not receive equal opportunities for skill development or access to training due to current or prior discrimination. Third is *culture* based systemic discrimination that arises due to differences in the cultural expectations of either the foreign-born faculty, *cultural mismatch*, or the administrators' own *cultural discrimination* in how they evaluate situations. We are also among the first to contribute to this literature by conducting a decomposition analysis and separating the direct and *systemic* parts of wage discrimination within an academic labor market and estimating the components of the *systemic* discrimination that are relevant for policy-makers.

Second, this work complements a large literature on wage discrimination, particularly racial disparities in wages in the US (Card and Lemieux (1996), Trejo (1997), Chandra (2000), Ginther *et al.* (2011), Bayer and Charles (2018)). Most of these studies compare the wage gaps between groups that are born in the US (e.g., Whites and African-Americans) with no effort to

[5] Onuchic (2022) provides a nice overview of the recent development in the discrimination literature. Most of the work related to systemic discrimination happens in sociology and law, for instance, (De Plevitz, 2007, Powell, 2007).

separate out foreign-born status. Another strand in the literature studies gender wage disparities but does not account for how foreign-born status might exacerbate or mitigate the effects found (Ginther and Hayes, 1999). We complement both of these literatures by estimating the wage gap due to foreign-born status.

Third, we contribute to the literature on wage discrimination in academia (Corley and Sabharwal, 2007, Blau and Kahn, 2017, Chen and Crown, 2019). The literature on group-based wage disparity in academia is mainly focused on the gender wage gap or African Americans-Whites wage gap but, like the general literature, largely neglects a potential wage gap due to the foreign-born status.[6] Outside of the published academic literature, a number of universities have conducted their own self-studies documenting wage differentials based on gender and race (see, for example, U of Texas and UC Berkeley reports). None of those reports, to our knowledge, have analyzed foreign-born or immigrant status as a source of discrimination among academic faculty, which is an important oversight that our work seeks to remedy.

One of the main difficulties in evaluating the wage gap between foreign and US-born is the lack of a rich set of control variables on the qualification of individuals that may affect wages. Often salaries at public universities are readily available, but faculty output and conditions of employment are often difficult to capture. In academia, the other difficulty lies in obtaining data on a wide range of universities and departments that differ in their characteristics. Many other studies studying group-based wage gaps are often limited to either one university or one type of department (Hilmer and Hilmer, 2022). We overcome these challenges by using the novel survey data of scientists from 52 LGU universities with a rich set of variables that control for the productivity and quality of scientists. Our survey data gives us broad coverage in the academic spectrum covering different types of universities, faculty from various departments from agriculture-related social science to Agricultural Engineering, and different stages of faculty careers.

The nature of the Agricultural and Life Science departments (Plant Sciences, Agricultural Social Sciences, Ecology, Animal Sciences, Biology, Food and Nutrition Sciences, and Agri-

[6] An exception is a study from 2007 studying the wage gap of foreign and US-born faculty in starting salaries (Corley and Sabharwal, 2007).

cultural Engineering Sciences) provides a number of unique features to study wages among foreign and US-born scientists. First, these departments usually fall under and belong to the Colleges of Agriculture and Life Sciences (CALS) or similarly constituted colleges. Most of the research in such colleges is related to the agricultural, life science, and food industries in the US, and some faculty have extension and outreach appointments to collaborate and conduct research and outreach with local farmers, small and medium enterprises, and local communities. Foreign-born faculty might find extension and outreach appointments challenging for various reasons, and they might be less successful in being employed in those jobs. Also, CALS do not include any departments like Foreign Language or Cultural Studies, where Foreign-born faculty may have a comparative advantage over US-Born scientists. Secondly, CALS faculty have large similarities across different universities. Faculty are usually involved in a similar set of research topics since most of those research topics are delimited and incentivized by US Department of Agriculture (USDA) funding. In addition, all of these universities are public universities, most of which have salary transparency which would tend to make them less susceptible to overt discrimination. These characteristics of the departments under CALS make for a suitable laboratory in which to study the wage gap between foreign and US-born scientists.

Faculty at public research universities, such as LGUs, are a relatively homogeneous group in training, education, and the tasks that faculty conduct (Chen and Crown, 2019). Almost all faculty have PhDs, have similar hiring and tenure processes, and are required to teach and publish in academic journals. The academic world also provides ways for managers to measure faculty outputs, although many measures are imperfect, and much of a faculty member's work will go unmeasured. Ideally, faculty wages should be equalized conditional on their overall merit as measured through productivity, time effort, experience, and academic positions. [7]

[7] Access to different types of academic positions is potentially endogenous to foreign-born status. In the estimates that follow, we provide estimates that do and do not control for position type since, potentially, entry into a position (e.g., department chair) may be subject to discriminatory bias.

2 Methods

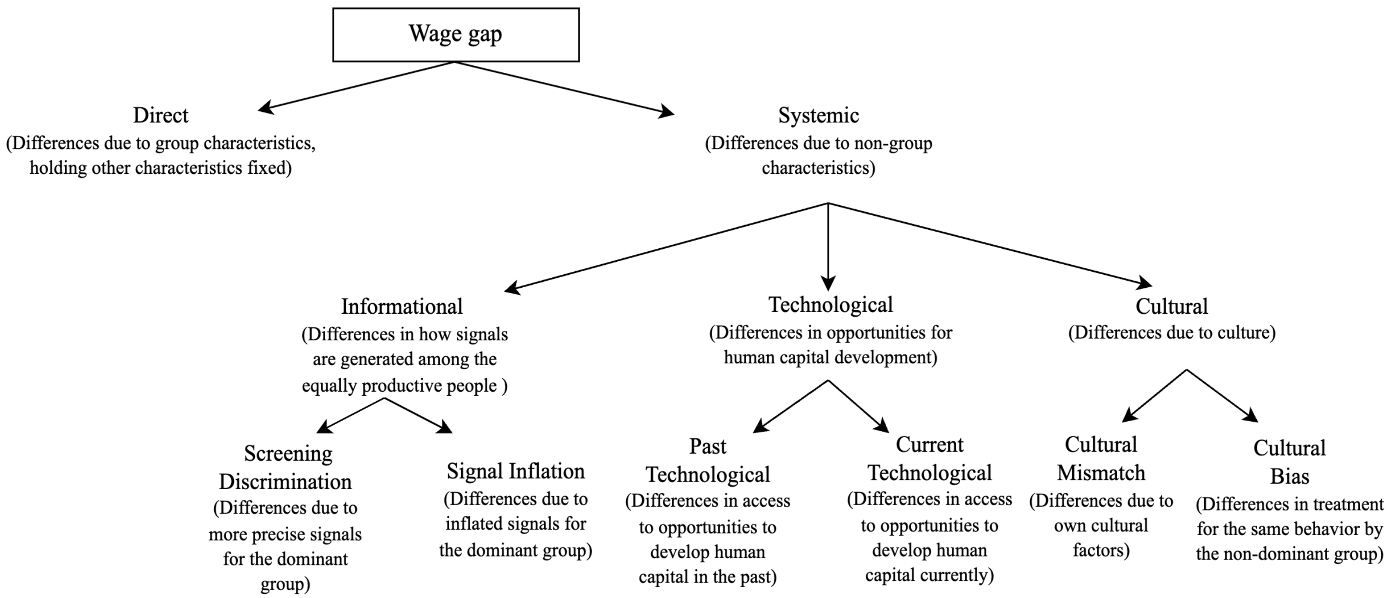
2.1 A framework for discrimination

We design a framework to document various types of discrimination that could drive a potential wage gap, then divide those types into different causes and mechanisms, and show how they relate to each other at various levels in Figure 1. Our framework builds on the discussion in Bohren *et al.* (2022), which documents some of these components, but we add nuance and new mechanisms, such as *cultural discrimination*. In so doing, our work builds on, expands, and formalizes their ideas into a full-fledged descriptive framework. We use the end nodes of this framework to point to types and mechanisms of discrimination that we can test with our data and econometric methods.[8] The tests for different types of discrimination are mostly done in the Mechanisms section below.

The framework starts with a total wage gap, which is then decomposed into the two types of discrimination: *Direct* and *Systemic*. *Direct* discrimination is the explicit differential treatment based on group identity, such as discrimination solely based on racial, religious, or country of origin categories, irrespective of the individual's qualities. It is straightforward to understand and is the feature most often estimated in work estimating wage gaps. On the other hand, *systemic* discrimination is facially neutral in that it does not explicitly discriminate due to group identity, even while the system disadvantages and discriminates against members of specific groups. In this case, it is the system, institution, rules, or group behavior that systematically disadvantages individuals from certain categories of people. For example, a Dean deciding on a raise may not put any criterion (facially neutral policy) on foreign-born or US-born status, but they might put extra value on the faculty being fluent in the American English accent. *Systemic* discrimination disadvantages the out-group due to systems that are less beneficial to the out-group even while they are facially neutral about group membership. We outline the types of systemic discrimination outlined in Figure 1 below.

[8] We are not able to fully test all of the end nodes set out in Figure 1 in some cases due to data limitations (e.g., cultural discrimination) in other cases due to timing that does not match our data, such as *screening discrimination*, which happens when faculty are hired.

FIGURE (1) Framework for the Sources of Discrimination in Salaries



2.1.1 Specifying types of systemic discrimination

The framework shows three integral sources of *systemic* discrimination: *informational*, *technological*, and *cultural* discrimination. When a wage gap exists between different groups, one can potentially test for each of these types of *systemic* discrimination.

Informational discrimination represents differences in how signals are generated among or received from equally productive people across groups. People may be better at evaluating same-group individuals, which could lead them to favor their own type, even though they do not have an *a priori* preference for similar individuals. Discrimination occurs because they can more accurately distinguish information between high and low-quality individuals within their own group (Cornell and Welch, 1996). Under informational discrimination, we might, for example, find that a higher proportion of US-born faculty in the hiring (or wage-deciding) committee could lead to hiring (or allocating higher wages to) US-born applicants (faculty).

Informational discrimination can be divided into two focal parts. The first part is *Screening* discrimination that could happen when the signal for one group (US-born) is more precise (low-variance) than the other group (foreign-born) (Bohren *et al.*, 2022).[9] *Screening* discrimination is not measurable within our data set since it is most likely to happen at the hiring stage, and we collect our survey data on faculty well beyond their hiring stage.[10] The second type of *informational* discrimination is *signal inflation* which emerges from systematically higher (inflated) signals for one group, which leads to favorable actions for that group over another. *Signal inflation* is readily testable as a mechanism in our data because we observe measures of productivity, such as hours worked or journal articles produced, that are commonly used inputs to determining salary outcomes. Under *signal inflation*, we would expect to see US-born faculty get more credit for working more hours or producing more and higher quality publications than foreign-born faculty.

Technological discrimination refers to mechanisms that discriminate due to differences in opportunities to develop human capital. *Technological* discrimination has two pivotal parts. The first part is discrimination in *past* opportunities to develop human capital, and the second is differences in *current* opportunities to develop human capital. First, it might be that lack of *past* opportunities mean that out-groups have fewer of certain types of valuable credentials that are valued for salary raises. We test this mechanism using non-English language undergraduate degrees as a past difference in human capital development. In the second type of technological discrimination, out-group members are prevented from accessing human capital, increasing opportunities in the present day. For example, out-group faculty might receive fewer invitations to conferences or to serve on review panels. Below we test for this mechanism using the correlation of foreign-born status with the number of presentations a faculty member made.[11]

A third mechanism, *cultural* discrimination, describes how cultural differences between dominant and non-dominant groups may cause systemic discrimination. There are two types

[9] There is a large literature in economics which mainly focuses on differentiating between taste-based and statistical discrimination (Aigner and Cain, 1977, Becker, 2010, Guryan and Charles, 2013). One might think that *direct* discrimination could be a part of taste-based discrimination or *screening* is a part of statistical discrimination. However, (Bohren *et al.*, 2022) argue that taste-based or statistical discrimination would be inappropriate to describe as *systemic* discrimination.

