Differential retention contributes to racial/ethnic disparity in U.S. academia

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Abstract

Several racial and ethnic identities are widely understood to be under-represented within academia, however, actual quantification of this under-representation is surprisingly limited. Challenges include data availability, demographic inertia and identifying comparison points. We use de-aggregated data from the U.S. National Science Foundation to construct a null model of ethnic and racial representation in one of the world's largest academic communities. Making comparisons between our model and actual representation in academia allows us to measure the effects of retention (while controlling for recruitment) at different academic stages. We find that, regardless of recruitment, failed retention contributes to mis-representation across academia and that the stages responsible for the largest disparities differ by race and ethnicity: for Black and Hispanic scholars this occurs at the transition from graduate student to postdoctoral researcher whereas for Native American/Alaskan Native and Native Hawaiian/Pacific Islander scholars this occurs at transitions to and within faculty stages. Even for Asian and Asian-Americans, often perceived as well represented, circumstances are complex and depend on choice of baseline. Our findings demonstrate that while recruitment continues to be important, retention is also a pervasive barrier to proportional representation.

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Abstract

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Keywords

diversity, ethnicity, race, scientific workforce, under-representation in science

Introduction

Large segments of society are under-represented in academic Science and Engineering (S&E) [1,2]. For example, in 2017, 12% and 0.7% of the general U.S. population were Black and American Indian/Alaskan Native respectively, compared to 10% and 0.5% of students graduating with a bachelor's degree, and 4% and 0.2% of tenured faculty [3]. Critically, the groups that are most under-represented in S&E are the fastest growing in the U.S. population [2].

Understanding and addressing mis-representation (representation that differs from a baseline expectation of proportional representation) within academia is important for numerous reasons. First, mis-representation of groups can indicate that access is not equitably distributed and that some groups have been excluded from academia [4,5]. Second, mis-representation can mean that some of the best minds are excluded from academia [4]. Furthermore, because members of under-represented groups across various axes (gender, race, experience) can produce innovative work at higher rates than those of well represented groups [6], current mis-representation may be lowering overall academic productivity. Third, although researchers individually have unique perspectives (and thus biases), diversity across researchers can minimize collective bias and improve objectivity [4]. Finally, representation in academia can facilitate a virtuous cycle: academics, as instructors and thought-leaders, are often role-models to those considering professional scholarship, so a diverse academic environment can help draw talent from all segments of society/backgrounds [7].

A critical step in addressing mis-representation is determining where and when disparities occur. Historically, U.S. academia has been primarily composed of White scholars with under-represented minorities systematically excluded from the late 1800s through to the 1970s [2] . Although U.S. academia (especially at the undergraduate stage) has become more diverse in the past 40 years, most racial/ethnic groups are still under-represented compared to the general U.S. population [2]. Mis-representation at any stage in academia can be driven by recruitment into -- as well as retention within -- that stage [8,9]. Past efforts to increase under-represented groups have primarily focused on recruitment into the undergraduate stage, and have seen limited success [10]. Increasingly there is a call for addressing factors that shape retention of under-represented groups in academia post-undergrad [9–12].

Despite its widespread existence and importance, mis-representation across academia is challenging to study for a number of reasons. First, defining an appropriate baseline for racial/ethnic minorities can be challenging. Critically, U.S. demographics are continuously changing [13], and yet academic training is a multi-decade process, which means comparisons of current academia to current census data are ignoring a potential lag effect. This heterogeneity obscures any clear targets for what diversity 'should' look like. Second, data are often lacking, either on the number of individuals (e.g., low sample size of under-represented groups) or over time (e.g., long enough data to look for temporal trends). Thus, many studies that aim to test for race/ethnicity-based differences often lack the sample size or statistical power [14]. Finally, analyses can only be as disaggregated as the categories underlying the data. Studies often lump together several minority groups into a broad 'under-represented minority' (URM) category [15].

Here, we combine two approaches to overcome these hurdles and quantify mis-representation across racial/ethnic groups and across academia. We leverage large national datasets collected by the United States National Science Foundation (NSF) on the racial and ethnic composition of all U.S. Science and Engineering academics from undergraduate students to tenured professors, spanning 25 years for students and faculty (seven years for postdocs). We generate a baseline expectation for the racial/ethnic composition of academia by developing a null model [16,17] that dynamically accounts for historical changes in racial/ethnic compositions. Using these two tools, first, we quantify what racial/ethnic composition we would expect to see in academia, in a scenario where individuals of each race/ethnicity were equally likely to have an academic career (the null model). Second, we determine to what degree the actual representation of each racial/ethnic group in each stage of academia (e.g., doctoral student, professor) is higher, equal, or lower than that predicted by the null model. This approach allows us to control for recruitment and measure the effects of differential retention. Finally, we show that the deviance from the null model differs by racial/ethnic group and by academic stage. Our results provide a novel perspective on the status of diversity in academia, the critical role of retention, and the challenges academics continue to face.

Methods

We constructed a model of academia (Fig. 1) in the United States as a series of stages with inputs (from the previous stage) and outputs (to the next stage or move out of academia). We parameterized our model structure with data collected by NSF for Science and Engineering fields (Biological and agricultural sciences; Earth, atmospheric, and ocean sciences;

Mathematics/computer sciences; Physical sciences; Psychology; Social sciences; Engineering) for the years 1991-2016. We used our model to generate simulated ‘predictions’ of the representation we would expect of each federally categorized racial/ethnic group (Asian, Black/African-American, Native Hawaiian/Pacific Islander, Hispanic/Latino, American Indian/Alaskan Native, White, More Than One Race) in each stage of academia under the null assumption of no race/ethnicity-based differences in retention. With our approach, we can control for recruitment at one stage of academia and measure the effects of retention to future stages. That is, what ‘should’ representation in academia look like if there were no race- or ethnicity-based differences in tendency to move between stages or out of academia, and how does actual representation differ?

Data

We used data compiled by the National Science Foundation (NSF) on the structure of academia (number of scholars in each academic stage, time spent in each stage), the racial/ethnic composition of scholars at each stage, and the approximate age distribution of scholars in each stage (see Supplementary Material section 1, Figs. S1-S5, Tables S1-S2). Data on the number of bachelors and PhD degrees came from the NSF reports on Science and Engineering Degrees [18] and Women, Minorities, and Persons with Disabilities (WMPD) [3], data on the number of graduate students and postdoctoral scholars came from the NSF Survey of Graduate Students and Postdoctorates in Science and Engineering [19], and data on the number of assistant and tenured professors came from the 2019 NSF report on Science and Engineering Indicators [20]. The length of time in each stage came from the 2018 NSF report on Science and Engineering Indicators [21] for graduate students, the NSF report on Postdoc Participation of Science, Engineering, and Health Doctorate Recipients [22] for postdocs and the integrated data system Scientists and Engineers Statistical Data System (SESTAT) for faculty.

Data on the racial/ethnic composition of undergraduate and PhD students as well as assistant and tenured professors came from the WMPD reports [3]. Data on postdoctoral researchers (2010 onward) came from NSF Surveys of Graduate Students and Postdoctorates in Science and Engineering [23], and data prior to 2010 was estimated as the average of representation in the graduate student and assistant professor stages. The student data in the NSF WMPD reports only includes racial/ethnicity data for U.S. citizens and permanent residents. To account for international students, we used the NSF reports on Doctorate Recipients from U.S. Universities [23] for data on the proportion of permanent vs temporary resident PhD recipients and the racial/ethnic composition of temporary resident PhD recipients. Count data on the number of scholars of each racial/ethnic group were converted to proportions and data were smoothed with a 5-year window moving average.

Finally, we used NSF data on the approximate age range of scholars at each stage by pulling data from the SESTAT database and determining the most representative ages of each stage. These age ranges were: 15 to 24 years old (undergraduate students), 20 to 29 (graduate students), 25 to 39 (Ph.D. recipients), 25 to 44 (postdoctoral researchers), 30 to 49 (assistant professors) and 35 to 59 (tenured professors). We used this data to determine which subset of the general population we should compare each academic stage to. We determined the racial composition of the age class corresponding to each academic stage based on data from the National Center for Health Statistics and the U. S. Census Bureau [13].

Model structure

We constructed a model of academia as a series of stages (Fig. 1), building on previously developed methods [16]. We considered five academic stages: undergraduate students, graduate students, postdoctoral researchers, assistant professors and tenured professors. We used the time spent in each stage to estimate a turnover rate for that stage which, in combination with the number of scholars in each stage, gave us an estimate of the number of scholars that would have either transitioned from one stage to the next or transitioned outside of the system for each year (see Supplementary Material section 2, Fig. S6, Table S3).

Model simulation

We simulated the flow of scholars through our null model of academia over time, assuming there was no racial/ethnic bias in movement patterns of scholars (see Supplementary Material section 3, Fig. S7-S9, Tables S3-S4). We initialized model simulations in a given starting year t_0 with NSF data on the racial/ethnic composition of each stage in that same year. For each year going forward, we fed in NSF data on racial/ethnic composition at a particular stage (e.g., undergraduate students), and used our model to predict the racial/ethnic composition at the other stages (e.g., graduate students). We simulated the model under four scenarios (based on turnover rate and turnover type) to capture uncertainty in the details of transitions for faculty. For turnover rate, we considered ‘slow’ (8 years spent as an assistant professor and 30 years as a tenured professor) and ‘fast’ (5 years as assistant and 20 years as tenured) turnover rates. For turnover types, we considered ‘supply’ (assistant professors achieved tenure at a specified rate, and excess tenured professors were retired accordingly), and ‘demand’ (tenured professors retired at a specified rate and excess assistant professors becoming tenured left academia) scenarios. To consider the overall effects of retention, we initialized the model by setting the number of scholars in each class to the data from 1991 (t_0 = 1991), and fed in racial/ethnic data at the undergraduate stage (and at the PhD stage for international students, the earliest stage this data was available; see above) each year until 2016, and measuring simulated output at all other stages, for each of the four scenarios above. To consider the effects of retention within each stage of academia, we again initialized the model with 1991 data, but fed in racial/ethnic data at each stage and measuring the model output at the next stage (e.g, feed in graduate student data, measure postdoc data), and then took the average output across each of the four scenarios.

Testing model predictions

To test our null hypothesis that there is no racial/ethnic bias in transitions within academia, we compared the racial/ethnic composition predicted by our null model to the actual composition from NSF data. To quantify relative representation, we used metric

$$\theta_i(t,k) = \frac{\hat{f}_i(t,k) - f_i(t,k)}{\hat{f}_i(t,k)} \qquad [1]$$

where $\hat{f}_i(t,k)$ and $f_i(t,k)$ are the observed and simulated (respectively) fraction of individuals in stage i at time t from racial/ethnic group k (see Supplementary Material, section 4). To measure confidence in our results, we considered a 5% increase or decrease in each $\hat{f}_i(t,k)$ and $f_i(t,k)$ values, recalculated $\theta_i(t,k)$ for these, and mark this range of values with confidence intervals.

Results

First, we considered the effects of retention across a full academic career while controlling for recruitment at the undergraduate stage (Fig. 2). Our null model predicts that representation of scholars in most groups is still changing over time, indicating that parity would not yet have been reached, even under a null model (Fig. 2 and Fig. S7, solid coloured lines). We also find that increasing representation of non-White scholars (driven by changing undergraduate demographics) does not come with a decrease in the absolute number of White scholars; rather this is driven by an overall increase in the absolute number of scholars in each stage (Fig. 3). Our null model predicts that representation of White scholars would be lower than levels actually observed in academia while all other groups (including Asian scholars, who are not traditionally considered an under-represented minority [3]) would be higher than observed (Fig. 2, coloured lines versus dots). These deviations indicate that race/ethnicity-based biases occur after graduating with a science or engineering undergraduate degree, suggesting differential retention within academia.

Second, we can compare our model results to census data, allowing us to consider the effects of recruitment, although indirectly. Here, we compare model predictions (which assume recruitment at the undergraduate stage and control for retention at other stages) with the U.S. general population census data (which included individuals who both were and were not ‘recruited’ into academia). Our null model predicts that, even if retention were the same across racial groups, representation of White and Asian scholars in academia would still be higher than in the U.S. general population while all other groups would still be lower (Fig. 2 and Fig. S7, black lines).

The differences between the racial composition of the null model and the general population indicate differential recruitment into academia, showing that there are race/ethnicity-based biases in entering academia. Intriguingly, taken together, our results indicate that Asian scholars can be considered overrepresented in U.S. academia if the baseline for comparison is the U.S. general population, but can be considered under-represented in U.S. academia if the baseline for comparison is student degree recipients. This result is driven by the fact that many U.S. PhD recipients are international students (temporary residents; Fig. S5a-b), and that 60+% of these students are Asian scholars (Fig. S5d).

Third, we considered the effects of retention within each stage of academia (Fig. 4). Here, we control for recruitment at each stage of academia and measure the effects of retention to each subsequent stage. We quantify relative representation (driven by retention) as a metric θ, the deviance from the null model in representation, where positive values ($\theta > 0$) indicate a group has higher representation than the model predicts and negative values ($\theta < 0$) indicate a group has lower representation than predicted. We find that θ varies by racial/ethnic group and by stage transition within academia (Fig. 4). The transition from undergraduate degree to graduate student is captured well by the null model ($\theta \approx 0$, i.e., little differential retention at this transition). The biggest loss in representation (lowest retention) for Native American/Alaskan Native and Hawaiian/Pacific Islander scholars occurs in the transition to being a faculty member and staying within the faculty (Fig. 4). In contrast, the biggest loss in representation for Asian, Black and Hispanic scholars occurs in the transition from graduate student to postdoctoral researcher, and is the worst for Black representation (Fig. 4). Although temporal trends over 15 years show the system is approaching parity ($\theta \rightarrow 0$) for some race/ethnicity and stage combinations, deviance from parity is actually increasing for Black, Hawaiian and Native scholars in faculty positions (Fig. S8).