[10] We do find that foreign-born scientists are about 50% more productive than US-born scientists. This is suggestive evidence of screening discrimination in that only high-quality foreigners are hired in academia, which might not be the case for US-born scientists. Our data is consistent with this story. However, we do not test for this evidence, and further research would be needed to make a plausible claim on this mechanism.

[11] Due to many potential endogeneities related to these measures, we do not seek to estimate a causal regression model and only provide correlational evidence for this potential mechanism.

of potential *cultural* discrimination: *cultural mismatch* and *cultural bias*. *Cultural mismatch* describes cases where behavior considered correct or incorrect in the out-group, is different than the dominant group's cultural expectations and therefore puts them at a disadvantage. The mismatch of cultural expectations means that the out-group is discriminated against for not showing expected and rewarded behavior. An example of such a mismatch would be if an out-group finds it culturally inappropriate to ask for a salary raise, while this behavior is considered culturally appropriate, perhaps necessary, for members of the dominant group. A second type of discrimination, *cultural bias*, may occur when the same behavior that would be rewarded from members of a dominant group (e.g., asking for a raise, arguing in a meeting) is punished if done by members of the out-group. We are not able to test any of the types of *cultural discrimination* with our data but include them here in our framework for completeness.[12] We do return to the idea of cultural discrimination in the discussion of our results and mechanisms below as something that we can neither rule in nor out.

2.2 Estimation Strategy

We estimate the wage gap between native and foreign-born scientists using annual wage (level and log) as our dependent variable in regression with and without a large set of control variables. Our baseline estimation using ordinary least squares with university and field fixed effects takes the following form:

$$Y_{iu} = \beta_0 + \beta_1 Foreign_i + \gamma X_i + \eta_u + \lambda_f + \sigma_t + \varepsilon_{iu}. \tag{1}$$

Our outcome variables are *level and log annual salary* of a scientist i, in university u. *Foreign*, our key independent variable of interest, is an indicator if the scientist has an undergraduate degree from a country other than the US; η_u and λ_f are university of employment and field fixed effects; σ_t is a survey year fixed effect; the X_is are the individual characteristics of the scientist. Standard errors are clustered at the university level to control for university-level

[12] One would likely need to conduct some kinds of experiments with manipulations of cultural situations and norms in order to test this type of cultural discrimination. This is a useful angle for future work.

heteroskedasticity (Barham *et al.*, 2019).[13] The primary coefficient of interest is $\hat{\beta}_1$, representing the estimated wage gap for foreign-born scientists relative to US-born scientists. The log transformation of the outcome variable is commonly used in the labor market wage literature to improve the model's fit by transforming the distribution of the dependent variable to a more normally-shaped bell curve. We also provide the results from the un-transformed dependent variable to provide readily understood outcome metrics in dollar values and, in case outliers might provide important and informative data points.

The estimation strategy we use is common in the labor market discrimination literature, where we compare the outcomes of majority (the US-born) and minority (foreign-born) groups and control for the characteristics that determine wages (Cahuc *et al.*, 2014). Typically, that literature takes as evidence of labor market discrimination that the coefficient of interest, $\hat{\beta}_1$, is negative. We follow that convention here.

We include a baseline specification with no controls as well as specifications that control for individual and university characteristics. Among those controls, we include an indicator for the tenure status, which is equal to one if the faculty are tenured and zero otherwise.[14] Secondly, we control for their years of experience by calculating the total number of years since they completed their Ph.D. Generally, total salaries are partially determined by administrative and extension appointments due to bonuses and other compensation such as summer salary. To account for this, we also control for the formal condition of employment with dummy variables for extension and administrative appointments.

Other important determinants of wages may include the scientists' academic effort and research productivity. We measure their academic effort by asking researchers how many hours they typically spend per week on the academic work of research, teaching, administration, and extension and outreach. Secondly, in the academic enterprise, the publication of scholarly articles, books, and reports reflects the scientists' production of knowledge. To control for the research productivity, we include the self-reported total number of journal articles published

[13] One can think of the treatment as being how a university administrator in charge of hiring, promotion, and salary raises treats a person with foreign-born status relative to others. In this case, our treatment will vary by university, making clustering at the university level the appropriate choice.

[14] For the missing values of the tenure status, we impute tenure status equal to one if the faculty rank is either Associate Professor or Full Professor.

by the faculty in the past five years before the survey. Such a count measure does ignore the quality of the published journals since highly cited journal articles may get compensated differently than journal articles with fewer citations. To address this concern, we also estimate some models with quality-adjusted publications, where the value of a publication is adjusted by its relative citation rate compared to other publications in the same field of the same year. We use the Web of Science (WOS) data to collect citation data for each publication for the last five years of the survey to calculate quality-adjusted publications.[15]

We also control for the gender of the faculty to control for the large body of evidence on the wage gap between men and women, both in an academic setting (Ginther and Hayes, 1999, Chen and Crown, 2019) and in general workplaces (Blau and Kahn, 2017). We include the survey year fixed effects since we have the data collected in 2005 and 2015. As our two surveys have a gap of almost a decade which experienced the great recession of 2008, we compare US and foreign-born scientists within each of these survey years to control for any time characteristics common to the whole faculty. Finally, we control for university and field fixed effects, which presumes that the differences in average salary across the two groups are uncorrelated with the US-Foreign born composition in those universities and fields.

When we test for mechanism effects and types of systemic discrimination, we interact our foreign-born dummy variable with other variables, Z_i, such as research productivity or the home country of the scientist. We use the following estimation equation to test different potential mechanisms that may explain variations in the salaries of the US and foreign-born faculty,

$$Y_{iu} = \beta_0 + \beta_1 Foreign_i + \beta_2 Z_i + \beta_3 Z_i * Foreign_i + \gamma X_i + \eta_u + \lambda_f + \sigma_t + \varepsilon_{iu}. \tag{2}$$

Here, our outcome of interest is $\hat{\beta}_3$, which determines whether the mechanism in question, Z_i, differentially affects foreign-born faculty salaries. For instance, one version of Z_i is the total number of journal articles, which, when interacted with foreign-born status, provides a

[15] We, however, lose a significant portion of the sample, since we could not find the WOS data for all the scientists. Thus, our primary specifications do not include quality-adjusted publications. While this is imperfect, the evidence in the literature suggests a strong positive relationship between the quantity and quality of published articles (Huang, 2016).

test for *signal inflation* effects in which foreign-born might receive lower levels of credit for publications. Similarly, if Z_i is an indicator for whether a foreign-born scientist is from the country with undergraduate instruction in a non-English language, the estimated coefficient $\hat{\beta}_3$ provides a test for the existence of past technological discrimination.

2.3 Decomposition Strategy

Following the literature on wage discrimination, we also employ the Kitagawa-Oaxaca-Blinder (Kitagawa (1955), Oaxaca (1973), and Blinder (1973)) decomposition to decompose the estimated salary gap into various components of the control variables. This method is generally used to study labor market outcomes by different groups such as gender or racial status (Chen and Crown (2019)). The Kitagawa-Oaxaca-Blinder decomposition divides the differences in outcomes between two groups (here US and foreign-born faculty) into a part that is explained by covariates, *direct* discrimination based on the observable characteristics and a residual part that is unexplained or *systemic* discrimination.

Let the outcome be Y for two groups, F and US, indicating foreign and US-born scientists, respectively. In a naive specification, we estimate

$$\begin{aligned} Y_F &= X_F \beta_F + u_F \\ Y_{US} &= X_{US} \beta_{US} + u_{US}. \end{aligned} \tag{3}$$

In this equation, X is a vector containing predictors, and β_F and β_{US} contain slope parameters. u_F and u_{US} are error terms. The wage gap between the US and foreign-born scientists can then be expressed as

$$\begin{aligned} E(Y_{US}) - E(Y_F) &= E(X_{US})\hat{\beta}_{US} - E(X_F)\hat{\beta}_F \\ &= (E(X_{US}) - E(X_F))\hat{\beta}_{US} + E(X_F)(\hat{\beta}_{US} - \hat{\beta}_F). \end{aligned} \tag{4}$$

where $E(\beta_{US}) = \hat{\beta}_{US}$, $E(\beta_F) = \hat{\beta}_F$, $E(u_F) = 0$ and $E(u_{US}) = 0$ by assumption.

We decompose the wage gap between native and foreign-born scientists into a (*direct*) portion explained by differences in the characteristics, $(E(X_{US})-E(X_F))$; and an unexplained (*systemic*) portion $(\hat{\beta}_{US}-\hat{\beta}_F)$ that is due to how the foreign and US-born scientists are paid differently for the same characteristics of $E(X_F)$.

3 Data and Descriptive Statistics

3.1 Survey of LGU Scientists

The paper uses detailed survey data from agricultural and life science faculty conducted in 2005 and 2015 at the 52 Land Grant Universities. The surveys have information on gender, age, academic position, salary, department, appointment types, and productivity, amongst other variables. To conduct the surveys, we obtained a census of faculty names from university web directories and created the cross-sectional sample frame, and then randomly selected scientists and sent them a web-based survey. In each survey, we sent surveys to about 3,000 randomly selected agricultural and life science scientists from all U.S. LGUs.[16]

The faculty belong to the departments in the colleges of agriculture and life sciences of public LGUs.[17] Both surveys had a sample frame that included all tenure-track faculty scientists in agricultural and life science departments at these LGUs. We restrict the sample to tenured or tenure-track faculty members since the compensation structure of the non-tenure-track faculty is usually different from tenure-track faculty. The response rate was about 40% in 2015 and 60% in 2005, measured as the fraction of scientists who responded to at least one question. We do not expect any response rate bias and rely on the estimates provided in Barham *et al.* (2017) that suggest no significant differences in response rate based on the universities' observed characteristics nor by field of study. In our final sample, we have 1045 scientists in 2005 and 644 scientists in 2015. Additional details about the surveys, including

[16] The Institutional Review Board (IRB) at UW-Madison approved each of these surveys.

[17] We categorize scientists' field of studies into 7 categories: Plant Sciences (e.g., agronomy, entomology, horticulture, plant pathology), Social Sciences (e.g., agricultural economics, rural sociology, agricultural or life science communications), Ecology (e.g., conservation biology, fisheries, wildlife ecology), Animal Sciences, Basic Biological sciences (e.g., biochemistry, genetics, microbiology), Food and Nutrition Sciences, and Agricultural Engineering. At universities where these departments were moved outside of a college of agriculture, we included the equivalent departments in whatever colleges where they were.

sampling information, is available in Appendix A.

Our treatment variable of foreign-born status is an indicator equal to one if the scientist has a Bachelor's degree from a university outside of the US. The surveys do not ask a question about the country of birth of the faculty, so we use the country of the bachelor's institution as a proxy for the faculty's country of birth. Further, if the observations of bachelor degrees are missing, we searched online the university and its country from the scientists' publicly available academic profiles. There is a total of 52 countries among the undergraduate institutions of scientists in the data.[18] Our measure of foreign-born status is likely to create some measurement error due to an undercount of foreign-born status. While it is unlikely that many US-born academics have bachelor's degrees from foreign universities (our spot checks have confirmed this), there are potentially a number of foreign-born scientists who have US bachelor's degrees. Since we currently categorize such foreign-born scientists with US bachelor's degrees as US-born, this will attenuate the effects we have in favor of not finding an effect or underestimating an effect.[19]

The primary outcome variable is the total annual compensation of faculty members in levels and the natural logarithm of that value. The surveys ask for the total annual compensation from the university for the previous year under the following categories: base salary, stipend, internal and external research funds, summer teaching, and any other compensation. We conducted a web search to find the missing salary information for about 16% of the faculty who did not answer the question. Appendix Table 23 shows that there are no significant differences between the characteristics of the faculty who reported their salary and those for whom we found the salary through a web search. Our main focus is on total salary because it is often used in the wage gap literature (Chen and Crown, 2019), but we also conduct robustness checks with base salary as an outcome variable.

Our data have some advantages over commonly used data on salary from official public

[18] Appendix C shows the list of countries of undergraduate institutions of scientists.

[19] An alternative interpretation of what we call foreign-born would be to decide the measure is of having a foreign bachelor's degree, irrespective of country of birth. In this case, there is no measurement error or attenuation bias, but the interpretation of our results is less straightforward in part because of the very high correlation between foreign-born status and having a foreign bachelor's degree. We believe the major source of discrimination would be due to foreign-born status rather than foreign bachelors degree status.

records. First, we collect data from individuals who have better information on all the sources of their salaries. In contrast, the public records of salary may miss some sources of salary and may have non-trivial measurement issues. Secondly, our surveys ask for a detailed salary breakdown, distinguishing between base salary and total salary. The salary reported in the public records is typically the total salary and cannot distinguish between the base and total salary. Third, our surveys cover the salary information from all of the 52 LGUs in the US, while public records of salary are not easily accessible for many public universities, creating potential sample selection issues. Furthermore, in our data, faculty report the salaries combined from multiple departments if they have compensation from multiple departments.[20] Public records, however, often count the faculty multiple times if the faculty has appointments from multiple departments making the salaries appear to be different than the actual.

With those benefits, our survey data do come with several important limitations that are worth noting. First, we have survey data rather than the census of the faculty, as some of the works in this literature have. Second, by using self-reported salary information, we may have some bias due to certain types of faculty over- or under-reporting their salaries.[21] Third, in self-reported data, faculty will, in most cases, round off their salaries to the nearest 5 or 10 thousand dollar value, which may create inaccuracies in our data. We, however, expect that such noise due to rounding will be minimal. Appendix B shows how we deal with the cleaning of the salary variable and discussion on potential biases. Figure 2 shows the kernel density estimates of the salary variable in levels and logarithms.

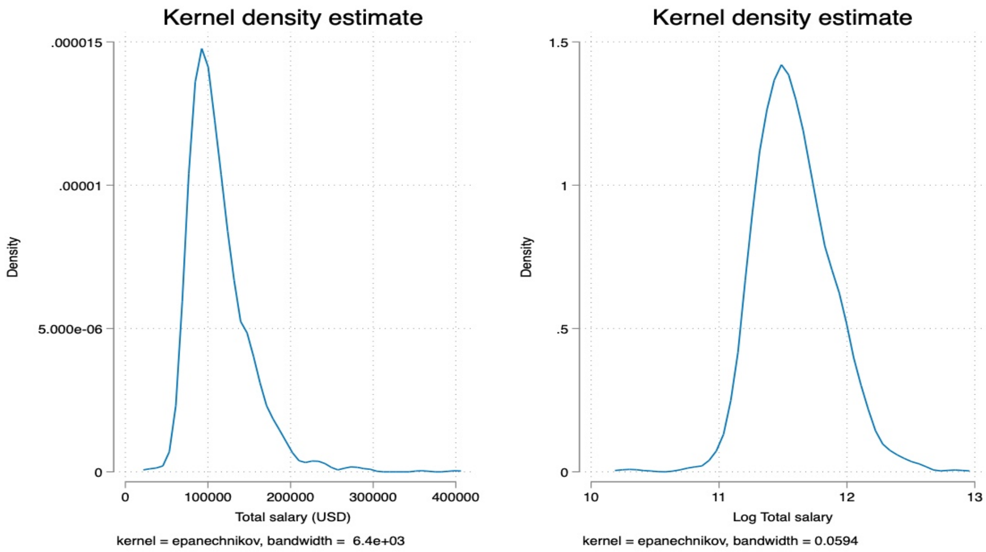
3.2 Descriptive Statistics

We begin with some descriptive evidence on foreign and US-born faculty. Table 1 shows the characteristics of the 1,698 faculty of our sample in the survey years 2005 and 2015. On average, foreign-born faculty earn about $7,400 less than US-born faculty, without controlling for

[20] Our surveys do not ask questions related to multiple appointments from different departments. We assume the salary reported by the researcher is compensation from multiple departments if they have multiple appointments.

[21] The literature on the gender wage gap suggests that women tend to under-report their successes and potentially their salary. We do not know if the same is true for the foreign-born faculty, but if present, this may create noise in the reporting of salary information. We expect that the noise is uncorrelated with the foreign-born status.

FIGURE (2) Outcome Variables: Total annual salary and log of total annual salary



any individual or university characteristics. We find foreign-born faculty are less likely to have a tenured position and have four years less experience than US-born faculty, measured by total years after the Ph.D. Also, 21% of US-born have formal administrative appointments, whereas a smaller percentage, 15%, of foreign-born hold formal administrative appointments. These differences suggest that foreign-born scientists are, on average, younger, less experienced, and have appointment types that may have lower salaries. We, however, find that foreign-born faculty report slightly more weekly working hours and produce about 52% more journal articles during the previous five years compared to US-born faculty.

In order to show potential differences in salaries in a way commonly used by universities, we plot salaries against years of experience.[22] Figure 3 presents a scatter plot with a fitted regression line for the salaries as a function of years since Ph.D. for US and foreign-born faculty. This figure shows very subtle differences, if any, suggesting the need for a regression analysis to identify differences, as we do below. We also plot the mean salary over the different levels of the number of journal articles (Figure 4). The figure suggests that US-born scientists earn higher wages than foreign-born faculty for the same number of journal articles, as would be the case if there was *signal inflation*. To understand whether the gap is statistically significant

[22]Discussions with some Deans and Associate Deans in colleges of agriculture and life science have suggested this is a common practice among administrators.

TABLE (1) Sample Characteristics of US and Foreign-Born LGU Scientists

	US-Born (Mean)	Foreign-Born (Mean)
Total salary (USD)	114,284.22	106,860.30
Tenured (Y/N)	0.83	0.67
Experience (No. of years)	20.78	16.64
Male	0.77	0.75
Weekly Work (Hrs.)	52.99	55.91
Journal Articles (Nos.)	12.82	19.54
Extension Appoint. (Y/N)	0.33	0.27
Administration Appoint. (Y/N)	0.21	0.15
Fields		
Ag/Engineering	0.20	0.12
Animal Science	0.04	0.11
Biology	0.33	0.33
Plant Science	0.10	0.09
Ecology	0.10	0.15
Food/Nutrition	0.17	0.07
Social Sciences	0.07	0.13
Observations	1400	258

Note: The table shows the summary statistics of the characteristics of the LGU scientist for the survey years 2015 and 2005. All dollar amounts are in 2015 dollars and are adjusted for CPI inflation.

or whether the gap persists after controlling for the individual characteristics, we turn to the regression analysis.

4 Results

4.1 Main Results

Panel A and B in Table 2 show the OLS estimates of equation (1) showing the wage gap between US and foreign-born faculty in levels and logs, respectively. We find a statistically significant and economically meaningful wage gap between US and foreign-born faculty in all specifications. Column 1 in panels A and B show the results with the most parsimonious model with no control variables suggesting that foreign-born scientists earn $7,424 or 6.1%, [23] less in average annual wages than US-born scientists in the 52 land-grant universities in

[23] $\approx exp(-0.063) - 1$

FIGURE (3) Wages and Experience

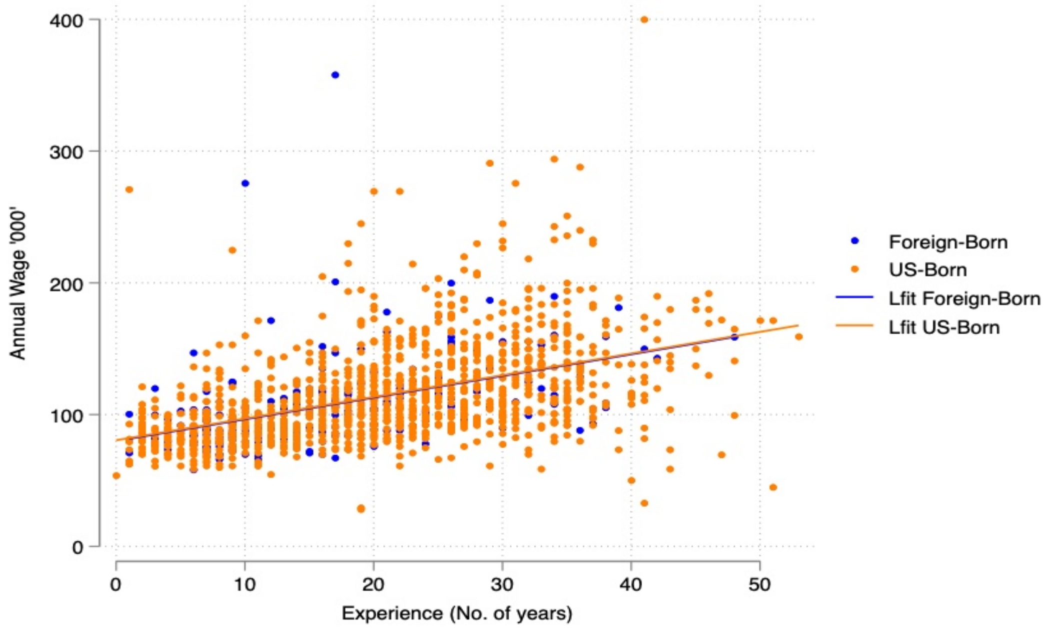
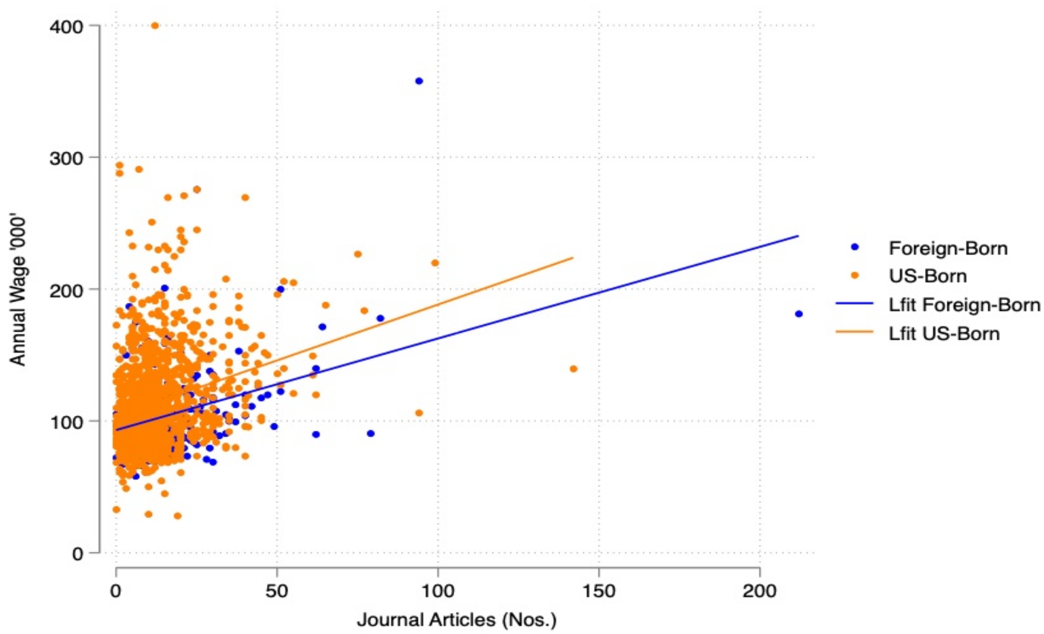