Discussion

The novelty of our work is three-fold: we provide new findings on the patterns, causes, and consequences of misrepresentation racial/ethnic groups within US Science and Engineering academia. In terms of patterns, we present one of the most extensive assessments of misrepresentation, by contrasting one of the world's largest public datasets on demographics of scholars with a null model of representation. Past studies have demonstrated that some racial/ethnic groups are misrepresented at some stages [15,24], or within some disciplines [17], however it was not previously clear to what extent these observations scaled up to affect cross-discipline patterns at the national level. Here, we quantitatively show that they do. The breadth and resolution of our analysis allows us to separate effects by racial/ethnic group (rather than lumping all non-White scholars together, as past studies have done), thus demonstrating that retention at each academic stage differs by race/ethnicity. The representation patterns that we uncover also highlight the importance of explicitly defining a baseline against which to measure representation. For example, we find that although Asian representation in academia is higher than in the general U.S. population, it is simultaneously lower than would be predicted based on student demographics. Much of the racial/ethnic diversity in PhD recipients derives from immigration rather than retention of minority scholars (Fig S5e-f). Most international PhD students are from India and China [25] and 70% of foreign-born PhD doctorates stay in the U.S.

after receiving their degree [26], which fit with our finding that non-U.S. born Asian scholars are a critical input into U.S. academia (Fig. S9).

In terms of causes, we demonstrate definitively that failed retention of Black, Indigenous, and Hispanic scholars is a substantial contributor to misrepresentation in academia. We find that although representation of non-White scholars in academia is increasing, it is doing so slower than expected under our null model predictions. In other words, although recruitment into academia at the undergraduate stage is numerically the largest driver of representation, it alone does not explain the lack of parity. Our findings show that training diverse students is not enough; there is a substantial drop in racial/ethnic representation between students (graduate and undergraduate) and researchers (postdocs and faculty), and bias in retention appears to be increasing in some cases (Fig. S8, transitions to faculty for Black and Native scholars and within faculty for Native scholars). Overall, these results provide quantitative evidence to support calls for increased focus on inclusion/retention along with recruitment [9–12]\cite{whittaker2014, bach2006, callahan2017, puritty2017} and show that neither time, nor simple pushes to increase recruitment are panaceas to this societal challenge.

The patterns and causes discussed above have a number of consequences. First, failed retention in academia is most problematic for representation of Black and Indigenous scholars (Fig. 4); thus, paths forward must draw on understanding the specific cultural context of these scholars as well as the challenges and discrimination that they face within academia [27–29]. Second, our finding that the most problematic transitions within academia vary by race and ethnicity indicates that different racial/ethnic groups need support at different stages [8]. Thus, policy change to address misrepresentation within academia must account for the interactive effects between race/ethnicity and academic stage; a one-size-fits all solution is insufficient. Finally, it is clear that faculty do not reflect the diversity of undergraduate students., limiting the number of students who can ‘see themselves’ represented among their instructors [7].

There are three key future directions that could build on our study. First, future work could use different null models to test factors acting prior to undergraduate degrees (K-12 education, or within the undergraduate years), or to consider variants on the career trajectory we considered (e.g., removing the postdoctoral stage, allowing for time spent in industry jobs between academic positions, or more explicitly modelling variation in the time spent in different stages). Second, our approach would be greatly complemented by the collection and analysis of longitudinal datasets (tracking the same individuals over time)[1]. For example, as definitions of race/ethnicity change over time, scholars may move between race/ethnicity categories [30]. Non-U.S. born scholars similarly change categories: they are not counted by race/ethnicity while they are temporary residents (e.g. as students; [31]), but ‘become’ minorities with permanent residency. Longitudinal data would also help distinguish between the possible scenarios of high input and low retention versus low input and high retention. Third, future work could explore our research questions at different scales. One could ask whether representation of scholars by race/ethnicity varies across fields within S&E as is true for gender [16]. For example, Asian scholars are under-represented in Ecology even as they appear overrepresented in S&E [32]. The category ‘Asian’ is incredibly broad, masking a huge amount of diversity itself [33]; different scholars having very different experiences based on cultural background and history [34]. Adopting an intersectional

1 Personal correspondence with Karen Hamrick (NSF-National Center for Science and Engineering Statistics) on January 5, 2021, indicating that longitudinal versions of the NSCG and SDR data are in development and are planned for future release.

perspective will almost certainly change our understanding of representation [35], with many axes of identity (e.g. economic background, religion, disability, sexual orientation, gender, etc) also impacting recruitment and retention [36]. Women of colour are especially likely to face distinct challenges that can be masked by considering gender and race/ethnicity separately [37]. Finally, future work could attempt to project how long it would take to reach equity in the future under varying social and policy scenarios. While this may seem like a simple extension of our model, a simplistic forecast would be misleading at best, as predicting future dynamics requires assumptions about future changes in academic labour pools and US demographics. However, our model can be adapted to provide a framework for evaluating different future scenarios and policy outcomes.

How then do we solve current mis-representation in academia? To create solutions we must draw on social, cognitive and psychological frameworks to understand the factors contributing to mis-representation [9,38], to explicitly address the alignment of cultural identities with STEM identities [28] , and to guide both intervention programs and their metrics of success [39]. It is also critical to recognize that a low relative representation in a stage can be due to problems that accumulated across earlier stages [40]; thus low representation at a particular stage may not be best served by intervention at that or the previous stage alone. Measuring whether these interventions are working will require that demographic data is collected consistently and transparently [41]. Where possible, data should be disaggregated to fully understand patterns. For example, motivational factors can vary by racial/ethnic group [27] and likely also differ with time spent in the US, especially in formative years [42] and with socio-economic and cultural background. Data collection that consistently accounts for both race/ethnicity and nativity/residence time will result in clearer understanding than current methods based on residency categories. Finally, recruitment and retention must both be addressed [43]. Recruitment into academia is not the only problem and thus a focus on increasing numbers of minority undergraduates is not enough [9]. Individuals in under-represented versus well-represented groups can have different reasons for pursuing career avenues and thus potentially different reasons for leaving academia [44].

Although many academics wish to think of academia as unbiased and point to biases in earlier stages and recruitment into academia itself as driving disparities in academia [8,10], our findings indicate this is not the case: retention within academia is critical too. Furthermore, recruiting under-represented scholars into a system (academia) that is not equipped to retain them is likely a set up for all-around failure. These findings show that neither time, nor simple pushes to increase recruitment are panaceas to this societal challenge. Models identifying the impacts and extent of these biases (such as we have presented here) are a necessary part of developing and evaluating solutions. However, we should not lose sight of the fact that numbers in our model represent real people. Much work remains to address these representation problems in order to build an academia that truly reflects and realizes the potential of the society it aims to serve.

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Data, code and materials

No new data was collected for this study, all data used is publicly available and linked to from the supplementary information. The model code and results generated for this study are available via GitHub (https://github.com/allisonkshaw/academiamodel) and will be deposited in Data Dryad upon manuscript acceptance.

Authors contributions

Conceptualization (AKS, NS, DES); Methodology and Analysis (AKS, CA, JMC, MV, YY, NS, DES); Software (AKS); Data collection, compilation and curation (AKS, CA, JMC, MV); Writing – Leading (AKS); Writing – Supporting (CA, JMC, TLM, MV, YY, NS, DES); Visualization (all authors); Project Leadership (AKS).

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Figure 1. Model schematic of academia as a series of stages, where individuals either move to the next stage, or move outside of the system (academia) to other career paths. Black text indicates NSF data, blue text indicates estimated data. The stages for graduate students (*G*) and tenured professors (*T)* are split into sub-partitions (grey lines), representing pre- and post-exam stages for graduate students and equally spaced intervals for tenured professors.

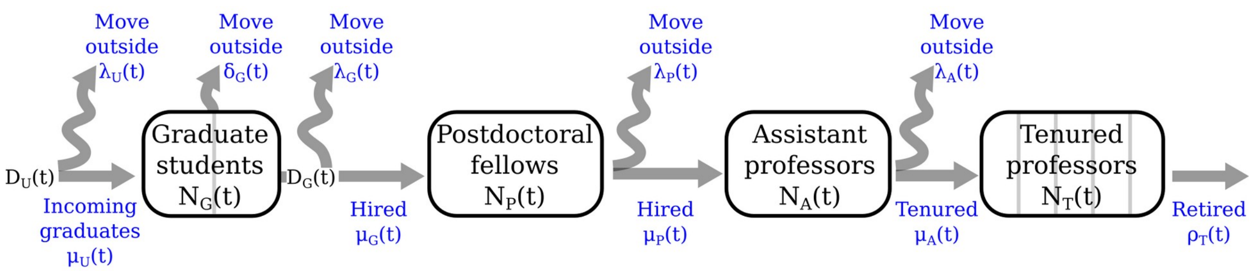


Figure 2. The representation (i.e., the proportion of scholars in that stage that identify as that race or ethnicity) of the four largest American race/ethnicity categories (rows) in each academic stage (columns) over time comparing: null model predictions (coloured solid lines), academia data (dots are raw data, dotted lines are smoothed data), and census data for the U.S. overall population (black solid lines) and US age-specific population (black dashed line). Mismatch between model and academia data indicate race/ethnicity-based biases of retention within academia, mismatch between model and census indicates race/ethnicity-based biases in recruitment into academia. Postdoc data before 2010 was unavailable, was estimated as the average of the graduate student and assistant professor data, and is greyed out in the figure. (See Figure S7 for additional race/ethnicity categories)

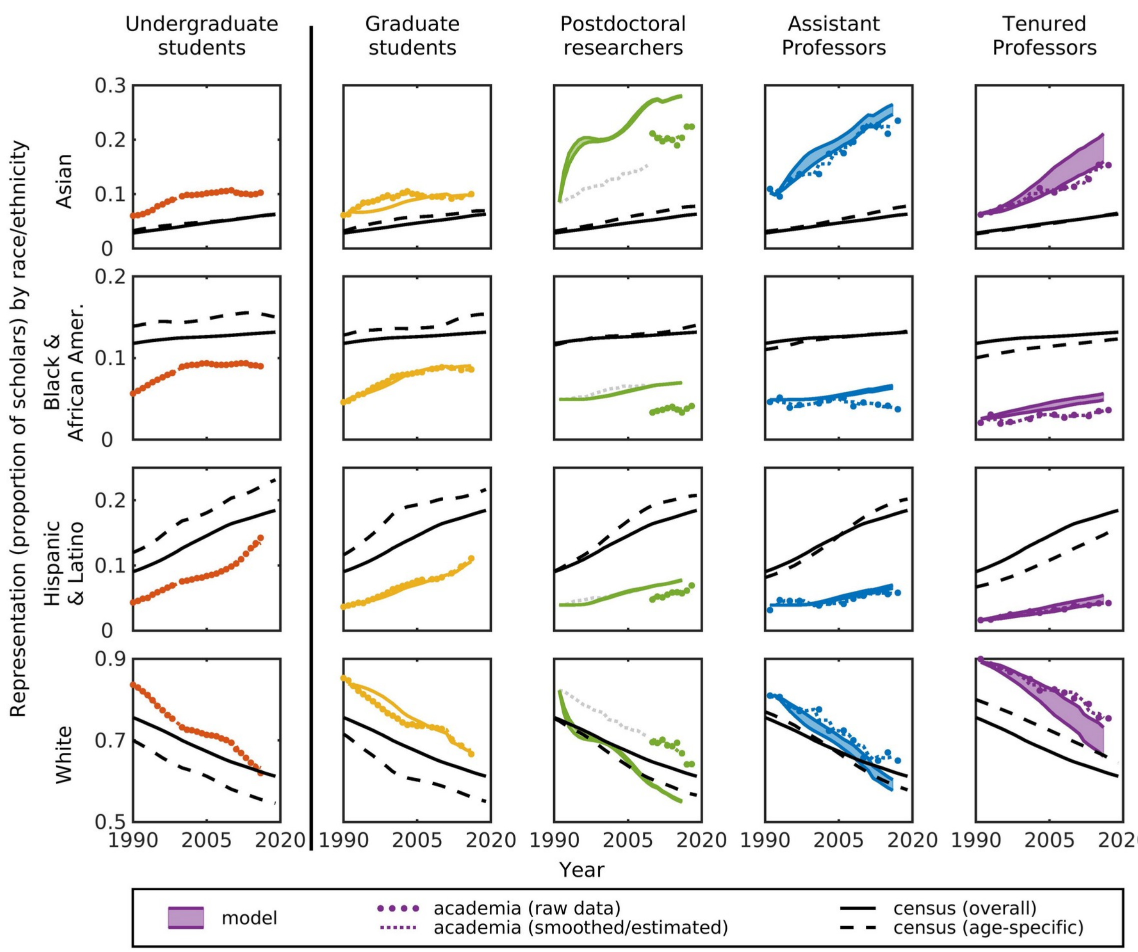


Figure 3. The absolute number (in thousands) of scholars that are White (solid black line) and all other races/ethnicities (solid grey line) in each stage (panel) over time.