FIGURE (4) Wages and Journal Articles



Note: Figures (2) and (3) use the data of 2005 and 2015 surveys of LGU scientists. The figures plot the data of the sample faculty, unconditional on any other characteristics.

the US. As we move from columns 1 to 2, we find that including controls of the individual characteristics essentially has no effects on the direction and the statistical significance of the estimates, but the wage gap reduces to $5,129 in levels and 3.7% in log wages. The control variables also all have the expected signs and magnitudes. For instance, tenured faculty or more experienced faculty earn higher wages, as do those having formal administrative appointments. Working more hours per week and producing more journal articles in the last 5 years also have a positive impact on the annual wages. We also find that male faculty earn more than female faculty by almost $950 or 1.2%, but that coefficient is not statistically different from zero in most specifications.[24]

Further, we introduce survey year fixed effects in column 3 and find them to have only a modest effect on the estimated wage gap between foreign-born and US-born scientists. The estimates of a wage gap increase slightly to $5,319 or 4.0%. Next, we introduce field-fixed effects in column 4 to more effectively capture the field-specific confounders. We find that accounting for the field of study essentially does not affect the wage gap. This suggests that the wage gap between foreign and US-born faculty within the field of study is almost the same as that across the fields. Similarly, we introduce university fixed effects in column 5 to capture the university-specific confounders. There is a modest change in the estimates to about $5,000 or 3.7%, but this indicates that the differences in the foreign and US-born faculty composition across universities are not driving the observed wage disparity. We also run the specification with scientists' Ph.D. granting university fixed effects in Appendix Table 14 as a way to account for the quality of the faculty. The estimates are virtually unchanged in that additional specification.

Finally, we introduce field and university fixed effects together in column 6 and the estimates remain consistent. The wage gap between foreign and US-born faculty is $5,164 or 3.9%. Taken together, these results are consistent and suggest that it is unlikely that university and field-specific confounders are driving our results. This also suggests that the wage

[24] The magnitude of the gender gap we find in some specifications is similar to those found in a recent study of salaries in agricultural economics, which is one of the fields in our sample (**?** (2022)), but we do not find as consistent significance. Since we do not find important differences across fields, it is reasonable to expect that an estimate from one field would translate to similar estimates across all CALS fields.

gap between the US and foreign-born scientists within universities and fields is similar across universities and fields.

TABLE (2) OLS Estimation of Annual Total Salary Earned by US and Foreign-born Faculty

	(1)	(2)	(3)	(4)	(5)
Panel A	**Outcome Variable: Salary in ’000 (Level)**				
Foreign Born	-7.424**	-5.321**	-5.366**	-5.083**	-5.319**
	(3.076)	(2.331)	(2.175)	(2.450)	(2.346)
Tenured (Y/N)		8.356***	8.396***	8.843***	8.943***
		(2.088)	(2.216)	(1.934)	(2.046)
Experience (No. of years)		1.340***	1.385***	1.259***	1.300***
		(0.110)	(0.110)	(0.112)	(0.109)
Extension Appointment (Y/N)		-0.510	0.073	-1.126	-0.750
		(1.853)	(1.851)	(1.788)	(1.790)
Admin. Appointment (Y/N)		20.058***	19.461***	20.973***	20.559***
		(2.467)	(2.593)	(2.308)	(2.378)
Weekly Work (Hrs.)		0.445***	0.463***	0.389***	0.406***
		(0.096)	(0.098)	(0.097)	(0.097)
Journal Articles (Nos.)		0.596***	0.639***	0.535***	0.577***
		(0.118)	(0.120)	(0.120)	(0.120)
Male		1.433	2.430	2.847	3.531*
		(1.859)	(1.851)	(1.939)	(1.898)
Observations	1,423	1,347	1,332	1,347	1,332
R-squared	0.005	0.363	0.385	0.437	0.453
Panel B	**Outcome Variable: Salary (Log)**				
Foreign Born	-0.063***	-0.040**	-0.041**	-0.039**	-0.041**
	(0.023)	(0.017)	(0.016)	(0.017)	(0.017)
Tenured (Y/N)		0.104***	0.104***	0.111***	0.112***
		(0.018)	(0.018)	(0.016)	(0.017)
Experience (No. of years)		0.011***	0.011***	0.010***	0.010***
		(0.001)	(0.001)	(0.001)	(0.001)
Extension Appointment (Y/N)		0.001	0.005	-0.004	-0.003
		(0.015)	(0.015)	(0.014)	(0.014)
Admin. Appointment (Y/N)		0.154***	0.150***	0.162***	0.159***
		(0.018)	(0.019)	(0.016)	(0.017)
Weekly Work (Hrs.)		0.004***	0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Journal Articles (Nos.)		0.005***	0.005***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Male		0.016	0.023	0.028*	0.032**
		(0.014)	(0.014)	(0.014)	(0.014)
Observations	1,423	1,347	1,332	1,347	1,332
R-squared	0.006	0.399	0.420	0.483	0.498
Survey Year FE	No	Yes	Yes	Yes	Yes
Field FE	No	No	Yes	No	Yes
University FE	No	No	No	Yes	Yes

Note: The data is a cross-section of surveys conducted in 2005 and 2015. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is the ‘University of Wisconsin-Madison’. See text for variable description. The salary is adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

4.2 Testing 'Direct' vs. 'Systemic' discrimination

We next conduct a decomposition of group difference of means using the Kitagawa-Oaxaca-Blinder (Kitagawa (1955), Oaxaca (1973), Blinder (1973)) decomposition to divide the wage gap between US and foreign-born scientists into values explained by other covariates and left unexplained. The results of the OLS estimations presented above provide inference on the characteristics that contribute to the salary allocation; however, it does not show how these characteristics may or may not contribute to wage discrimination between the US and foreign-born scientists. The Kitagawa-Oaxaca-Blinder decomposition accounts for both the explained *direct* factors (differences in the observed characteristics of the scientists) and unexplained *systemic* factors (differences in treatment of the US and foreign-born scientists with similar characteristics).

TABLE (3) Kitagawa-Oaxaca-Blinder decomposition

	Annual Salary ($) '000		Log Annual Salary	
VARIABLES	Differential	Decomposition	Differential	Decomposition
Prediction_1	114.491***		11.602***	
	(2.035)		(0.016)	
Prediction_2	106.532***		11.534***	
	(2.737)		(0.022)	
Difference	7.960***		0.068***	
	(3.086)		(0.023)	
Explained		2.651		0.027
		(2.250)		(0.019)
Unexplained		5.309**		0.041**
		(2.635)		(0.019)
Observations	1,332	1,332	1,332	1,332

Note: We use the following variables for this decomposition: Tenure status, years after Ph.D., an indicator for extension and administrative appointments, weekly hours spent for academic work, number of journal articles published in last five years, gender, survey year, a field of research, and current university. We use twofold decomposition as explained in Jann (2008). Standard errors appear in parentheses and are clustered at the university level. *** p<0.01, ** p<0.05, * p<0.10.

The decomposition in Table 3 reports the mean predictions by groups and their differences in the first panel.[25] The mean total salary for US-born is $114,491, and for foreign-born is $106,532, yielding a salary gap of $7,960. In the second column of the decomposition output, the wage gap is divided into two parts. The first part is the explained, or *direct* discrimination, which indicates the mean wage gap due to the differences in the characteristics of the US and

[25] We also show the estimates with the threefold decomposition in Appendix D.

foreign-born scientists. The second part is unexplained, or *systemic* discrimination, which reflects the mean increase in foreign-born scientists' salaries if they had the same characteristics as US-born scientists. Table 3 suggests that differences in the characteristics between these two groups of scientists account for about 33% of the wage gap of $7,960 or 40% of the wage gap of 6.8% in log salary.[26] This means that if US-born and foreign-born scientists had the same observational characteristics, the wage gap would be about 67% in level and 60% in the log of its estimated value.

TABLE (4) Kitagawa-Oaxaca-Blinder decomposition

	(1)	(2)	(3)	(4)
	Annual Salary ($) '000		Log Annual Salary	
VARIABLES	Explained	Unexplained	Explained	Unexplained
Tenured	1.037**	-4.743	0.015***	-0.017
	(0.415)	(3.093)	(0.005)	(0.027)
Experience	5.623***	8.098	0.044***	0.032
	(1.295)	(3.768)	(0.010)	(0.028)
Extension Appoint.	0.023	1.515	0.001	0.012
	(0.163)	(1.336)	(0.001)	(0.010)
Administration Appoint.	0.984	-0.142	0.007	-0.005
	(0.570)	(0.886)	(0.004)	(0.007)
Academic Weekly Work (hrs.)	-1.417***	10.151	-0.011***	0.064
	(0.394)	(11.865)	(0.003)	(0.082)
Journal Articles	-4.053***	2.148	-0.033***	0.031
	(1.192)	(4.768)	(0.009)	(0.028)
Male	0.040	-2.216	0.001	0.005
	(0.083)	(3.189)	(0.001)	(0.022)
Survey Year 2015	-0.183	2.555	-0.002	0.023
	(0.245)	(2.097)	(0.002)	(0.015)
University	0.000	8.547*	-0.000	0.067**
	(0.080)	(4.562)	(0.001)	(0.032)
Field	0.624*	-8.729	0.005*	-0.046
	(0.352)	(5.883)	(0.003)	(0.044)
Total	2.651	5.309**	0.027	0.041**
	(2.250)	(2.635)	(0.019)	(0.019)

Note: The estimates are for the Kitagawa-Oaxaca-Blinder Decomposition that decomposes the explained and unexplained variation in the US-Foreign scientists' wage gap into components explained by various characteristics. We use threefold decomposition as explained in Jann (2008). Standard errors appear in parentheses and are clustered at the university level. *** p<0.01, ** p<0.05, * p<0.10.

We further explore the Kitagawa-Oaxaca-Blinder decomposition by decomposing those differences into components explained by various characteristics in Table 4. Consistent with the regression analysis in Table 2, we find experience and tenured positions play the largest roles, explaining 70% and 13% of the wage gap in levels, respectively (column 1). Other factors have relatively modest effects, and some effects are negative. For instance, the estimates

[26]The total US-foreign-born wage gap is equal to the sum of explained (2,651 in level and 0.027 in logs) and unexplained part (5,309 in level and 0.041 in logs).

for journal articles and academic weekly working hours are negative and significantly different from zero, which suggests that if foreign-born and US-born faculty produced the same number of journal articles or work the same hours, the wage gap would be even higher. This result is consistent with *signal inflation* for US-born scientists in which they receive more credit for journal articles or work more hours relative to their foreign-born peers.