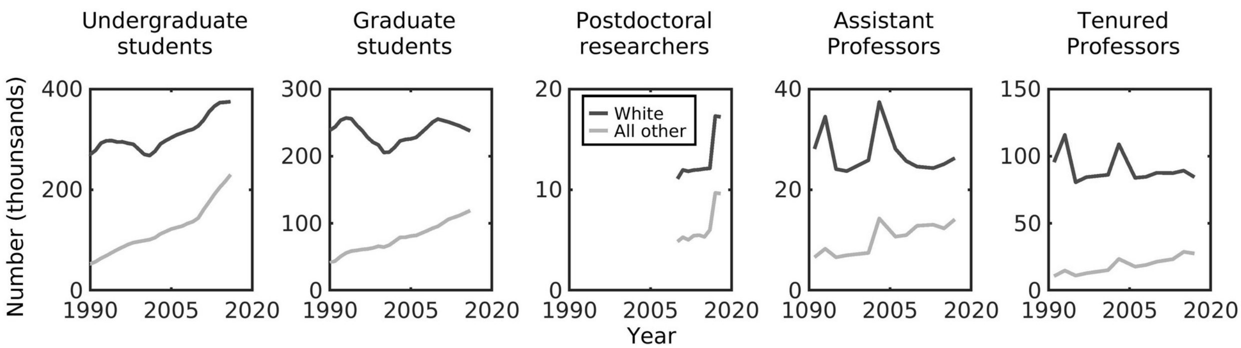
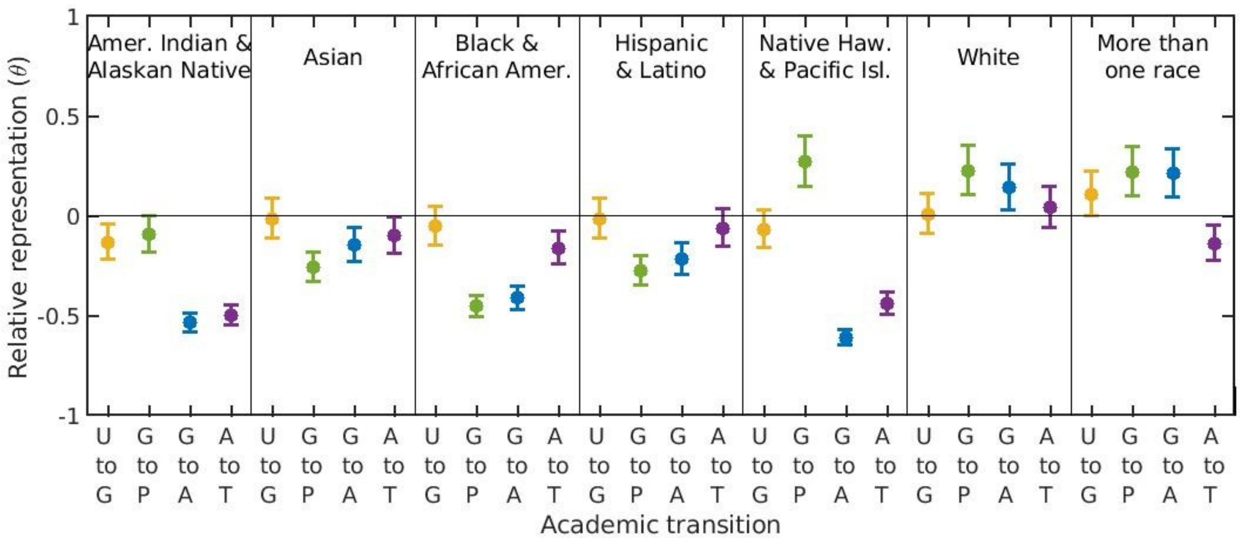


Figure 4. The relative representation (θ [eqn 1]; comparing data and the null model) over 15 years (1991-2016) of each race/ethnicity category through one of the transitions within academia: undergraduate to graduate student (*U* to *G*), graduate student to postdoctoral researcher (*G* to *P*) or to assistant professor (*G* to *A*), and assistant to tenured professor (*A* to *T*). Positive or negative values indicate a race/ethnicity category faces correspondingly positive or negative bias across that transition. Confidence intervals mark the range of θ values that result from a 5% increase or decrease in representation in either the data or model.



Supplementary Material for

Differential retention contributes to racial/ethnic disparity in U.S. academia

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1 Data

We used three broad types of data from the National Science Foundation (NSF) in our work: (i) data on the structure of academia (number of scholars in each academic stage, time spent in each stage), (ii) data on the racial/ethnic composition of scholars at each stage, and (iii) data on the approximate age range of academics. Whenever there were multiple versions of the same data availabile for a given year (e.g., in different versions on the same report, or when classifications changed within a timeseries), we used the most recent data for a given year. We limited our analysis to the period 1991-2016 where almost all data was available (except for racial/ethnic data on postdoctoral researchers which was only available for 2010 onward).

1.1 Structural Data

The structural data we used consisted of timeseries of the number of bachelors and PhD degrees awarded, the number of enrolled graduate students, and the number of employed postdoctoral researchers, assistant professors and tenured professors, as well as estimates of the length of time spent as a graduate student, postdoctoral researcher, assistant professor and tenured professor. Data on the number of bachelors and PhD degrees came from the NSF reports on Science and Engineering Degrees (1), and Women, Minorities, and Persons with Disabilities (WMPD) (2), data on the number of graduate students and postdoctoral scholars came from the NSF Survey of Graduate Students and Postdoctorates in Science and Engineering (3), and data on the number of assistant and tenured professors came from the NSF report on Science and Engineering Indicators (4). The length of time in each stage came from the NSF report on Science and Engineering Indicators (5) for graduate students, the NSF report on Postdoc Participation of Science, Engineering, and Health Doctorate Recipients (6) for postdocs and the integrated data system Scientists and Engineers Statistical Data System (SESTAT) for faculty. The specific sources for all structural data are given in Table S1 and in "Data Report Details" Section below, and the timeseries of structural data are plotted in Figure S1. Missing data were linearly interpolated; for example, faculty data was only collected approximately every two years, and undergraduate data was missing for the year 1999 (data with interpolation given in Figure S2).

1.2 Race/Ethnicity Data

The racial/ethnicity data we used consisted of timeseries data for the number of earned bachelors degrees, enrolled graduate students, and employed postdoctoral researchers, assistant professors and tenured professors by race/ethnicity. From 1991 to around 2010 NSF used five groups for race/ethnicity: 'White', 'Asian or Pacific Islander', 'Black', 'Hispanic', and 'Native American/Alaskan Native' (plus an additional group for unknown).

Around 2010, the group 'Asian or Pacific Islander' was split into 'Asian' and 'Native Hawaiian or Other Pacific Islander'. At the same time, the group 'More than one race' was added. When the number of individuals in a group was quite small (this occurred for both Native American / Alaskan Native and Native Hawaiian / Pacific Islander in both assistant professor and tenured professor stages in some years) the specific number of individuals was masked instead of being reported. In these cases, we guestimated the number of individuals from other group data. For example, if the total number of individuals of a race/ethnicity was reported for faculty as a whole, we split this number evenly among groups to approximate the number of individuals of that race/ethnicity in each faculty stage. Data on the racial/ethnic composition of undergraduate and PhD students as well as assistant and tenured professors came from the WMPD reports (2). Data on postdoctoral researchers (2010 onward) came from NSF Surveys of Graduate Students and Postdoctorates in Science and Engineering (3), and data prior to 2010 was estimated as the average of representation in the graduate student and assistant professor stages. The student data in the NSF WMPD reports only includes racial/ethnicity data for U.S. citizens and permanent residents. To account for international students, we used the NSF reports on Doctorate Recipients from U.S. Universities (7) for data on the proportion of permanent vs temporary resident PhD recipients and the racial/ethnic composition of temporary resident PhD recipients. The specific sources for all race/ethnicity data are given in Table S2 and in the "Data Report Details" Section below, and the timeseries of race/ethnicity data are plotted in Figures S3, S4, and S5. Count data on the number of scholars of each racial/ethnic group were converted to proportions and data were smoothed with a 5-year window moving average.

The specific number of individuals reported for each race/ethnicity group was not necessarily representative of the actual number of individuals of that race/ethnicity, for two main reasons. First, some individuals did not report their race/ethnicity (often reported as a separate group, 'unknown'). Second, race/ethnicity data for undergraduate and graduate students was only provided for U.S. citizens and permanent residents; race/ethnicity for temporary residents was not recorded. However, race/ethnicity data for U.S. temporary residents was recorded for graduating PhD students (see Figure S5). Thus, when applying the race/ethnicity data, we used the proportion of individuals of each race/ethnicity rather than the actual count data (plotted in Figure S4). We calculated proportions using only data for a known race/ethnicity (i.e., we excluded the 'unknown race' group). For example, if there were 500 individuals in a stage, of which 150 were White, and 50 Asian, and 300 unknown race/ethnicity, we recorded this stage as being 0.75 White and 0.25 Asian. Finally data were smoothed with the 'smoothdata' function in Matlab, using a moving average over a window of size 5 years and omitting missing data.

1.3 Age Data

Finally, we used NSF data on the approximate age range of scholars at each stage by pulling data from the integrated data system SESTAT (Scientists and Engineers Statistical Data System, https://www.nsf.gov/statistics/sestat/), and determining the most representative ages of each stage. We selected the National Survey of Recent College Graduates (NSRCG) for undergraduate and graduate stages (year 2010), and the Survey of Doctorate Recipients (SDR) for postdoc, assistant and tenured professor stages (year 2015). For undergraduate and graduate students we created a table showing the most recent degree type (labeled "M_ED_MR_DEGREE_TYPE") in function of ages ("U_DEM_AGE_RCG_PUB"), and specified the population by the field of study for the most recent degree ("M_ED_MR_MAJOR_ED_GRP_MAJOR_NEW"). We selected the fields (i) biological, agricultural and environmental life sciences, (ii) physical Sciences, (iii) computer and mathematical sciences, and (iv) engineering. The total number of scholars per age class in the undergraduate stage was calculated as the sum of Bachelor and Master degrees across the four fields. Similarly, the total number of graduate scholars was obtained by summing up the number of doctorate degrees in each field. Then, we plotted the total number of undergraduate and graduate scholars in function of age, and selected the most representative time spent in each of these two stages. We applied the same method for the other three stages. Notably, we created a table considering the academic position of postdoc ("E_JOB_EMPLR_ACAD_POSITION_POSTDOC") or tenure status ("E_JOB_EMPLR_EDUC_INST_TENURE_STAT"), in function of ages grouped by 5-year intervals ("U_DEM_AGE_GROUP_5_YR_GROUPING_PUB"), and specified the population by the field of study for the highest degree ("O_ED_HD_MAJOR_ED_GRP_MAJOR_NEW"). Overall, the age ranges we used were: 15 to 24 years old (undergraduate students), 20 to 29 (graduate students), 25 to 39 (Ph.D. recipients), 25 to 44 (postdoctoral researchers), 30 to 49 (assistant professors) and 35 to 59 (tenured professors). We used this data to determine which subset of the general population we should compare each academic stage to.

Next, we determined the racial composition of the age class corresponding to each academic stage based on data from the National Center for Health Statistics and the U. S. Census Bureau (8). To compute our racial composition by academic stage for the "American Indian/Alaska Native', "Asian", "Black/African American", "White", and "Hispanic/Latino' categories from 1990 to 2016, we compiled estimates of resident population of the US by year, single-year of age, bridged-race category, and Hispanic origin produced by the National Center for Health Statistics under a collaborative arrangement with the U. S. Census Bureau (8). We compiled similar data from 2000 to 2016 for the "Native Hawaiian/Pacific Islander" and "Two or More Races" categories from the 2019 Population Estimates by Age, Sex, Race and Hispanic Origin (9) and National Intercensal Tables: 2000-2010, both produced by the U. S. Census Bureau (10).

See below for how each dataset was used.

2 Model structure

We constructed a model of academia as a series of stages with movement between them or out of the system (Figure 1 main text; modified from (11). Our model has five discrete stages: undergraduate studies (U), graduate studies (G), postdoctoral fellowships (P), assistant professorships (A; tenure-track) and tenured professorships (T). Individuals that move out of each stage either move up and fill empty positions in the next stage, or move out of the system.

We generated the structure of our model from NSF data. The number of academics in the U.S. has changed over time, so we set the size of each stage i in each year t ($N_i(t)$) from data on the actual number graduate students, postdoctoral fellows, assistant professors, and tenured professors, using data from NSF reports (see Table S1 for specific data sources, and Figure S2 for data). We used the time spent in each stage to estimate a turnover rate for that stage which, in combination with the number of scholars in each stage, gave us an estimate of the number of scholars that would have either transitioned from one stage to the next or transitioned outside of the system for each year.