Columns 2 and 4 represent the unexplained, or systemic part of the decomposition, which is due to differences in how foreign-born and US-born are compensated for the same characteristics and account for the 67% of the wage gap between foreign and US-born scientists.[27] The similar results with the log of the annual wages in columns 3 and 4 complement these findings.

4.3 Robustness Checks

While we control for a large set of variables to provide transparency in our estimations, it is possible that the results are confounded by measurement errors and the potential endogeneity of our controls. To examine our results' robustness to these issues, we use three robustness checks. First, we control for the quality of scientists' production by using quality-adjusted publications by citation rates. Secondly, we estimate the models without the potentially endogenous terms measuring working hours and job appointment types. Finally, we evaluate whether the wage gap is being driven by specific effects on different parts of the wage distribution. We do this with two types of regressions, one where we restrict the salary measure to base salaries and a second where we estimate a quantile regression to test effects in different parts of the wage distribution.

We quality adjust our measure of faculty productivity because the quality of the articles might be more important than the quantity in determining scientist salaries. If we do not account for the quality of the publications, or the quantity and quality of publications are not strongly correlated, or quality is correlated with foreign-born status, then there might be a bias in quantifying the true productivity of the scientists. To address this, we use the Web of Science (WOS) data to collect the number of citations for each publication produced by the surveyed

[27]=5.309/7.96

scientists in the five years before the survey date. We then create a quality-adjusted measure in which publication numbers are inflated or deflated by the normalized relative citation level of that scientist compared to others in his/her field of study. [28] The raw data means to show that the gap in production between US and foreign-born scientists widens even more when the publications are quality-adjusted. Regression estimates in Table 5 that use quality-adjusted publications as an independent variable suggest that the wage gap even widens more after controlling for the quality-adjusted publications even while the coefficient on publications is not significant.

TABLE (5) Estimation with Quality adjusted Publications

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Outcome Variable: Total Salary '000 (level)**					
Foreign Born	-7.424**	-6.721**	-6.633**	-6.549**	-7.268**	-7.374**
	(3.076)	(3.163)	(3.106)	(2.940)	(3.378)	(3.216)
QA Cites/Pubs (Field)		0.280	0.360	0.332	0.120	0.091
		(0.488)	(0.562)	(0.485)	(0.530)	(0.457)
Observations	1,423	850	850	844	850	844
R-squared	0.005	0.355	0.360	0.401	0.444	0.475
Panel B	**Outcome Variable: Total Salary (Log)**					
Foreign Born	-0.063***	-0.056**	-0.055**	-0.055***	-0.062***	-0.063***
	(0.023)	(0.022)	(0.022)	(0.020)	(0.023)	(0.021)
QA Cites/Pubs (Field)		0.002	0.003	0.003	0.000	0.000
		(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Observations	1,423	850	850	844	850	844
R-squared	0.006	0.399	0.404	0.446	0.500	0.532
Controls	No	Yes	Yes	Yes	Yes	Yes
Field FE	No	No	No	Yes	No	Yes
University FE	No	No	No	No	Yes	Yes

Note: The control variables are- tenure status, experience, extension and administrative appointment (formal), weekly working hours, the number of journal articles, gender, and quality-adjusted citations per publication. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The dependent variable is a reported total salary in levels and logs adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

[28] We show the descriptive statistics in the Appendix Table 15. The citation level is normalized to 1 for a publication in a field (e.g., plant sciences) that has the average number of citations for a publication in that year. A publication with 10% more citations would have a level of 1. In doing the publication and citation search on WOS, we lose a substantial number of data points due to the confounding of names and an inability to identify the specific scientist in question. Such confounding is especially frequent for Asian names such as Park, Yang, or Kim. Since this confounding is non-random and very likely related to the foreign-born status, we believe that these estimates, while they account for a potential quality bias, introduce another type of bias that is of an unknowable direction.

Secondly, we check whether potential endogeneity or reverse causality in working hours and appointment type might be driving our results. The relationship between salary and working hours could reflect a reverse causality in which a higher salary induces people to work more. To alleviate this concern, we run the same specifications as before but drop the 'weekly working hours' variable. The estimates change slightly, but not economically significant, from -3.9% to -3.2% for the log salary after dropping the weekly working hours variable (Table 6).

TABLE (6) Estimates with Dropping Weekly Working Hours

Outcome Variables:	Salary in '000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign Born	-7.424**	-4.415*	-4.343*	-0.063***	-0.033*	-0.033**
	(3.076)	(2.236)	(2.241)	(0.023)	(0.017)	(0.016)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,423	1,350	1,335	1,423	1,350	1,335
R-squared	0.005	0.363	0.443	0.006	0.398	0.488

Note: Control variables are tenure status, experience, extension appointment (formal) indicator, number of journal articles, gender and survey time effects. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The salary is adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

Further, it is possible that better access to administrative appointments by US-born scientists is driving the wage gap results. For instance, on average US-born scientists are more likely to have administrative appointments compared to foreign-born scientists. These administrative duties may drive up the salary of US-born scientists compared to foreign-born scientists. [29] We check the robustness by restricting our sample to only scientists who do not have any formal administrative appointments. Panel A in Table 7 suggests that the estimates on the log wages are still statistically significant and have almost the same magnitude as the main results in Table 2. Also, we run the specifications by dropping the 'administrative appointment' variable in panel B of Table 7. The results suggest that administrative appointment does not drive the wage gap upward, and even without including administrative appointments, the results are close to the previous estimates and statistically significant.

[29] Note that such a disproportionate movement of US-born scientists into administrative appointments could also be seen as discriminatory, but for the purposes of our robustness check related to selection into administration, we want

TABLE (7) Estimates with Restrictions on Administrative Appointments

Outcome Variable:	Salary in '000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Panel A:	*Restricting to Scientists with No Formal Administrative Appointments*					
Foreign Born	-4.211	-4.642*	-4.475*	-0.042*	-0.041**	-0.041**
	(3.155)	(2.360)	(2.258)	(0.024)	(0.018)	(0.015)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,123	1,073	1,066	1,123	1,073	1,066
R-squared	0.002	0.319	0.418	0.003	0.357	0.471
Panel B:	*Dropping 'Administrative Appointment' variable*					
Foreign Born	-7.424**	-6.292**	-6.133**	-0.063***	-0.047**	-0.047**
	(3.076)	(2.469)	(2.518)	(0.023)	(0.018)	(0.018)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,423	1,347	1,332	1,423	1,347	1,332
R-squared	0.005	0.330	0.411	0.006	0.368	0.458

Note: In panel A, the control variables are tenure status, experience, extension and administrative appointment (formal), the number of journal articles, and gender. In Panel B, we drop administrative appointments, and the remaining covariates are the same. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The dependent variable is reported total salary in levels and logs and adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

Third, we extend our estimation to test if differences in base salaries are a contributing factor to the wage gap. While our previous regressions find evidence of a salary gap in total salary in both levels and logs, we find mixed evidence of a gap in the base salary. Results suggest that base salary does not significantly account for this gap in logs but accounts for a significant gap in levels (Appendix E Table 16). The wage gap in base salary, however, is smaller than the wage gap in total salary. These results may suggest that the additions to base salary from grants, summer teaching, etc., may not be equally available to foreign-born scientists, and this could be a part of the *systemic* discrimination we uncover.

Finally, we also test whether the wage gap results we find are driven by specific parts of the wage distribution with quantile regression. In particular, if our results were driven by

to test whether this is the main driving factor for our results.

important differences in the top or bottom of the wage distribution. The result of estimating our main equation with a quantile regression is shown in the Appendix for the 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ quantiles of the salary distribution (Appendix Table 21). The estimates suggest that the wage gap increases with higher salaries but finds a significant wage gap across all quantiles. This latter result suggests that our estimate of a wage gap is robust to different parts of the wage distribution.

5 Mechanisms

We next unpack potential mechanisms for the salary gap between native and foreign-born scientists. Specifically, we categorize the mechanisms into *direct* and *systemic* parts, as described in Figure 1. To test for the *direct* discrimination, we estimate whether the wage gap is due to different geographic regions in the world that may replicate the commonly studied White and African American or Latin American wage gap in the US. Secondly, we test for the *systemic* discrimination. To do so, we test whether the estimated wage gap is due to *informational* discrimination (signal inflation) or *technological* discrimination (learning in the English language during undergrad, birth country's income level, current academic networks, or formal administrative appointments).[30]

5.1 Direct Discrimination

First, we test for evidence of a wage gap based on the continents of origin.[31] Table 8 shows the estimation results, with the baseline category set as 'North America X US-born.' The results suggest that the wage gap is much higher and statistically significant for scientists from Sub-Saharan Africa (12%) and Latin America & the Caribbean (8.8%). These estimates are consistent with the literature on the wage gap between Whites and African or Hispanic Amer-

[30] We are unable to test other aspects of the theoretical model Figure 1 such as screening discrimination and cultural discrimination due to data limitations. We should also caution the reader here that many of our mechanism tests involve dividing the sample into ever smaller pieces. This results in sample sizes that often do not have the necessary power to detect the true effects in the data.

[31] Since we do not have a big enough number of foreign-born faculty, we cannot test this by country, which might otherwise be preferable.

icans in the general labor market in the US (Trejo, 1997). Meanwhile, we find almost null wage gap results (0.1%) for scientists from South Asia. For other regions, we find notable magnitudes of the wage gap; however, the results are not statistically different from zero (East Asia 3.1%, Europe & Central Asia 3.7%, Middle East & North Africa 10%, North America 4.2%).

TABLE (8) OLS Estimation of salary earned by scientists for the year 2005 and 2015 cross-sectional data, results across regions

Outcome Variables:	Salary in '000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign born X East Asia	-8.635*	-4.414	-3.460	-0.082**	-0.036	-0.032
	(4.973)	(3.979)	(3.875)	(0.033)	(0.026)	(0.024)
Foreign born X Europe & Central Asia	-6.357	-4.514	-5.024	-0.046	-0.028	-0.038
	(5.152)	(3.673)	(3.594)	(0.045)	(0.032)	(0.029)
Foreign born X Latin America & Caribbean	-9.172	-9.036*	-11.558**	-0.076	-0.073*	-0.092**
	(6.903)	(5.076)	(4.771)	(0.061)	(0.044)	(0.036)
Foreign born X Middle East & North Africa	12.298	-14.324	-15.901	0.104	-0.108	-0.105
	(14.924)	(11.974)	(12.047)	(0.125)	(0.101)	(0.097)
Foreign born X North America	-9.023**	-6.570	-7.072*	-0.060	-0.039	-0.043
	(4.305)	(4.211)	(4.175)	(0.037)	(0.036)	(0.036)
Foreign born X South Asia	-6.792	-5.907*	-1.914	-0.049	-0.032	-0.001
	(7.279)	(3.494)	(3.015)	(0.061)	(0.030)	(0.026)
Foreign born X Sub-Saharan Africa	-22.750**	-10.937**	-14.501***	-0.202**	-0.095**	-0.127**
	(9.398)	(4.594)	(4.960)	(0.090)	(0.046)	(0.050)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,417	1,342	1,329	1,417	1,342	1,329
R-squared	0.007	0.375	0.454	0.008	0.410	0.499

Note: Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The baseline category is 'North America X US Born.' The control variables are the same as in Table 2. *** p<0.01, ** p<0.05, * p<0.10.