2.1 Estimating Transitions

Each of the transitions was estimated as follows (see Figure S6 for results). For each year and each stage, we estimated the number of individuals leaving each stage based on transition rates and changes in stage sizes as

$$\rho_i(t) = \left(\frac{1}{\tau_i}\right) N_i(t) \tag{S1}$$

for stages $i = \{\text{G, P, A, T}\}$ where τ_i is the average number of years spent in stage i (see Table S3 for all model parameters). Simultaneously, we estimated the number of openings in each year and each stage as

$$\omega_i(t) = N_i(t+1) - N_i(t) + \rho_i(t) \ . \tag{S2}$$

In most cases, $\rho_i(t) \geq \omega_{i+1}(t)$, that is, the number of openings in stage $i+1$ could easily be filled by individuals leaving stage i. Thus, we partitioned individuals leaving stage i ($\rho_i(t)$) into those moving up to the next stage,

$$\mu_i(t) = \omega_{i+1}(t) \tag{S3a}$$

and those leaving the system,

$$\lambda_i(t) = \rho_i(t) - \omega_{i+1}(t) \ . \tag{S3b}$$

However, there were two other scenarios that occasionally occurred. First, when $\omega_i(t) < 0$ (i.e., too few individuals were leaving stage i than possible, given the change in stage from year to year), we adjusted $\rho_i(t)$) as

$$\rho_i(t) = N_i(t+1) - N_i(t) \tag{S4a}$$

in order to make $\omega_i(t)$ non-negative,

$$\mu_{i-1}(t) = \omega_i(t) = 0 \ . \tag{S4b}$$

Second, when $\rho_i(t) < \omega_{i+1}(t)$ (i.e., too few individuals were leaving stage i to fill openings in stage $i+1$), we either increased the number of individuals leaving stage i when possible, or else assumed the remaining openings were filled by individuals from outside the system being modeled (e.g., coming from other scientific disciplines or returning to academia after having previously left).

2.2 Estimation Details: A to T transition

Each year within each simulation was run over time according to the following steps.

First, we estimated the number of retiring tenured professors by eqn. (S1) with $i = T$. We estimated the number of assistant professors needed to fill these tenured slots by eqn. (S2) with $i = T$. If this was a negative number of assistant professors, we adjusted it according to eqn. (S4). We estimated the number of assistant professors being tenured (and thus available to fill T slots) by eqn. (S1) with $i = A$. If $\rho_A(t) < \omega_T(t)$ (i.e., too few assistant professors were estimated as being tenured), we adjusted $\rho_A(t)$ as

$$\rho_A(t) = \omega_T(t) \tag{S5}$$

i.e., assuming that more assistant professors were tenured than initially estimated. We did not pull individuals from outside the system at this transition as it these seem likely to be rare (e.g, that an individual transitions from an assistant professor in one field to a tenured professor in a different field, or from a non-academic position to a tenured position). Otherwise, if $\rho_A(t) \geq \omega_T(t)$ we used eqn. (S3) to estimate the transition rates with $i = A$. This method effectively assumes that the rate individuals move from A to T is driven by the rate tenured professors retire (ρ_T) and that any 'excess' assistant professors receiving tenure leave the system. We refer to this as a 'demand' view of faculty turnover ('demand' in terms of empty T slots determines the A to T transition).

We thus consider a second alternative scenario, what we call a 'supply' view of faculty turnover, where 'supply' in terms of assistant professors receiving tenure determines the A to T transition. For this method, we estimated the number of retiring tenured professors by eqn. (S1) with $i = T$, estimated the number of assistant professor recieving tenure by eqn. (S1) with $i = A$, and calculated the change in the T stage as

$$\Delta_T(t) = N_T(t+1) - N_T(t) \ . \tag{S6}$$

If $\Delta_T(t) > \rho_A(t)$ (i.e., too few assistant professors were estimated as being tenured to fill the minimum number of T slots), we adjusted $\rho_A(t)$ as

$$\rho_A(t) = \Delta_T(t) \tag{S7}$$

i.e., assuming that more assistant professors were tenured than initially estimate, and set $\rho_T(t) = 0$ (no tenured professors retire this year). Otherwise, if $\Delta_T(t) < \rho_A(t)$, we set

$$\rho_T(t) = \rho_A(t) - \Delta_T(t) \ , \tag{S8}$$

i.e., that retirement of T is assumed to exactly ofset the number of A being tenured, minus the new T slots that have become available.

The 'demand' scenario likely overestimates the number of faculty receiving tenure and then leaving academia, while the 'supply' scenario likely underestimates the number of faculty leaving academia after tenure and before retirement. We run simulations under both scenarios to serve as upper and lower bounds.

2.3 Estimation Details: P to A transition

Next, we estimated the number of postdoctoral researchers needed to fill these assistant professor slots by eqn. (S2) with $i = A$. We estimated the number of postdoctoral researchers available to fill A slots by eqn. (S1) with $i = P$. If $\rho_P(t) < \omega_A(t)$ (i.e., too few postdoctoral researchers were estimated as being available), we adjusted $\rho_P(t)$ as

$$\rho_P(t) = \omega_A(t) \tag{S9}$$

i.e., assuming that more postdoctoral researchers were hired than initially estimated. Otherwise, if $\rho_P(t) \geq \omega_A(t)$ we used eqn. (S3) to estimate the transition rates with $i = P$.

2.4 Estimation Details: G to P transition

Next, we estimated the number of graduate students needed to fill these postdoc slots by eqn. (S2) with $i = P$. We estimated the number of graduate students leaving that stage by eqn. (S1) with $i = G$. We assumed that only students leaving the G stage with a PhD degree can fill the P slots, so we estimated the number of graduate students available to fill P slots by $D_G(t)$, the number of PhD degrees granted in year t. If $D_G(t) \geq \omega_P(t)$ we used a modified version of eqn. (S3) to estimate the transition rates where individuals moving from stage G to stage P as

$$\mu_G(t) = \omega_P(t) \ , \tag{S10a}$$

those leaving the system with a PhD degree as

$$\lambda_G(t) = D_G(t) - \omega_P(t) \ , \tag{S10b}$$

and those leaving stage G before their degree as

$$\delta_G(t) = \rho_G(t) - D_G(t) \ . \tag{S10c}$$

2.5 Estimation Details: U to G transition

Finally, we estimated the number of undergraduate students needed to fill these graduate student slots by eqn. (S2) with $i = G$. We assumed that only students leaving the U stage with a degree can fill the G slots, so we estimated the number of undergraduate students available to fill G slots by $D_U(t)$, the number of undergraduate degrees granted in year t. We used a modified version of eqn. (S3) to estimate the transition rates where individuals moving from stage U to stage G as

$$\mu_U(t) = \omega_G(t) \tag{S11a}$$

and those leaving the system with an undergraduate degree as

$$\lambda_U(t) = D_U(t) - \omega_G(t) \ . \tag{S11b}$$

2.6 Estimation Details: Subpartitions

Since ethnic/racial composition may vary within each stage (especially for longer career stages), we split some stages into sub-partitions. This enabled us to model different racial/ethnic compositions for each sub-partition within a stage. This also ensured that when individuals were moved out of a partitioned stage, they were taken from the oldest sub-partition. We split the graduate student stage into two sub-partitons and split the tenured professor stage into five sub-partition. We assumed that graduate students spent 3 years in the first sub-partition (approximately until qualifying exams) and then $\tau_G - 3$ in the second partition. We assumed that tenured professors spent $\tau_T/5$ in each of the five sub-partitions. Transitions between sub-partition were estimated based on turnover time. Graduate students leaving the system before receiving a degree ($\delta_G(t)$) were pulled from both sub-partitions (half from each), but graduate students leaving the stage with a doctoral degree were assumed to come only from the second sub-partition. Tenured professors retiring ($\rho_T(t)$) were pulled only from the last sub-partition.

3 Model simulations

3.1 Simulation details

With our model structure in place, we then simulated the flow of individuals through the system. We assumed that at each transition, the fraction of individuals staying in the system versus moving outside did not vary with race/ethnicity (i.e., individuals of different races were equally likely to stay in the system). Therefore individuals entering a given stage were drawn from the stage below in proportion to their representation in the lower stage. We calculated $n_i(t, k)$ the simulated number of individuals of each race/ethnicity k in each stage i over time t as follows. The initial number of individuals of each race/ethnicity was taken from National Science Foundation data in a starting year t_0, except for the case of postdoctoral fellows where race/ethnicity data was not available before 2010. In this case, we assumed initial proportion for each race/ethnicity that was the average of the values for graduate students and assistant professors. See Table S2 for data sources.

The survey data for undergraduate degrees and enrolled graduate students only included race/ethnicity data for US citizens and permanent residents; temporary residents were reported as a separate category with no race/ethnicity data. Temporary residents make up a large proportion of graduate students and have a different racial/ethnic composition than US citizens and permanent residents (see Figure S5). In contrast, survey data for graduate degrees did report race/ethnicity data for all graduates across residency types, so we used this data at the transition point from graduate students G to postdoctoral researchers P. Race/ethnicity data by citizenship for PhD degrees was not available before 2000. However, data on race/ethnicity data by citizenship for the doctoral workforce was available for the years 1991 and 1993, and was thus used and interpolated to approximate race/ethnicity data for temporary resident PhD recipients between 1991 and 1999.

Next, for each year going forward, we fed in NSF data on racial/ethnic composition at a particular stage (e.g., undergraduate students), and used our model to predict the racial/ethnic composition at the other stages (e.g., graduate students). We calculated the number of individuals of race/ethnicity k in each stage in the next year $(t + 1)$. The number of graduate students is given by

$$\begin{aligned} n_G(t+1,k,1) = \underbrace{n_G(t,k,1)}_{\text{initial}} - \underbrace{\beta_G(t) f_G(t,k,1)}_{\text{move up}} - \underbrace{0.5\delta_G(t) f_G(t,k,1)}_{\text{leave system}} \\ + \underbrace{\mu_U(,t) f_U(t,k)}_{\text{move in}} \end{aligned} \tag{S12a}$$

for the first subpartition in G and

$$n_G(t+1,k,2) = \underbrace{n_G(t,k,2)}_{\text{initial}} - \underbrace{D_G(t)f_G(t,k,2)}_{\text{graduate}} - \underbrace{0.5\delta_G(t)f_G(t,k,2)}_{\text{leave system}} + \underbrace{\beta_G(t)f_G(t,k,1)}_{\text{move in}} \tag{S12b}$$

for the second subpartition in G, where $f_i(t,k)$ is the fraction of individuals of race/ethnicity k in stage i in year t and $\beta_G(t)$ is the number of individuals that move between G subpartitions in year t.

The number of postdoctoral researchers is given by

$$n_P(t+1,k) = \underbrace{n_P(t,k)}_{\text{initial}} - \underbrace{\mu_P(t)f_P(t,k)}_{\text{move up}} - \underbrace{\lambda_P(t)f_P(t,k)}_{\text{leave system}} + \underbrace{\mu_G(t)R(t)f_G(t,k,2)}_{\text{move in (perm. res.)}} + \underbrace{\mu_G(t)(1-R(t))V(t,k)}_{\text{move in (temp. res.)}} . \tag{S12c}$$

where $R(t)$ is the fraction of PhD degrees that go to U.S. citizens and permanent residents in year t (thus, $1-R(t)$ go to temporary residents), and $V(t,k)$ is the fraction of U.S. temporary resident PhD recipients of race/ethnicity k in year t. The number of assistant professors is given by

$$n_A(t+1,k) = \underbrace{n_A(t,k)}_{\text{initial}} - \underbrace{\mu_A(t)f_A(t,k)}_{\text{move up}} - \underbrace{\lambda_A(t)f_A(t,k)}_{\text{leave system}} + \underbrace{\mu_P(t)f_P(t,k)}_{\text{move in}} . \tag{S12d}$$

The number of tenured professors is given by

$$n_T(t+1,k,1) = \underbrace{n_T(t,k,1)}_{\text{initial}} - \underbrace{\beta_T(t,1)f_T(t,k,1)}_{\text{move up}} + \underbrace{\mu_A(t)f_A(t,k)}_{\text{move in}} \tag{S12e}$$

for the first subpartition in T,

$$n_T(t+1,k,j) = \underbrace{n_T(t,k,j)}_{\text{initial}} - \underbrace{\beta_T(t,j)f_T(t,k,j)}_{\text{move up}} + \underbrace{\beta_T(t,j-1)f_T(t,k,j-1)}_{\text{move in}} \tag{S12f}$$

for subpartitions 2 through 4 ($j = 2,3,4$) in T, and

$$n_T(t+1,k,5) = \underbrace{n_T(t,k,5)}_{\text{initial}} - \underbrace{\rho_T(t)f_T(t,k,5)}_{\text{retire}} + \underbrace{\beta_T(t,4)f_T(t,k,4)}_{\text{move in}} \tag{S12g}$$

for the last (fifth) partition in T.

3.2 Simulation scenarios

We considered four types of scenarios for our simulations (based on turnover rate and turnover type), which capture uncertainty in the details surrounding transitions for faculty in academia. Although we found NSF data on the average length of time spent as a PhD student and as a postdoctoral researcher (Table S1), we could not find similar data on the average time spent on the tenure-track or as a tenured professor. Instead, we considered (i) a 'slow' turnover within the faculty, estimating the time spent on the tenure-track (τ_A) as 8 years and the time spent as a tenured professor (τ_T) as 30 years, and (ii) a 'fast' turnover within the faculty, estimating τ_A as 5 years and τ_T as 20 years. We also considered that the rate individuals moved between the A and T stages was driven by (i) 'supply' (i.e, rate of A achieving tenure), and (ii) 'demand' (i.e., rate of T retiring). We thus considered four combinations of scenarios: fast-supply, fast-demand, slow-supply and slow-demand.

3.3 Simulation sets

We ran three sets of simulations, each run under the four scenarios described above.

First, to study the overall effects of retention (Figure 2 in the paper), we started simulations in year $t_0 = 1991$ and ran them for 25 years (the full range of available data), feeding NSF data on the race/ethnicity of graduating undergraduates, and simulating the expected race/ethnicity of graduate students, postdoctoral researchers, assistant professors, and tenured professors. We used five initial groups for race/ethnicity: 'White', 'Asian or Pacific Islander', 'Black', 'Hispanic', and 'Native American/Alaskan Native'. Around 2010 (year differs slightly across academic stages), the group 'Asian or Pacific Islander' was split into 'Asian' and 'Native Hawaiian or Other Pacific Islander' in the NSF data and the group 'More than one race' was added. Accordingly, we adjusted the simulated individuals in our model starting in the year 2012 (the first year that these two new groups were available for all academic stages). We partitioned the simulated individuals in the 'Asian or Pacific Islander' group into 'Asian' and 'Native Hawaiian or Other Pacific Islander' groups based on the relative proportion of these two groups in the NSF data for 2012. Similarly, we set the proportion of simulated individuals in the 'More than one race' group based on the relative proportion of that group in the NSF 2012 data, and pulled these simulated individuals evenly from the other simulated groups.

Second, to isolate the effects of retention within each stage of academia (Figure 4 in the paper), we fed in NSF data on the race/ethnicity at each stage and quantified the expected outcome at the following stage. Specifically, we simulated expected results for graduate students based on our model run with NSF undergraduate student data, expected results for postdoctoral researchers and assistant professors based on NSF graduate student data, and expected results for tenured professors based on NSF assistant professor data. This second set of simulations was also started in the year $t_0 = 1991$, running them for 25 years.

Third, to examine how the effect of specific transitions within academia changed over time, we started simulations in different starting years ($t_0 = 1991, 1996, 2001, 2006$) and ran each simulation for 10 years. Here again we simulated expected results for each stage based on our model run with NSF data at the previous stage.

All simulations and calculations were done using *Matlab*.

3.4 Testing model predictions

Finally, we compared the racial/ethnic composition predicted by our null model to the actual composition from NSF data. We quantified this comparison with the metric

$$\theta = \frac{d_i(t,k) - f_i(t,k)}{f_i(t,k)} \tag{S13}$$

where $d_i(t,k)$ and $f_i(t,k)$ are the NSF data and model prediction, respectively, of the proportion of stage i in year t that is made up of race/ethnicity k. Here, $\theta > 0$ indicates that a racial/ethnic group has higher representation in a stage than is predicted by the null model and $\theta < 0$ means lower representation than predicted.

We calculated confidence intervals around θ values, as follows. For each combination of $d_i(t,k)$ and $f_i(t,k)$, we considered what effect an error of $\epsilon = 5\%$ would have. We calculated four bounds to the θ metric:

$$\theta_1' = \frac{(1-\epsilon)d_i(t,k) - (1-\epsilon)(t,k)}{(1-\epsilon)f_i(t,k)} \tag{S14a}$$

$$\theta_2' = \frac{(1-\epsilon)d_i(t,k) - (1+\epsilon)(t,k)}{(1+\epsilon)f_i(t,k)} \tag{S14b}$$

$$\theta_3' = \frac{(1+\epsilon)d_i(t,k) - (1-\epsilon)(t,k)}{(1-\epsilon)f_i(t,k)} \tag{S14c}$$

$$\theta_4' = \frac{(1+\epsilon)d_i(t,k) - (1+\epsilon)(t,k)}{(1+\epsilon)f_i(t,k)} \tag{S14d}$$

and used the largest and smallest value of these four to set the upper and lower bounds of the confidence interval around the θ value.

3.5 Supplementary Results

In addition to the results in the main text, several supplementary results are included below. Table S4 provides numerical value of representation in each stage for each race/ethnicity. Figure S7 shows a comparison of represenation comparing the model results, academia data and census data. Figure S8 shows the temporal trends in the θ metric value. Figure S9 shows a comparison of two model versions – one accounting for the race/ethnicity of temporary resident international scholars who receive their PhDs in the U.S., and one ignoring the race/ethnicity of this group.

4 Data Report Details

Below are details of each data source used.
[08-307] NSF Publication 08-307. 2008 National Science Foundation, Division of Science Resources Statistics, Postdoc Participation of Science, Engineering, and Health Doctorate Recipients. (http://www.nsf.gov/statistics/infbrief/nsf08307)
2008 report, Table 2: Median duration of most recently completed postdoc

[GSPD] Survey of Graduate Students and Postdoctorates in Science and Engineering. (https://www.nsf.gov/statistics/srvygradpostdoc/)
2018 report, Table 1-9a: number of graduate students by science field for 1975–2018
2018 report, Table 1-10a: number of graduatd students by engineering field for 1975–2018
2018 report, Table 1-9b: number of postdoctoral researchers by science field for 1975–2018
2018 report, Table 1-10b: number of postdoctoral researchers by engineering field for 1975–2018
2010 report, Table 34: postdoctoral researchers, by race/ethnicity for 2010
2016 report, Table 34: postdoctoral researchers, by race/ethnicity for 2011-2016
2017 report, Table 2-2: postdoctoral researchers, by race/ethnicity for 2017
2018 report, Table 2-2: postdoctoral researchers, by race/ethnicity for 2018

[S&E Degrees] Science and Engineering Degrees: 1966–2012. (https://www.nsf.gov/statistics/2015/nsf15326/)
2015 report, Table 5: number of bachelor's degrees by field for 1966-2012
2015 report, Table 19: number of PhD degrees by field for 1966-2012

[SED] Survey of Earned Doctorates. (https://www.nsf.gov/statistics/srvydoctorates/)
2014 report, Table 17: doctorate recipients, by broad field of study and citizenship for 1984-2014 (every 5 years)
2015 report, Table 17: doctorate recipients, by broad field of study and citizenship for 1985-2015 (every 5 years)
2016 report, Table 17: doctorate recipients, by broad field of study and citizenship for 1986-2016 (every 5 years)
2017 report, Table 17: doctorate recipients, by broad field of study and citizenship for 1987-2017 (every 5 years)
2018 report, Table 17: doctorate recipients, by broad field of study and citizenship for 1988-2018 (every 5 years)
2010 report, Table 19: doctorate recipients, by race/ethnicity and citizenship for 2000–2010
2018 report, Table 19: doctorate recipients, by race/ethnicity and citizenship for 2009–2018

[SE-ind] Science and Engineering Indicators, National Science Board. (https://ncses.nsf.gov/indicators)

2019 report, Table S3-7: number of assistant and tenured professors by field for 1973-2017
2018 report, Table 2-3: median time to degree by field for 1985-2015

[WMPD] Women, Minorities, and Persons with Disabilities in Science and Engineering report.
(https://www.nsf.gov/statistics/women/)
2019 report, Table 5-3: number of bachelor's degrees by field for 2006-2016
2019 report, Table 7-4: number of PhD degrees by field for 2006–2016
1994 report, Table 5-19: bachelors degrees by race/ethnicity for 1981-1991
2002 report, Table 3-8: bachelors degrees by race/ethnicity for 1990-1998
2009 report, Table C6: bachelors degrees by race/ethnicity for 1996-2007
2019 report, Table 5-3: bachelors degrees by race/ethnicity for 2006-2016
2002 report, Table 4-6: graduate students by race/ethnicity for 1990-1999
2009 report, Table D-1: graduate students by race/ethnicity for 1999-2006
2011 report, Table 3-1: graduate students by race/ethnicity for 2008-2010
2013 report, Table 3-1: graduate students by race/ethnicity for 2012
2017 report, Table 3-1: graduate students by race/ethnicity for 2014
2019 report, Table 3-1: graduate students by race/ethnicity for 2016
1994 report, Table 8-11: PhD workforce by race/ethnicity and citizenship for 1991
1996 report, Table 5-33: PhD workforce by race/ethnicity and citizenship for 1993
1994 report, Table 8-18: faculty by race/ethnicity for 1991
1996 report, Table 5-28: faculty by race/ethnicity for 1993
1998 report, Table 5-10: faculty by race/ethnicity for 1995
2000 report, Table 5-19: faculty by race/ethnicity for 1997
2004 report, Table H-26: faculty by race/ethnicity for 2001
2007 report, Table H-28: faculty by race/ethnicity for 2003
2009 report, Table H-28: faculty by race/ethnicity for 2006
2011 report, Table 9-26: faculty by race/ethnicity for 2008
2013 report, Table 9-26: faculty by race/ethnicity for 2010
2015 report, Table 9-26: faculty by race/ethnicity for 2013
2017 report, Table 9-26: faculty by race/ethnicity for 2015
2019 report, Table 9-26: faculty by race/ethnicity for 2017

References

[1] National Science Foundation, National Center for Science and Engineering Statistics. Science and Engineering Degrees: 1966–2012. Detailed Statistical Tables NSF 15-326. Arlington, VA; 2015. Available from: http://www.nsf.gov/statistics/2015/nsf15326/.

[2] National Science Foundation, National Center for Science and Engineering Statistics. Women, Minorities, and Persons with Disabilities in Science and Engineering: 2019. Special Report NSF 19-304. Alexandria, VA; 2019. Available from: https://www.nsf.gov/statistics/wmpd.

[3] National Center for Science and Engineering Statistics. Survey of Graduate Students and Postdoctorates in Science and Engineering; 2018. Available from: http://ncsesdata.nsf.gov/gradpostdoc/.

[4] National Science Board NSF. Higher Education in Science and Engineering. Science and Engineering Indicators 2020. NSB-2019-7.; 2019. NSB-2019-7. Available from: https://ncses.nsf.gov/pubs/nsb20197/.

[5] National Science Board. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation; 2018. Available from: https://www.nsf.gov/statistics/indicators/.

[6] National Science Foundation, Division of Science Resources Statistics. Postdoc Participation of Science, Engineering, and Health doctorate Recipients; 2008. Available from: http://www.nsf.gov/statistics/infbrief/nsf08307.

[7] National Center for Science and Engineering Statistics NSF. Doctorate Recipients from U.S. Universities: 2018. Special Report NSF 20-301. Alexandria, VA; 2019. Available from: https://ncses.nsf.gov/pubs/nsf20301/.

[8] United States Department of Health and Human Services (US DHHS), Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS). Bridged-Race Population Estimates, United States July 1st resident population by state, county, age, sex, bridged-race, and Hispanic origin. Compiled from 1990-1999 bridged-race intercensal population estimates (released by NCHS on 7/26/2004); revised bridged-race 2000-2009 intercensal population estimates (released by NCHS on 10/26/2012); and bridged-race Vintage 2019 (2010-2019) postcensal population estimates (released by NCHS on 7/9/2020). Available on CDC WONDER Online Database. Accessed at http://wonder.cdc.gov/bridged-race-v2019.html on Oct 9, 2020; 2020.

[9] Annual Estimates of the Resident Population by Sex, Age, Race, and Hispanic Origin for the United States: April 1, 2010 to July 1, 2019 (NC-EST2019-ASR6H). U.S. Census Bureau, Population Division. June 2020; 2020.

[10] Intercensal Estimates of the Resident Population by Sex, Race, and Hispanic Origin for the United States: April 1, 2000 to July 1, 2010 (US-EST00INT-02). U.S. Census Bureau, Population Division. September 2011.; 2011.

[11] Shaw AK, Stanton DE. Leaks in the pipeline: separating demographic inertia from ongoing gender differences in academia. Proceedings of the Royal Society of London Series B: Biological Sciences. 2012;279(1743):3736–3741. Available from: `http://rspb.royalsocietypublishing.org/content/279/1743/3736.short`.

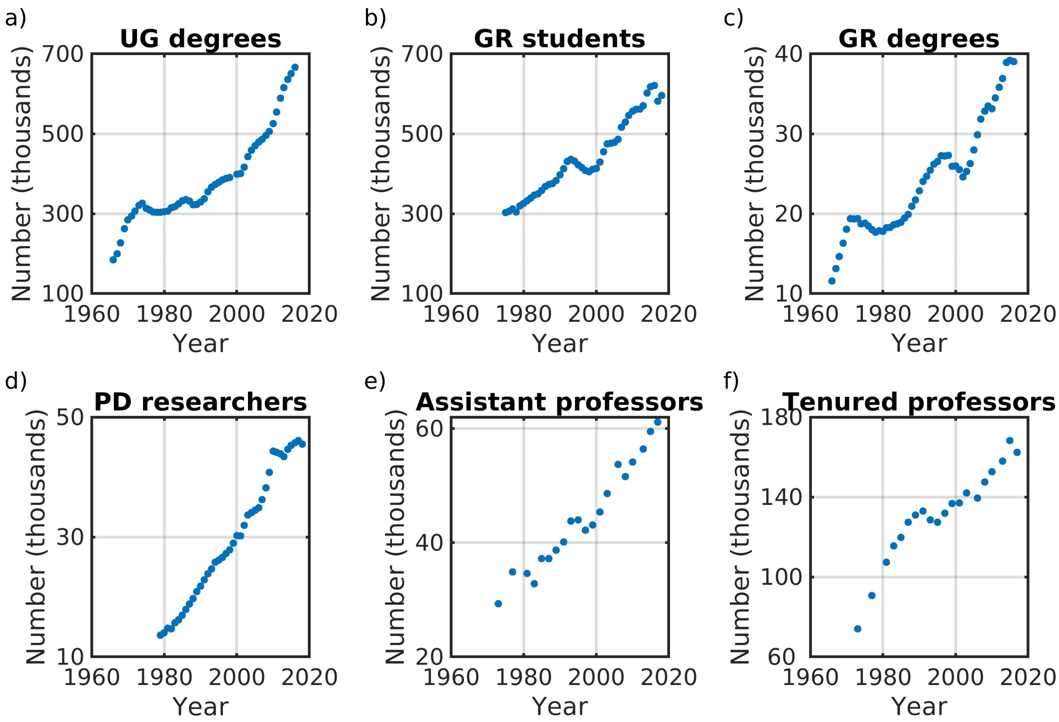

Figure S1: NSF timeseries raw data on (a) the number of bachelors degrees awarded, (b) the number of enrolled graduate students, (c) the number of PhDs awarded, (d) the number of postdoctoral researchers, (e) the number of assistant (tenure-track) professors, and (f) the number of tenured professors, across all of Science and Engineering in the US.