5.2 Systemic Discrimination

5.2.1 Informational Discrimination

We next test whether the wage gap exists due to a part of systemic discrimination, informational discrimination, where we can measure effects due to *signal inflation.* Signal inflation suggests that one group has some signals that are valued systemically more highly than similar signals from the other group (Bohren *et al.*, 2022). For instance, managers may provide higher wages to US-born scientists based on inflated signals and managers' inaccurate beliefs that US-born scientists are more productive (or produce better quality journal articles) than foreign-born scientists. We test this in Table 9 and Appendix Table 17 based on journal productivity measures as our signal.

In Table 9, we regress total salary on the interaction of foreign-born status and the number of journal articles. The coefficients on this interaction term are never statistically significant, even though its sign suggests that foreign-born scientists earned lower wages than US-born scientists for similar numbers of articles. We conduct a similar analysis in Appendix Table 17 with the quality-adjusted publications, and we find similar results with insignificant negative coefficients. The evidence suggests that signal inflation is not a statistically significant cause of the wage gap we find.

TABLE (9) Estimates on the Foreign-born status X Number of Journal Articles

	Salary '000'		Log Salary	
	(1)	(2)	(3)	(4)
Foreign Born X Journal Articles	-0.152	-0.141	-0.002	-0.002
	(0.265)	(0.268)	(0.002)	(0.001)
Foreign Born	-10.441**	-2.886	-0.074**	-0.007
	(4.919)	(4.065)	(0.034)	(0.024)
Journal Articles (Nos.)	0.847***	0.627***	0.007***	0.005***
	(0.116)	(0.099)	(0.001)	(0.001)
Observations	1389	1332	1389	1332
Controls	No	Yes	No	Yes
Wave FE	No	Yes	No	Yes
Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Control Variables are tenure status, experience, extension, and administration formal appointment indicator, weekly working hours, and gender.

5.3 Technological Discrimination

5.3.1 Due to Past Opportunities

In order to test technological discrimination, we test whether the estimated wage gap exists due to the discrimination in past opportunities for the foreign-born to develop their human capital. First, we look at the differential impacts of the language of instruction at the undergraduate universities attended by the scientists, which divides foreign-born status into Non-English and English bachelors institutions. Table 10 shows that foreign-born scientists who completed their Bachelor's degree from countries where the primary language of academic instruction is other than English have a statistically significantly higher wage gap than scientists who completed their degrees from countries with the primary language of academic instruction as English. The non-English Bachelor's degree scientists earn about $6,053 (column 3) or 4.9% (column 6) lower in annual wages after including control variables and fixed effects. The salary gap for foreign-born scientists with English as a primary language of academic instruction is lower in magnitude and not statistically different from those with US bachelor's degrees. These results suggest that the wage gap may be higher for foreign-born scientists who come from countries with a non-English language of instruction during their undergraduate degrees. These estimates suggest that a form of *technological* discrimination may exist due to the *past* opportunities to develop human capital related to the country of origin. These results are also consistent with other labor market studies that suggest English language proficiency has a significant positive impact on earnings (Tainer (1988), Trejo (1997)). Our results are also consistent with a recent study by Hanson and Liu (2021) suggesting that country of origin has a strong correlation with job choices and the comparative advantage of foreign-born workers in the US and that a benefit exists for workers from countries that are more linguistically similar to the US.

Second, we extend our home-country analysis to test for the *technological* discrimination that happened in the past by including the countries' Gross National Income (GNI), as defined by the World Bank's income categories. We presume countries with low national incomes invest less in education, which may translate into fewer opportunities to develop human capital.

TABLE (10) A: OLS Estimation of the total salary earned by scientists for the year 2005 and 2015 cross-sectional data

Outcome Variables:	Salary in ‘000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Foreign Born (Non-English UG)	-8.361**	-5.631*	-6.053**	-0.076**	-0.046**	-0.051***
	(4.130)	(2.917)	(2.811)	(0.030)	(0.020)	(0.018)
Foreign Born (English UG)	-5.588	-4.988	-4.331	-0.042	-0.034	-0.029
	(4.225)	(3.814)	(3.830)	(0.032)	(0.028)	(0.028)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,417	1,342	1,329	1,417	1,342	1,329
R-squared	0.005	0.363	0.453	0.005	0.398	0.498

Note: Control variables are tenure status, experience, admin and extension appointment (formal) indicator, number of journal articles, and gender. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is ‘University of Wisconsin-Madison’. The dependent variable is the reported total salary in thousand and adjusted for the 2015 CPI inflation. Biology is the omitted field. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

The World Bank documents low-income economies with GNI per capita $1,035 or less in 2019; lower middle-income economies are between $1,036 and $4,045; upper middle-income economies are between $4,046 and $12,535; high-income economies are $12,536 or more.[32] The results are shown in the Table 11, with the base category of ‘US-born X High-income.’ We find consistently negative effects for the foreign-born faculty with similar overall magnitudes. We, however, do not find a consistent pattern for the *technological* discrimination in the past based on the national income of the home country of the faculty. This suggests an overall wealth of a country of origin is not a determining factor.

5.3.2 Due to Current Opportunities

We next test whether the wage gap exists due to technological discrimination in current opportunities for advancement. For instance, foreign-born may be excluded from academic networks, which could be a cornerstone in developing the human capital that may affect current wages. We test the existence of differences in current opportunities using the number of conference and university presentations a scientist has delivered in the past year Table 12. We,

[32] Appendix Table 22 lists the countries with different income groups.

TABLE (11) OLS Estimation of salary earned by scientists for the year 2005 and 2015 cross-sectional data, results with Countries GNI per capita

Outcome Variables:	Salary in '000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign born X High Income	-5.802	-6.424**	-6.070*	-0.040	-0.043*	-0.041*
	(3.726)	(3.197)	(3.199)	(0.028)	(0.023)	(0.023)
Foreign born X Upper Middle Income	-8.585	-0.637	-1.268	-0.093**	-0.017	-0.024
	(5.755)	(4.471)	(4.373)	(0.040)	(0.029)	(0.026)
Foreign born X Lower Middle Income	-7.294	-10.815**	-8.642**	-0.059	-0.081**	-0.064*
	(6.197)	(4.112)	(3.828)	(0.052)	(0.034)	(0.032)
Foreign born X Low Income	-28.455***	-3.310	-3.110	-0.243***	-0.012	-0.019
	(5.182)	(4.399)	(4.546)	(0.057)	(0.024)	(0.046)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,417	1,342	1,329	1,417	1,342	1,329
R-squared	0.005	0.375	0.454	0.006	0.410	0.498

Note: Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The baseline category is 'North America X US Born.' *** p<0.01, ** p<0.05, * p<0.10.

however, find that the foreign-born are about 20-40% more likely to present their research work in various university and conference venues than their US-born counterparts. We do not think that the lack of access to the academic networks that come with presentations at conferences and universities is driving the wage gap. Thus, we do not find evidence for *technological* discrimination due to the current opportunities.

TABLE (12) Number of Presentations Delivered in the Past Year

	US-Born (Mean)	Foreign-Born (Mean)	Difference (US-Foreign)	P-Value
Acad. Conf. Presentations	3.46	4.26	−0.80	0.07
Department Presentations	0.79	1.02	−0.23	0.02
Within Univ. Presentations	0.78	0.84	−0.06	0.54
Other Univ. Presentations	1.25	1.80	−0.55	0.00
Observations	1213	202		

Secondly, we test whether US-born scientists are more likely to have formal administrative appointments, and that might be why they are compensated more than foreign-born scientists. We run a regression with the indicator of formal administrative appointment as a dependent variable (Appendix F Table 19). We find that foreign-born scientists are just 4.7 percent less likely to have a formal administrative appointment with a statistical significance at a 10% level. This mixed result suggests that having administrative appointments is likely not the major explanation of the differences in the wage gap, although it may contribute somewhat.

5.3.3 Cultural discrimination

Several other mechanisms could produce the results we find in our main estimations and be part of *cultural* discrimination. For instance, negotiation over salaries, bonuses, or promotions due to outside options could produce the results we have. Foreign-born scientists may face less bargaining power due to various reasons, including limited job opportunities relative to US-born scientists[33] or a lower probability to search for the outside offers. Studies on the gender wage gap suggest that men and women differ in average propensity to negotiate where women are less likely to negotiate, and that could reduce women's pay (Blau and Kahn (2017), Woolston *et al.* (2021)). Also, studies suggest that women are, on average, more risk-averse (Croson and Gneezy, 2009). These factors could also be applicable to the foreign-born population, who may be less likely to search for outside offers for various reasons, including less proficiency in communication in the English language or uncertainty involved in their visa status. The lack of outside options (either due to not soliciting or a structural inability to search) might reduce foreign-born faculty's bargaining power to ask for raises and bonus salaries.[34] Similarly, it is possible that universities have to incur some costs for the H1B visa applications, which makes departments pay less to the foreign-born. We think the visa cost might exist at the start of the career (Assistant prof.) since after a few years in service (Associate or Full Prof.), the foreign-born scientists may already have obtained either permanent residency or citizenship. We, however, do not find a wage gap for the Assistant Professors, meaning the visa cost is unlikely to explain the wage gap we find (Table 20).

Second, studies on the wage gap between African Americans and Whites in the US suggest that the gap is much higher in soft-skills jobs (persuasion, negotiation, or communication with

[33] Several jobs in academia and the non-academic world, including USDA jobs in the US, are strictly required to have either US citizen or permanent residence to apply.

[34] We also find evidence that a faculty's starting salary is not driving the results we find by limiting our analysis to only the assistant professors. This suggests that our results are not driven by initial negotiations over salaries at the junior professor hiring stage but more likely due to accumulated differences over time.

persons inside and outside of an organization) than in hard-skills jobs (Fan *et al.*, 2017). This mechanism could also be plausible for foreign-born scientists who might find communicating in a foreign language difficult or lack other soft skills due to cultural differences. Our estimates in Table 10 provide evidence for one of these soft skills, i.e., the language during undergraduate training. Similarly, it is possible that foreign-born do not get opportunities to show their soft skills as much as US-born scientists do. The lack of these opportunities is also part of the *technological* discrimination, which is based on the limited opportunities for human capital development due to prior discrimination.

Further, the wage gap may arise due to foreign-born faculty's self-selection into lower-pay faculty positions. Foreign-born faculty may be willing to accept jobs with lower pay if they prefer to join departments with more foreign-born faculty or are more likely to join universities with a lower pay scale. This self-selection into lower-paying jobs might drive their wages downward relative to US-born. Thus, the wage gap might be induced due to the foreign-born scientists' self-selection into lower-paying jobs instead of any labor market discrimination. Our estimates, however, are not consistent with this being the case for foreign-born scientists since our estimates are functionally the same when we include field and university fixed effects, and we have excluded non-tenure-track jobs, which would be the primary venue for scientists to self-select into lower-paying jobs. Further, our investigations show that the wage gap for assistant professors is very small and statistically insignificant (Table 20), which would not be the case if foreign-born scientists were choosing universities or fields with lower initial salaries.

6 Conclusion

We contribute to the literature on labor market discrimination by studying potential wage gaps for foreign-born faculty, using detailed novel survey data that allows us to include faculty characteristics that may affect faculty wages. We find that foreign-born LGU scientists earn about 4 percent ($5,164) lower wages than their native-born counterparts after controlling for the qualities that may affect the earnings. The results are statistically significant in all the specifications. We find using the Kitagawa-Oaxaca-Blinder decomposition that about two-thirds of this gap cannot be explained by the observable characteristics, which suggest a presence of labor market discrimination. We find evidence for *direct* and *technological* discrimination and less or inconsistent evidence for *informational* and *cultural* discrimination against foreign-born scientists. Our results are robust to alternative formulations of the data and econometric techniques.

Our preferred estimate of the wage gap is comparable to a few other estimates found in the literature. Trejo (1997) suggests that in the general population in the US, on average, Whites earn about 11 and 10 percent higher in weekly wages than Mexicans and African Americans, respectively (Trejo, 1997).[35] They also suggest that there are differences in the earnings across various generations of these races and returns to education and experience are higher for Whites compared to Mexicans and African Americans. Our estimates can also be compared with the studies in academia on the gender and racial wage gap. For instance, Chen and Crown (2019) shows that female faculty earn about 5.2% lower salaries than male faculty and Asians/Pacific Islanders earn about 4.8 lower than Whites in annual wages at the Ohio State University. Our results on English language effects are consistent with a recent study (Kreisberg, 2021) showing that the nativity matters, suggesting employers call back college-graduated native-born Latinos twice as frequently as college-graduated immigrant Latinos. The study documents the potential discrimination in hiring by the managers based on the concern about immigrants' language ability and by the organization based on immigrants' deportability (Kreisberg, 2021).

In terms of policy, our estimates suggest that US LGUs have more work to do in improving wage equity to achieve the meritocratic status to which they aspire. Estimates from this paper are crucial for policymakers interested in improving diversity, equity, and inclusion in US academia and could help in the universities' efforts for faculty retention. Our analysis suggests that the foreign-born faculty, on average, produce about 52% more journal articles than the US-born faculty, and they appear to be more qualified based on the observable characteristics. Despite the trappings of a meritocracy, the significant levels of inexplicably lower salaries for

[35] Trejo (1997) studies men aged 18 to 61, using the data of 1979 and 1989 Current Population Survey(CPS)).

foreign-born faculty at US LGUs should raise alarm bells for agricultural and life sciences college administrators as well as those across all major research universities. If university pay is meritocratic and based on observable outputs, we should expect foreign-born to earn higher wages based on their research productivity, but they do not. Some of the latest lawsuits by women faculty suggest that the pay scale in academia is not necessarily only based on merit.[36] Our work suggests that such inequities extend beyond gender potentially to a faculty member's country of origin.

This work is among the first to document the wage gap between US-born and foreign-born faculty. Our findings may, however, be specific to the public land grant universities or colleges of agriculture that are the focus of this work. While we have uncovered some of the potential correlates that seem to invoke these lower salaries, such as native language and country of origin, there are many others to be uncovered. For example, common academic policies that require faculty to obtain outside offers to receive a salary increase have been shown to have negative influences on institutional retention efforts and commitments towards organization (O'Meara, 2015). Such policies may also disproportionately disadvantage foreign-born faculty. Similarly, we find technological discrimination as a potential cause, but this may be more subtle and may be hard to eliminate with policies. We hope future research will delve into these types of effects in a wider academic world as well as uncover more drivers of this wage gap.

[36] See for example, the lawsuit at Rutgers, https://www.nytimes.com/2020/10/15/nyregion/rutgers-equal-pay-lawsuit.html

References

AGARWAL, R., GANGULI, I., GAULÉ, P. and SMITH, G. (2023). Why us immigration matters for the global advancement of science. *Research Policy*, **52** (1), 104659.

AIGNER, D. J. and CAIN, G. G. (1977). Statistical theories of discrimination in labor markets. *Ilr Review*, **30** (2), 175–187.

AKCIGIT, U., GRIGSBY, J. and NICHOLAS, T. (2017). Immigration and the rise of american ingenuity. *American Economic Review*, **107** (5), 327–31.

BARHAM, B., FOLTZ, J. and MELO, A. P. (2019). Academic engagement, commercialization, and scholarship: Empirical evidence from agricultural and life scientists at us land grant universities. In *Economics of Research and Innovation in Agriculture*, University of Chicago Press.

BARHAM, B. L., FOLTZ, J., AGNES, M. I. R., VAN RIJN, J. and BUTTEL, F. (2017). Modern agricultural science in transition: A survey of us land-grant agricultural and life scientists. *Staff Paper 584*.

BASSO, G. and PERI, G. (2020). Internal mobility: The greater responsiveness of foreign-born to economic conditions. *Journal of Economic Perspectives*, **34** (3), 77–98.

BAYER, P. and CHARLES, K. K. (2018). Divergent paths: A new perspective on earnings differences between black and white men since 1940. *The Quarterly Journal of Economics*, **133** (3), 1459–1501.

BECKER, G. S. (2010). *The economics of discrimination*. University of Chicago press.

BLAU, F. D. and KAHN, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of economic literature*, **55** (3), 789–865.

BLINDER, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, pp. 436–455.

BOHREN, J. A., HULL, P. and IMAS, A. (2022). *Systemic discrimination: Theory and measurement*. Tech. rep., National Bureau of Economic Research.

BUDIMAN, A. (2020). Key findings about us immigrants. *Pew Research Center*, **20**.

CAHUC, P., CARCILLO, S. and ZYLBERBERG, A. (2014). *Labor economics*. MIT press.

CARD, D. and LEMIEUX, T. (1996). Wage dispersion, returns to skill, and black-white wage differentials. *Journal of Econometrics*, **74** (2), 319–361.

CHANDRA, A. (2000). Labor-market dropouts and the racial wage gap: 1940-1990. *American Economic Review*, **90** (2), 333–338.

CHEN, J. J. and CROWN, D. (2019). The gender pay gap in academia: Evidence from the ohio state university. *American Journal of Agricultural Economics*, **101** (5), 1337–1352.

CORLEY, E. A. and SABHARWAL, M. (2007). Foreign-born academic scientists and engineers: producing more and getting less than their us-born peers? *Research in Higher Education*, **48** (8), 909–940.

CORNELL, B. and WELCH, I. (1996). Culture, information, and screening discrimination. *Journal of political Economy*, **104** (3), 542–571.

CROSON, R. and GNEEZY, U. (2009). Gender differences in preferences. *Journal of Economic literature*, **47** (2), 448–74.

DE PLEVITZ, L. (2007). Systemic racism: The hidden barrier to educational success for indigenous school students. *Australian Journal of Education*, **51** (1), 54–71.

ESPENSHADE, T. J., USDANSKY, M. L. and CHUNG, C. Y. (2001). Employment and earnings of foreign-born scientists and engineers. *Population Research and Policy Review*, **20** (1/2), 81–105.

FAN, C. S., WEI, X. and ZHANG, J. (2017). Soft skills, hard skills, and the black/white wage gap. *Economic Inquiry*, **55** (2), 1032–1053.

GINTHER, D. K. and HAYES, K. J. (1999). Gender differences in salary and promotion in the humanities. *American Economic Review*, **89** (2), 397–402.

—, SCHAFFER, W. T., SCHNELL, J., MASIMORE, B., LIU, F., HAAK, L. L. and KINGTON, R. (2011). Race, ethnicity, and nih research awards. *Science*, **333** (6045), 1015–1019.

GURYAN, J. and CHARLES, K. K. (2013). Taste-based or statistical discrimination: The economics of discrimination returns to its roots. *The Economic Journal*, **123** (572), F417–F432.

HANSON, G. H. and LIU, C. (2021). *Immigration and Occupational Comparative Advantage*. Tech. rep., National Bureau of Economic Research.

HILMER, C. E. and HILMER, M. J. (2022). Insights from a decade in the life of public ph. d.-granting agricultural economics departments. *Applied Economic Perspectives and Policy*, **44** (4), 2049–2063.

HUANG, D.-W. (2016). Positive correlation between quality and quantity in academic journals. *Journal of Informetrics*, **10** (2), 329–335.

JANN, B. (2008). The blinder–oaxaca decomposition for linear regression models. *The Stata Journal*, **8** (4), 453–479.

KEOHANE, L. W. (1996). Universities, colleges and the equal pay act: The fourth circuit analyzes a salary dispute in strag v. board of trustees. *Campbell L. Rev.*, **19**, 333.

KITAGAWA, E. M. (1955). Components of a difference between two rates. *Journal of the american statistical association*, **50** (272), 1168–1194.

KLINE, P., ROSE, E. K. and WALTERS, C. R. (2022). Systemic discrimination among large us employers. *The Quarterly Journal of Economics*, **137** (4), 1963–2036.

KREISBERG, A. N. (2021). Nativity penalty, legal status paradox: The effects of nativity and legal status signals in the us labor market.

OAXACA, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, pp. 693–709.

ONUCHIC, P. (2022). Recent contributions to theories of discrimination. *arXiv preprint arXiv:2205.05994*.

O'MEARA, K. (2015). Half-way out: How requiring outside offers to raise salaries influences faculty retention and organizational commitment. *Research in Higher Education*, **56** (3), 279–298.

POWELL, J. A. (2007). Structural racism: building upon the insights of john calmore. *NCL Rev.*, **86**, 791.

SHAMBAUGH, J., NUNN, R. and PORTMAN, B. (2017). Eleven facts about innovation and patents. *Economic facts-The Hamilton Project*, p. 1.

STEPHAN, P. E. and LEVIN, S. (2003). Foreign scholars in us science: Contributions and costs. *Science and the University*, **237**.

TAINER, E. (1988). English language proficiency and the determination of earnings among foreign-born men. *Journal of Human Resources*, pp. 108–122.

TREJO, S. J. (1997). Why do mexican americans earn low wages? *Journal of Political Economy*, **105** (6), 1235–1268.

TSUGAWA, Y., JENA, A. B., ORAV, E. J. and JHA, A. K. (2017). Quality of care delivered by general internists in us hospitals who graduated from foreign versus us medical schools: observational study. *bmj*, **356**.

WEBBER, K. L. (2012). Research productivity of foreign-and us-born faculty: differences by time on task. *Higher Education*, **64** (5), 709–729.

WOOLSTON, C. *et al.* (2021). Report exposes power gap at us universities. *Nature*, **592** (7853), 315–316.

Appendices

A Survey Data and sample selection and imputation of missing values

The goal of this nationwide survey, conducted by researchers at the University of Wisconsin-Madison's Program on Agricultural Technology Studies (PATS), is to develop an improved understanding of the state of land-grant agricultural research and graduate training. With grant support from the USDA's Hatch fund, this survey has waves in 2005 and 2015. The surveys were designed to inform academics and policymakers on the process, productivity, and incentives shaping research outcomes in agricultural colleges and scientists' opinions on major issues facing today's land-grant system.

The table below suggests the sample selection and imputation of missing values.

	2005	2015
Random Sample	1,960	2,315
Sample Completed Survey	1,187	711
Drop if No Tenure Track	1,135	691
Drop Cross-missing	1045	644
Final Sample	1045	644

There were a large number of missing values in both surveys. We dropped the observations of the scientists who were not on the tenure track (75 observations in both waves). We also dropped the observations which did not answer almost all the questions used in the analysis. As explained in Appendix B, we imputed the missing values for the main outcome and treatment variables.

B Salary and Foreign-Born Variable

The surveys ask the following question about the salary. "What was your level of compensation from your university in 2014 (2004)? (Please provide total compensation and indicate how much of total compensation came from base salary and other sources.)." The sources include a) base salary, b) stipend for administration, c) additional (internal funds, external funds, summer teaching), and d) other categories. We sum up these four categories to create a total salary variable. The final salary is the highest value between the total salary and the self-reported total compensation. Ideally, we expect these two salary variables to be the same; however, for some observations, we find differences in values, which is why we make the above conversion.