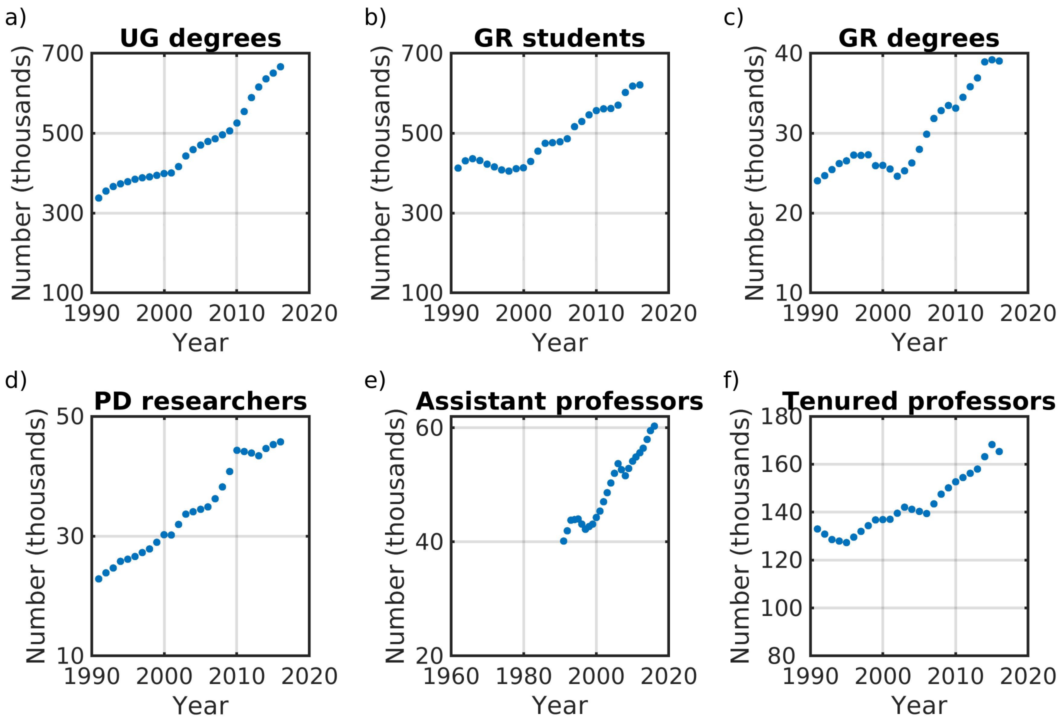

Figure S2: Interpolated and trimmed data on (a) the number of bachelors degrees awarded, (b) the number of enrolled graduate students, (c) the number of PhDs awarded, (d) the number of postdoctoral researchers, (e) the number of assistant (tenure-track) professors, and (f) the number of tenured professors, across all of Science and Engineering in the US.

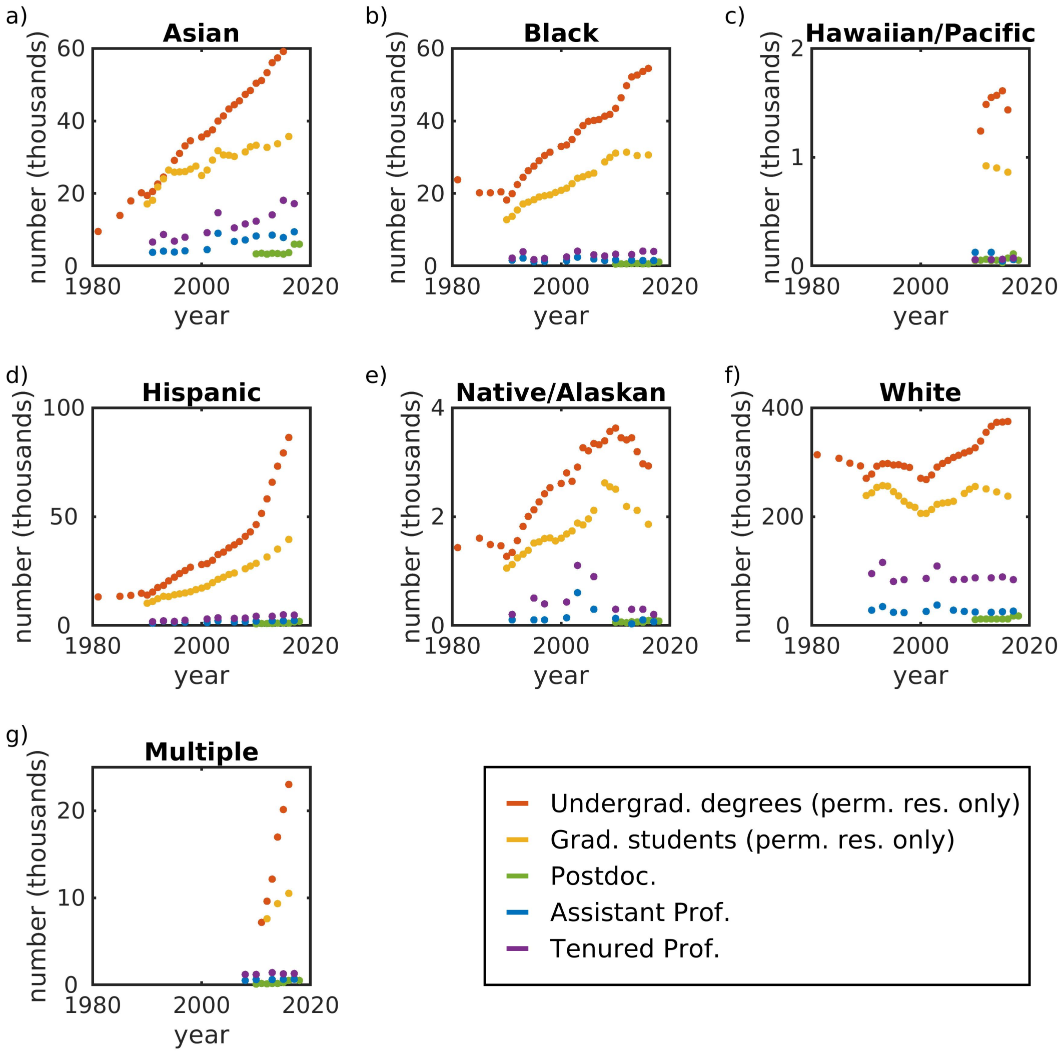

Figure S3: NSF timeseries data on the number of (a) Asian, (b) Black, (c) Hawaiian or Pacific Islander, (d) Hispanic, (e) Native American or Alaskan Native, and (f) White individuals in each stage: undergraduate degrees, graduate students, postdoctoral researchers, assistant professors and tenured professors. Note that race/ethnicity for undergraduate and graduate students is only recorded for US citizens and permament residents, not temporary residents (but see Figure S5 below).

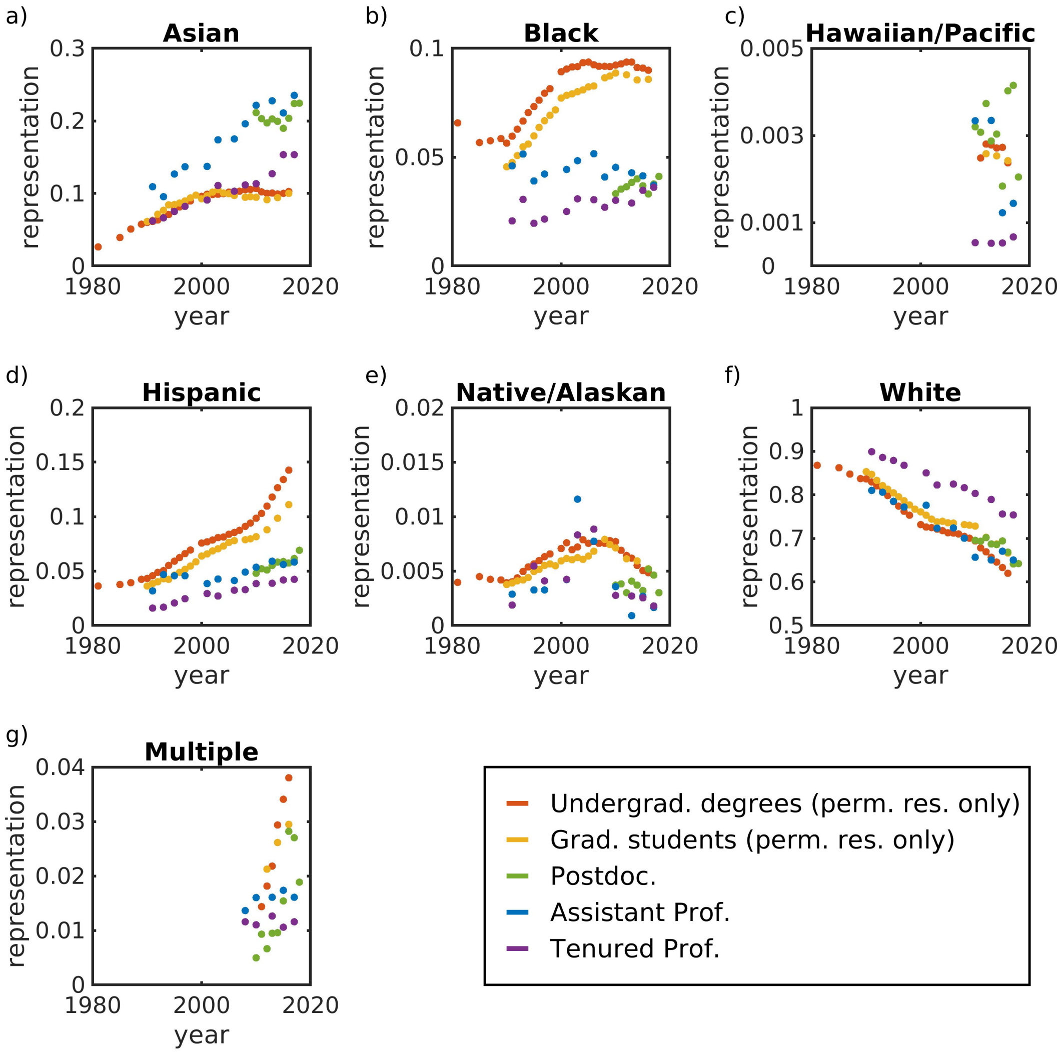

Figure S4: The proportion of individuals in each stage (undergraduate degrees, graduate students, postdoctoral researchers, assistant professors and tenured professors) that are (a) Asian, (b) Black, (c) Hawaiian or Pacific Islander, (d) Hispanic, (e) Native American or Alaskan Native, and (f) White. Note that race/ethnicity for undergraduate and graduate students is only recorded for US citizens and permament residents, not temporary residents (but see Figure S5 below).

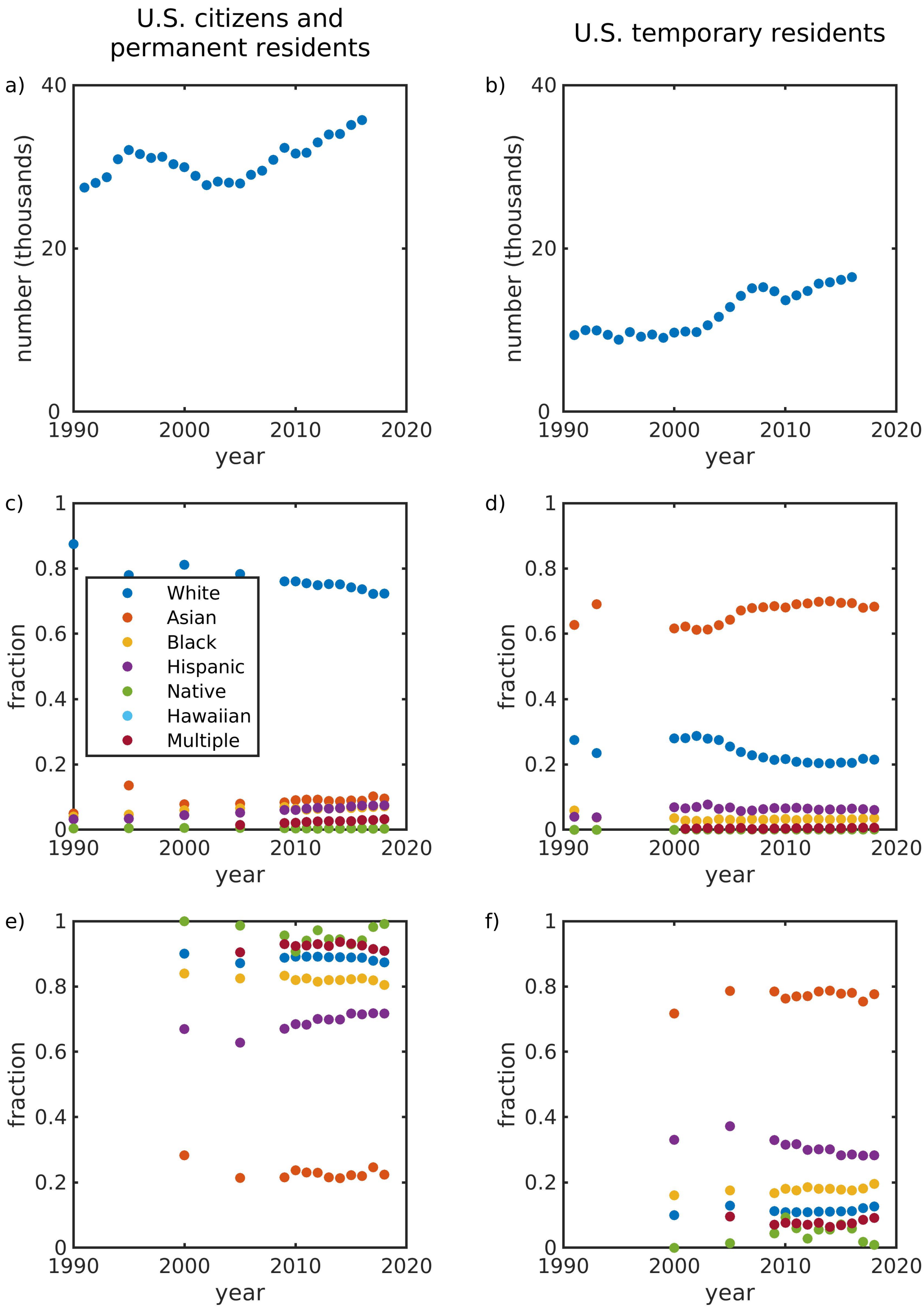

Figure S5: Composition of PhD recipients by residency. The number of PhD degree awardees who are (a) U.S. citizens or permanent residents and (b) temporary residents. The fraction of each race/ethnicity among (c) U.S. citizens or permanent resident PhD recipients and (d) temporary resident PhD recipients. The fraction of scholars of race/ethnicity that are (e) U.S. citizens or permanent residents and (f) temporary residents.

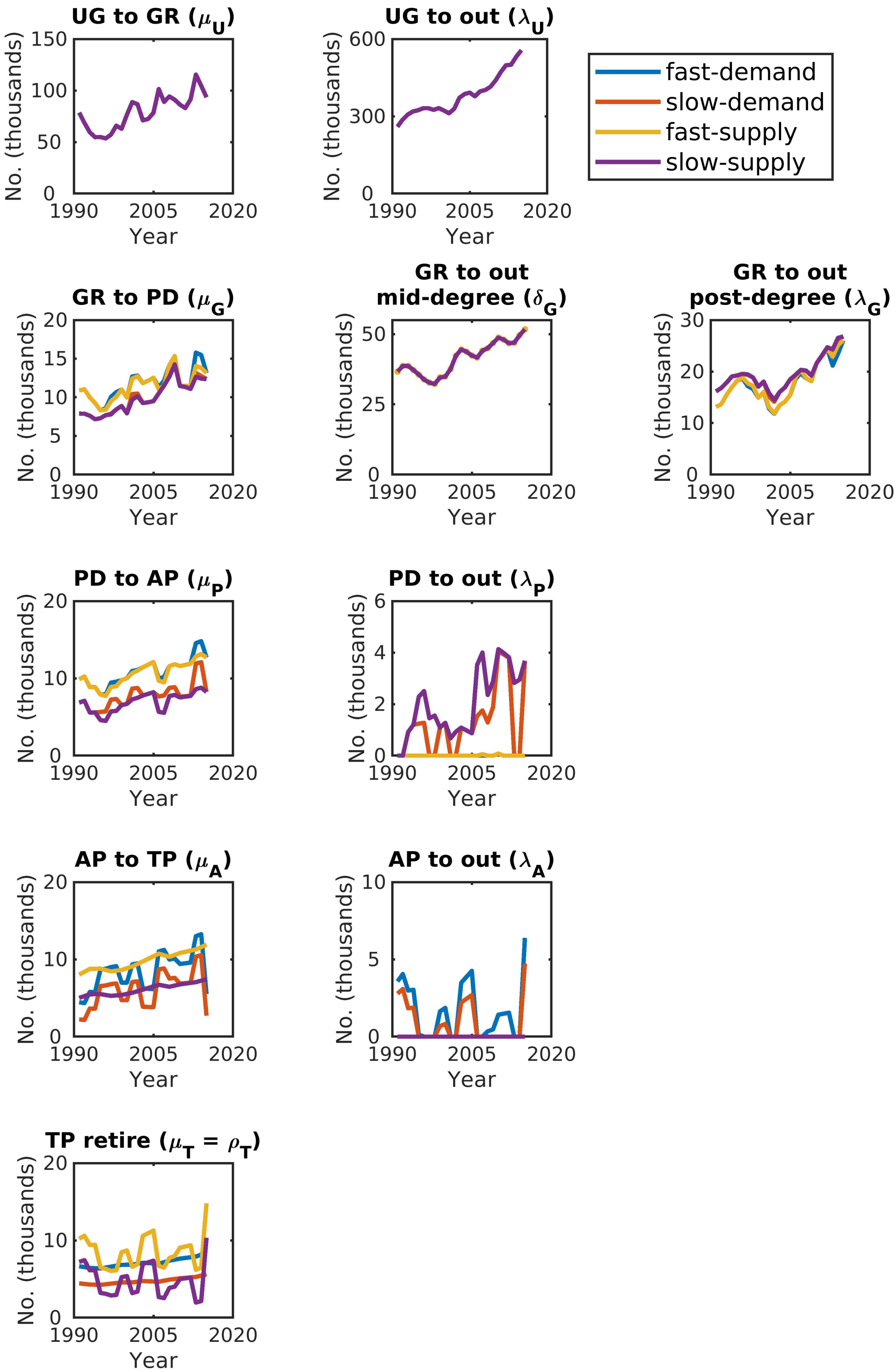

Figure S6: Timeseries estimates of the number of individuals making each of the 10 transitions in Figure 1 of the main text, as generated by our model for each of the four transitions for faculty scenarios: 'fast' and 'demand' (blue), 'slow' and 'demand' (red), 'fast' and 'supply' (yellow), 'slow' and 'supply' (purple) .

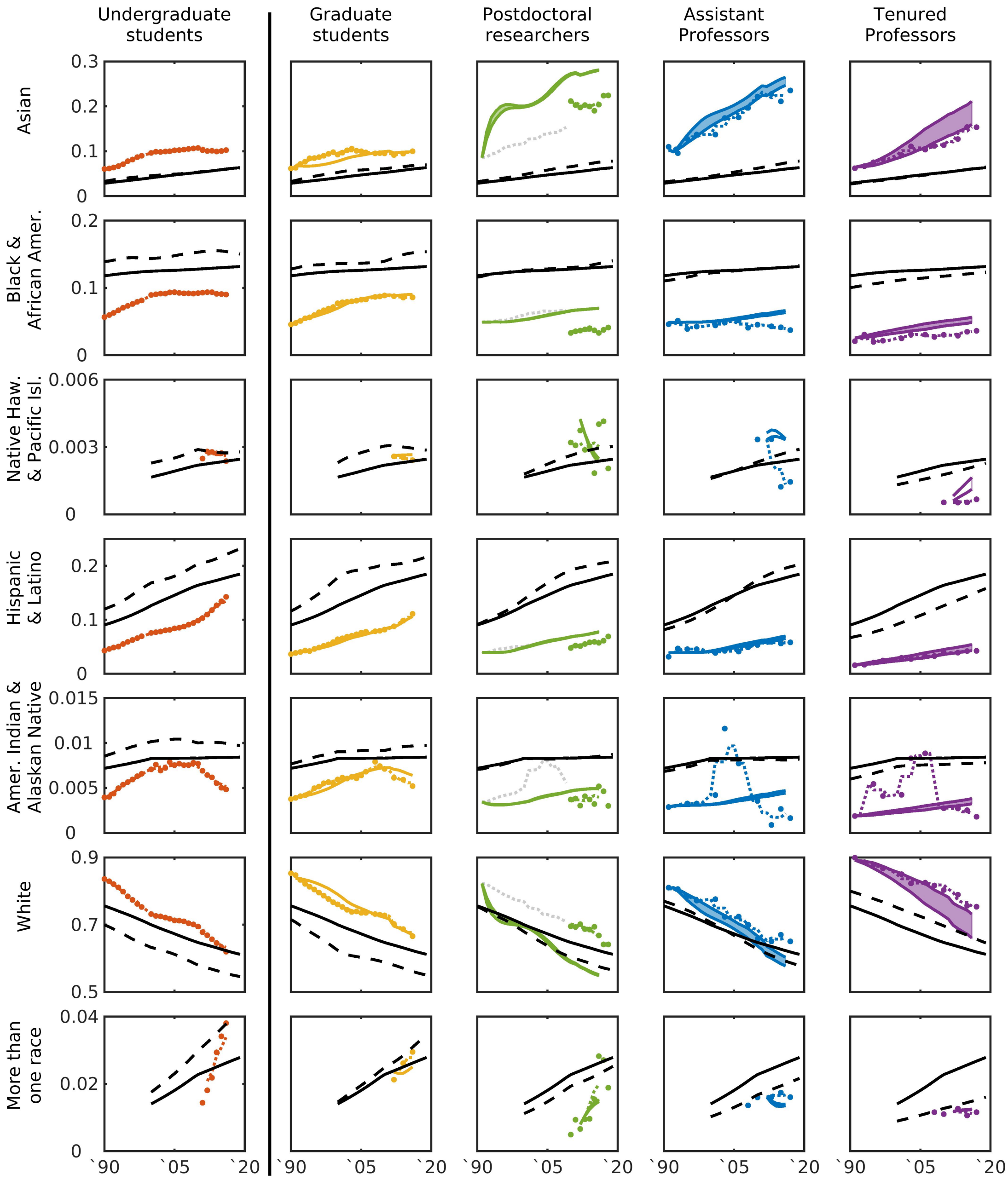

Figure S7: The representation of each race/ethnicity categories (rows) in each academic stage (columns) over time (i.e. the proportion of scholars in that stage that identify as that race or ethnicity) comparing: null model predictions (colored solid lines), academia data (dots are raw data, dotted lines are smoothed data), and census data for the U.S. overall population (black solid lines) and US age-specific population (black dashed line). Mismatch between model and academia data indicate race/ethnicity-based biases of retention within academia, mismatch between model and census indicates race/ethnicity-based biases in entering academia.

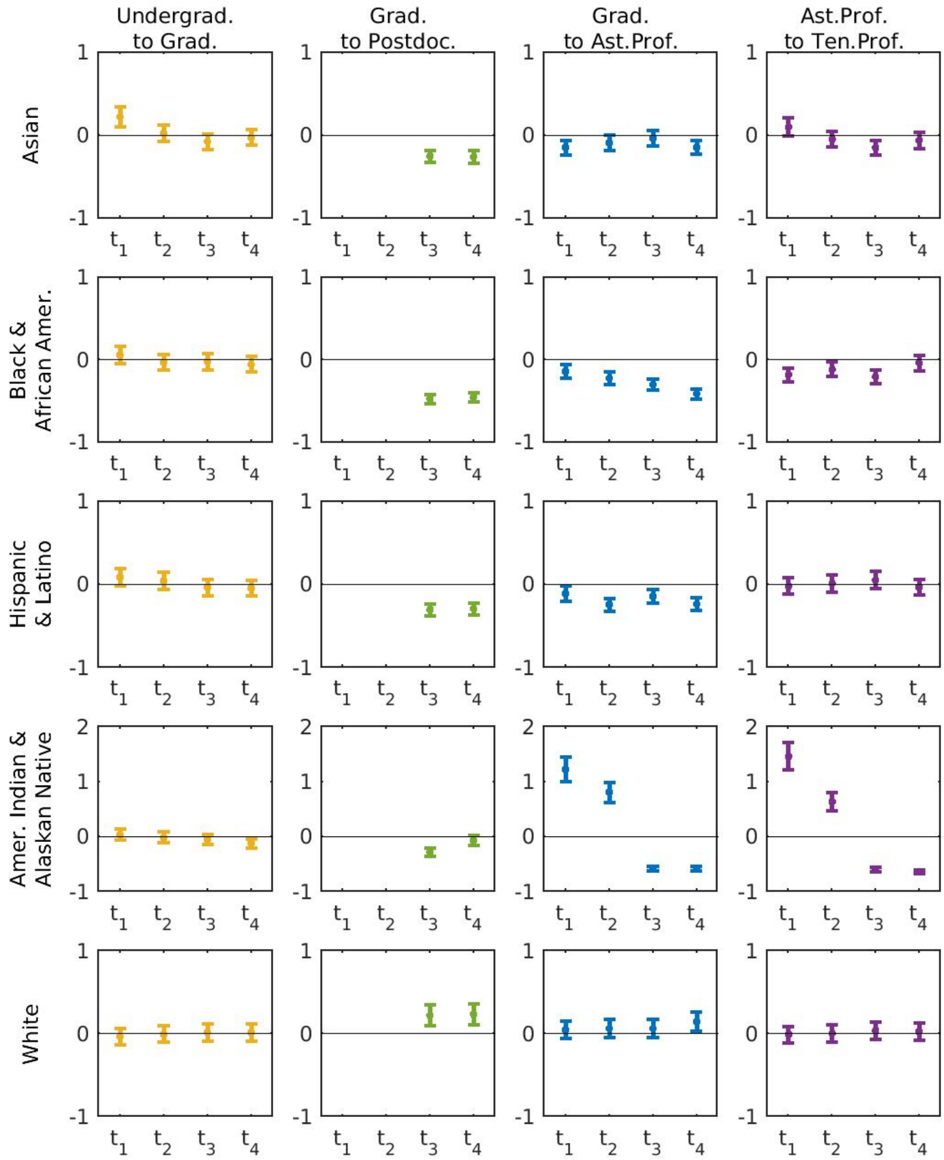

Figure S8: Temporal trends in the relative representation (θ; comparing data and the null model) of each race/ethnicity category (rows) through one of the transitions within academia (columns). Each point corresponds to a single set of simulations, which were started in one of four years $t_1 = 1991$, $t_2 = 1996$, $t_3 = 2001$, $t_4 = 2006$) and run for 10 years. Colors correspond to the stage where difference is measured (same colors as Figs. 2 and 4 in the main text). Positive or negative values indicate a race/ethnicity category faces correspondingly positive or negative bias across that transition. Results for the Grad. to Postdoc. transitions are omitted for t_1 and t_2 because these results rely on extrapolated data, thus comparisons between model and data holds less value. Results for Hawaiian/Pacific Islander and More than one race are not shown because there was only sufficient data for a single time point (t_4).