We assume the salary is missing if the salary reported is zero. We multiply the salary variable by 1000 if the salary is reported in 2 or 3 digits assuming scientists reported salary in thousands. We also search the missing, smaller (below fifty thousand USD), and extreme salary values from publicly available faculty databases. We drop six observations where the salary values are greater than five hundred thousand and four observations lower than ten thousand. Finally, we control inflation, and all the values of salary variables are in the 2015 US dollar.

Appendix table Table 24 shows the differences in characteristics of the faculty with non-missing and missing salaries. We find that these two groups are similar in most characteristics; however, foreign-born are more likely to have a missing salary. This non-reporting of the salary by the foreign-born faculty may create bias; nonetheless, which direction the bias goes is unclear. There could be several differences in cultures in different countries discussing salary. However, we cannot come up with theories that could suggest one direction of biases. Secondly, Appendix Table 23 shows the differences in the characteristics of the faculty who reported their salary and the faculty with missing salary information for whom we could find their salary through publicly available data. We find that these two groups are similar in all of their observable characteristics. We, however, could only find the salary information for 12 faculty whose salary information was missing.

To deal with the missing values of the 'Foreign-born' variable, i.e., the country of the bachelor's institute, we search the publicly available profiles of the scientists by google search.

We successfully find the bachelor's institutes of 89 scientists from the 2005 survey and 58 scientists from the 2015 survey.

C List of regions and countries and Faculty

Region	Number of Countries	Countries	No. of Scientists
East Asia & Pacific	9	Australia, China, Japan, New Zealand, Philippines, South Korea, Taiwan, Thailand, Vietnam	65
Europe & Central Asia	19	Belgium, Bulgaria, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Russia, Spain, Sweden, Switzerland, Turkey, UK	53
Latin America & Caribbean	9	Argentina, Brazil, Chile, Colombia, Guatemala, Jamaica, Mexico, Peru, Uruguay	20
Middle East and North Africa	4	Egypt, Iran, Israel, Lebanon	6
North America	2	Canada, US	1248
South Asia	3	Bangladesh, India, Nepal	18
Sub-Saharan Africa	6	Ethiopia, Ghana, Nigeria, Ivory Coast, South Africa, Uganda	7

D Kitagawa-Oaxaca-Blinder decomposition

TABLE (13) Kitagawa-Oaxaca-Blinder decomposition

	Salary in '000 ($)		Log Salary	
VARIABLES	Differential	Decomposition	Differential	Decomposition
Prediction_1	114.5***		11.60***	
	(1.103)		(0.008)	
Prediction_2	106.5***		11.53***	
	(2.659)		(0.0203)	
Difference	7.960***		0.0682***	
	(2.879)		(0.0221)	
Endowments		2.416		0.033*
		(2.742)		(0.020)
Coefficients		5.309**		0.041**
		(2.635)		(0.019)
Interaction		0.234		-0.007
		(2.294)		(0.015)
Observations	1,332	1,332	1,332	1,332

Note: We use threefold decomposition as explained in Jann (2008). *** p<0.01, ** p<0.05, * p<0.10.

E Robustness Checks

TABLE (14) Estimates with Ph.D. university Fixed Effects

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total Salary ('000)	Total Salary ('000)	Total Salary ('000)	Total Salary ('000)	Total Salary ('000)
Foreign Born	-8.244***	-5.431***	-5.385***	-4.993*	-5.070**
	(2.669)	(2.000)	(1.953)	(2.535)	(2.389)
Observations	1,384	1,315	1,301	1,315	1,301
R-squared	0.006	0.365	0.387	0.449	0.466
Foreign Born	-0.071***	-0.042***	-0.042***	-0.037*	-0.038**
	(0.020)	(0.015)	(0.015)	(0.019)	(0.019)
Observations	1,384	1,315	1,301	1,315	1,301
R-squared	0.007	0.406	0.428	0.503	0.518
Controls	No	Yes	Yes	Yes	Yes
Survey Year FE	No	Yes	Yes	Yes	Yes
Field FE	No	No	Yes	No	Yes
Ph.D. University FE	No	No	No	Yes	Yes

Note: The control variables are- tenure status, experience, extension and administrative appointment (formal), weekly working hours, the number of journal articles, gender, and quality-adjusted citations per publication. Standard errors are clustered at the Ph.D. university level. University fixed effects correspond to the Ph.D. university. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The dependent variable is reported total salary in levels and logs and adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

TABLE (15) Descriptive statistics for the Quality Adjusted Publications and Citations

	US-Born (Mean)	Foreign-Born (Mean)
QA Cites/Pubs (Field)	1.03	0.92
Pubs in 5 years(Web Of Science)	9.39	12.97
Cites in 5 years(Web Of Science)	213.91	285.22
Citations Per Pub.	32.05	28.13
QA Pubs(Field)	9.12	11.15
Observations	1400	258

TABLE (16) A: OLS Estimation of the salary earned by scientists for the year 2005 and 2015 cross-sectional data (Base Salary)

Outcome Variables:	Base Salary in '000 ($)			Log Base Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign Born	-6.962***	-3.359*	-4.299**	-0.055**	-0.023	-0.033
	(2.192)	(1.724)	(1.825)	(0.023)	(0.020)	(0.024)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,423	1,347	1,332	1,423	1,347	1,332
R-squared	0.006	0.372	0.477	0.003	0.235	0.325

Note: Control variables are tenure status, experience, extension and administrative appointment (formal), number of journal articles, and gender. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The salary is adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

F Mechanism

TABLE (17) Estimates on the Foreign-born status X Quality Adjusted Publications

	Salary '000'		Log Salary	
	(1)	(2)	(3)	(4)
Foreign Born X QA Citation / Article	-1.292	-1.926	-0.008	-0.012
	(1.873)	(1.668)	(0.016)	(0.014)
Foreign Born	-7.424*	-2.388	-0.069**	-0.029
	(3.926)	(3.822)	(0.028)	(0.024)
QA Citation/ Article	0.836	0.421	0.007	0.003
	(1.050)	(0.816)	(0.009)	(0.007)
Observations	890	861	890	861
Controls	No	Yes	No	Yes
Wave FE	No	Yes	No	Yes
Field FE	No	Yes	No	Yes
University FE	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Control Variables are tenure status, experience, extension and administration formal appointment indicator, weekly working hours, and gender.

TABLE (18) OLS Estimation of the total salary earned by scientists for the year 2005 and 2015 cross-sectional data (with interaction with the experience)

Outcome Variables:	Salary in '000 ($)			Log Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign Born	-34.361***	-0.305	-0.089	-0.307***	-0.013	-0.013
	(4.060)	(2.905)	(3.065)	(0.032)	(0.023)	(0.023)
Foreign Born X Years after PhD	1.646***	-0.246	-0.255*	0.015***	-0.001	-0.001
	(0.203)	(0.162)	(0.148)	(0.002)	(0.001)	(0.001)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	1,415	1,350	1,335	1,415	1,350	1,335
R-squared	0.031	0.364	0.444	0.039	0.398	0.489

Note: In panel A, the control variables are tenure status, experience, administrative appointment (formal), number of journal articles, and gender. In Panel B, we drop administrative appointments, and the remaining covariates are the same. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The dependent variable is reported total salary in levels and logs and adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

TABLE (19) OLS Estimation of the Indicator of Formal Administrative Appointment

VARIABLES	(1) Admin. Appointment (Y/N)	(2) Admin. Appointment (Y/N)	(3) Admin. Appointment (Y/N)
Foreign Born	-0.066***	-0.052*	-0.047*
	(0.024)	(0.026)	(0.026)
Controls	No	Yes	Yes
Survey Year FE	No	Yes	Yes
Field FE	No	No	Yes
University FE	No	No	Yes
Observations	1,630	1,551	1,533
R-squared	0.004	0.028	0.119

Note: The control variables are tenure status, experience, extension appointment (formal), number of journal articles, and gender. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

TABLE (20) A: OLS Estimation of base salary earned by Assistant Prof.

Outcome Variables:	Base Salary in '000 ($)			Log Base Salary		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Foreign Born	2.775*	0.777	-0.961	0.036*	0.011	-0.014
	(1.611)	(1.702)	(2.008)	(0.020)	(0.020)	(0.024)
Controls	No	Yes	Yes	No	Yes	Yes
Survey Year FE	No	Yes	Yes	No	Yes	Yes
Field FE	No	No	Yes	No	No	Yes
University FE	No	No	Yes	No	No	Yes
Observations	275	261	258	275	261	258
R-squared	0.010	0.128	0.521	0.010	0.113	0.524

Note: Control variables are tenure status, experience, extension and administrative appointment (formal), number of journal articles, and gender. Standard errors are clustered at the university level. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The salary is adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

G Other Tables

TABLE (21) Quantile Regression

Outcome Variables:	Total Salary in '000 ($)			Log Total Salary		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	q25	q50	q75	q25	q50	q75
Foreign Born	-4.769***	-4.517***	-6.089***	-0.044**	-0.047***	-0.054**
	(1.255)	(1.440)	(2.025)	(0.021)	(0.018)	(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,332	1,332	1,332	1,332	1,332	1,332

Note: Quantile regression uses the quantiles of the conditional distribution in the form of the linear function of the exogenous variables. Control variables are tenure status, experience, extension and administrative appointment (formal), number of journal articles, and gender. Bootstrap standard errors. University fixed effects correspond to the 52 land-grant universities. The baseline university for the university fixed effects is 'University of Wisconsin-Madison'. The salary is adjusted for the 2015 CPI inflation. Biology is the omitted field. *** p<0.01, ** p<0.05, * p<0.10.

TABLE (22) List of countries and GNI per capita

Countries	Income-Group
Australia, Belgium, Canada, Chile, Czech, Denmark, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Poland, South Korea, Spain, Sweden, Switzerland, Taiwan, UK, Uruguay, US	High income ($12,536 or more)
Argentina, Brazil, China, Colombia, Jamaica, Mexico, Peru, Russia, South Africa, Turkey	Upper-middle income ($4,046 to $12,535)
Bangladesh, Egypt, Ghana, India, Nigeria, Philippines, Vietnam	Lower-middle income ($1,036 to $4,045)
Nepal, Uganda	Low income ($1,035 or less)

TABLE (23) Faculty characteristics with missing and non-missing salary

	(1)	(2)	(3)
Variable	Non-Missing Salary	Missing Salary	Difference
Foreign Born	0.144	0.226	0.081***
Tenured	0.808	0.798	-0.010
Experience	20.044	21.150	1.106
Extension Appoint.	0.325	0.355	0.030
Administration Appoint.	0.198	0.194	-0.004
Weekly Work (hrs.)	53.543	53.035	-0.507
Journal Articles	13.679	13.931	0.253
Gender	0.772	0.731	-0.042
Observations	1,465	258	

Note: Results are the difference in means of the characteristics for faculty with non-missing and missing salary. *** p<0.01, ** p<0.05, * p<0.10.

TABLE (24) Faculty characteristics of reported salary and salary that we found online

Variable	(1) Reported Salary	(2) Found Salary	(3) Difference
Total Salary (000)	113.014	118.830	5.817
Log Total salary	11.591	11.520	-0.071
Foreign Born	0.145	0.083	-0.061
Tenured	0.807	0.833	0.026
Experience	20.043	20.167	0.124
Extension Appoint.	0.325	0.250	-0.075
Administration Appoint.	0.198	0.167	-0.032
Weekly Work (hrs.)	53.536	54.333	0.797
Journal Articles	13.668	14.917	1.249
Gender	0.772	0.750	-0.022
Observations	1,453	12	

Note: Results are the difference in means of the characteristics for faculty who reported their salary and faculty for whom we found the salary information with the online search. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.