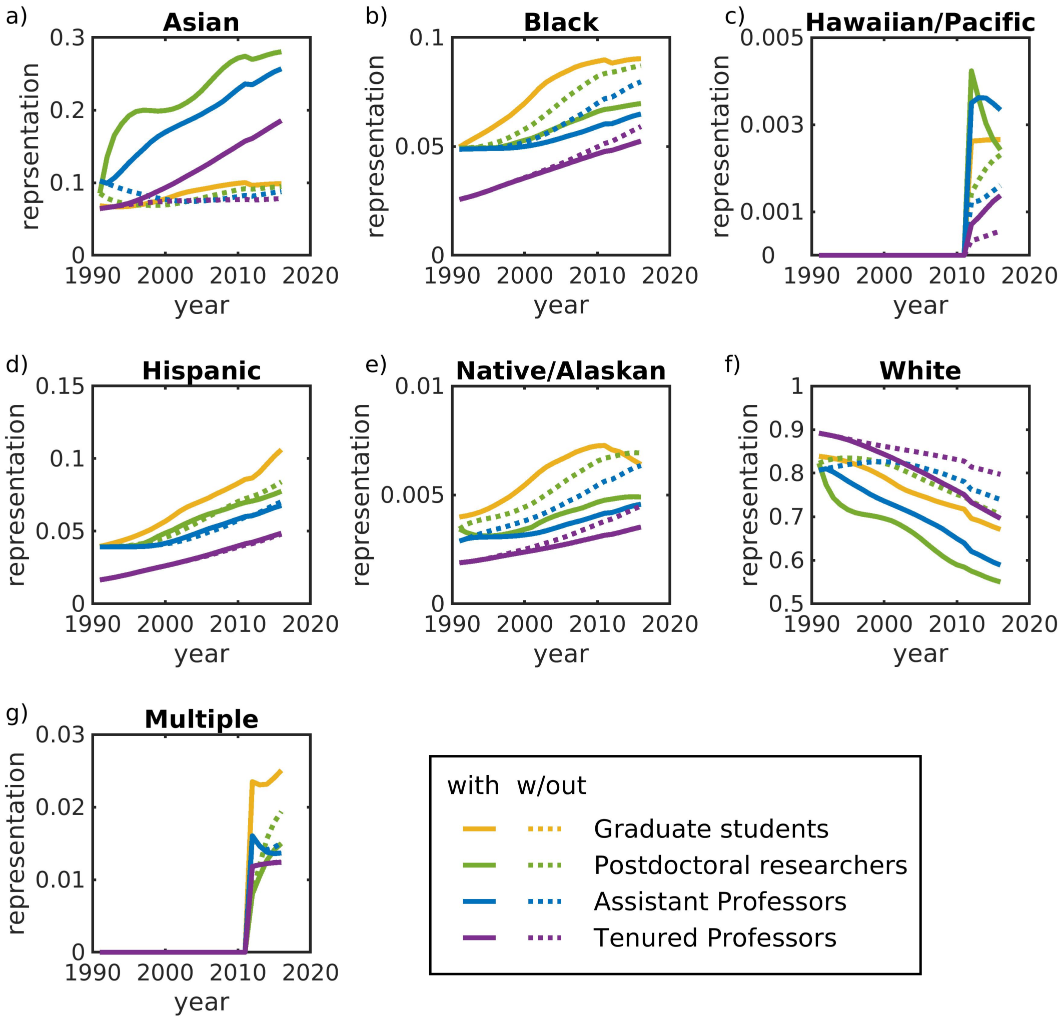

Figure S9: The representation of each race/ethnicity category (panels) in each academic stage (lines) over time, i.e. the proportion of scholars in that stage that identify as that race or ethnicity, comparing two versions of the model. The solid lines show the main model version which accounts for the race/ethnicity of temporary resident international scholars who receive their PhDs in the U.S. (i.e., the output at the graduate student stage matches the composition of PhD recipients, regardless of their residency). The dashed lines show a version of the model that ignores the race/ethnicity of international students (i.e., the output at the graduate student stage matches the composition of U.S. citizen and permentent resident PhD recipients).

Table S1: Data used for our model structure, years of data, and NSF report sources.

DATA	YEARS	SOURCE
	DEGREES ($D_i(t)$)	
# Bachelors degrees	1966-2012	S&E Degrees, 2015 report, Table 5
	2006–2016	WMPD, 2019 report, Table 7-4
# PhD degrees	1966-2012	S&E Degrees, 2015 report, Table 19
	2006–2016	WMPD, 2019 report, Table 5-3
	STAGE SIZE ($N_i(t)$)	
# graduate students	1975-2018	GSPD, 2018 report, Tables 1-9a, 1-10a
# postdoctoral researchers	1975-2018	GSPD, 2018 report, Tables 1-9b, 1-10b
# assistant professors	1973-2017	SE-ind, 2019 report, Table S3-7
# tenured professors	1973-2017	SE-ind, 2019 report, Table S3-7
	TIME IN STAGE (τ_i)	
graduate student	6.8 yrs	SE-ind, 2018 report, Table 2-30, 2015 data
postdoc	2*1.9 yrs	[08-307] 2008 report, Table 2, 2006 data
assistant professor	5-8 yrs	
tenured professor	20-30 yrs	

Table S2: Race/ethnicity data used for simulations and for comparisons against simulations, years of data, and NSF report sources.

DATA	YEARS	SOURCE
# Bachelors degrees	1981-1991	WMPD, 1994 report, Table 5-19
(data by race/ethnicity for	1990-1998	WMPD, 2002 report, Table 3-8
U.S. citizens and	1996-2007	WMPD, 2009 report, Table C6
permanent residents only)	2006-2016	WMPD, 2009 report, Table 5-3
# PhD students	1990-1999	WMPD, 2002 report, Table 4-6
(data by race/ethnicity for	1999-2006	WMPD, 2009 report, Table D-1
U.S. citizens and	2008-2010	WMPD, 2011 report, Table 3-1
permanent residents only)	2012	WMPD, 2013 report, Table 3-1
	2014	WMPD, 2017 report, Table 3-1
	2016	WMPD, 2019 report, Table 3-1
# PhD degrees	1984:5:2014	SED, 2014 report, Table 17
(data by residency,	1985:5:2015	SED, 2015 report, Table 17
permanent vs. temporary)	1986:5:2016	SED, 2016 report, Table 17
used to calculate $R(t)$	1987:5:2017	SED, 2017 report, Table 17
	1988:5:2018	SED, 2018 report, Table 17
# PhD degrees (data by race/ethnicity	2000–2010	SED, 2010 report, Table 19
for temporary residents)	2009–2018	SED, 2018 report, Table 19
used to calculate $V(t,k)$		
doctoral workforce (data by race/ethnicity	1991	WMPD, 1994 report, Table 8-11
for temporary residents)	1993	WMPD, 1996 report, Table 5-33
used to calculate $V(t,k)$		
# postdoctoral researchers	2010	GSPD, 2010 report, Table 34
(data by race/ethnicity)	2011-2016	GSPD, 2010 report, Table 34
	2017	GSPD, 2017 report, Table 2-2
	2018	GSPD, 2018 report, Table 2-2
# professors [assistant, tenured]	1991	WMPD, 1994 report, Table 8-18
(data by race/ethnicity)	1993	WMPD, 1996 report, Table 5-28
	1995	WMPD, 1998 report, Table 5-10
	1997	WMPD, 2000 report, Table 5-19
	2001	WMPD, 2004 report, Table H-26
	2003	WMPD, 2007 report, Table H-28
	2006	WMPD, 2009 report, Table H-28
	2008	WMPD, 2011 report, Table 9-26
	2010	WMPD, 2013 report, Table 9-26
	2013	WMPD, 2015 report, Table 9-26
	2015	WMPD, 2017 report, Table 9-26
	2017	WMPD, 2019 report, Table 9-26

Table S3: Model variables, parameters, meaning and sources.

Param.	Meaning	Source
t	time (year)	NA
i	stage (U, G, P, A, T)	NA
k	individual race/ethnicity	NA
$N_i(t)$	number of individuals in stage i in year t	see Table S1
$D_i(t)$	number of degrees of stage i awarded in year t (only $i = U, G$)	see Table S1
$R(t)$	fraction of PhD degrees to U.S. citizens / permanent residents in year t	see Table S2
$V(t, k)$	fraction of U.S. temporary resident PhD recipients in year t	
	that are of race/ethnicity k	see Table S2
τ_i	average number of years spent in stage i	see Table S1
$\rho_i(t)$	number of individuals potentially leaving stage i in year t	estimated
$\omega_i(t)$	number of openings available in stage i in year t	estimated
$\mu_i(t)$	individuals moving from stage i to stage $i+1$ in year t	estimated
$\lambda_i(t)$	individuals moving from stage i to outside the system in year t	estimated
$\delta_G(t)$	individuals leaving stage G (before degree) in year t	estimated
$\beta_i(t, j)$	individuals moving from subpartition j in stage i in year t	estimated
$n_i(t, k)$	number of k individuals in stage i in year t	simulated
$f_i(t, k)$	fraction of individuals in stage i in year t of race/ethnicity k	simulated

Table S4: The fraction of individuals at each stage of each race/ethnicity in the year 2016. 'Data' rows are smoothed NSF counts data and the census data. The remaining rows are what the model predicts (under null model of no bias) for four scenarios: 'fast-demand', ''fast-supply', 'slow-demand', and 'slow-supply' which are combinations of a 'demand' or 'supply view of faculty turnover and a 'fast' ($\tau_A = 5$, $\tau_T = 20$) or 'slow' turnover ($\tau_A = 8$, $\tau_T = 30$).

	Asian	Black & Af. Am.	Nat. Haw. & Pac. Is.	Hisp. & Lat.	Amer. In. & Alas. Nat.	White	More than one race
U.S. general population (census)							
data	0.0602	0.1305	0.0018	0.1779	0.0084	0.6230	0.0209
Undergraduate Students							
data	0.1007	0.0906	0.0026	0.1345	0.0051	0.6327	0.03388
Graduate Students							
data	0.0973	0.0856	0.0025	0.1047	0.0056	0.6765	0.0278
fast-demand	0.0988	0.0903	0.0027	0.1062	0.0064	0.6707	0.0251
fast-supply	0.0988	0.0903	0.0027	0.1062	0.0064	0.6707	0.0251
slow-demand	0.0988	0.0903	0.0027	0.1062	0.0064	0.6707	0.0251
slow supply	0.0988	0.0903	0.0027	0.1062	0.0064	0.6707	0.0251
Postdoctoral Researchers							
data	0.2082	0.0378	0.0030	0.0610	0.0040	0.6662	0.0198
fast-demand	0.2812	0.0698	0.0023	0.0779	0.0049	0.5486	0.0153
fast-supply	0.2807	0.0698	0.0024	0.0776	0.0049	0.5495	0.0151
slow-demand	0.2799	0.0696	0.0025	0.0772	0.0049	0.5510	0.0148
slow supply	0.2798	0.0696	0.0025	0.0772	0.0049	0.5513	0.0148
Assistant Professors							
data	0.2230	0.0392	0.0013	0.0571	0.0022	0.6604	0.0167
fast-demand	0.2648	0.0663	0.0033	0.0700	0.0047	0.5774	0.0135
fast-supply	0.2635	0.0660	0.0034	0.0695	0.0047	0.5795	0.0135
slow-demand	0.2525	0.0641	0.0033	0.0665	0.0045	0.5953	0.0137
slow supply	0.2468	0.0632	0.0033	0.0649	0.0044	0.6034	0.0140
Tenured Professors							
data	0.1537	0.0354	0.0006	0.0422	0.0022	0.7548	0.0111
fast-demand	0.2053	0.0553	0.0015	0.0527	0.0037	0.6690	0.0124
fast-supply	0.2110	0.0564	0.0016	0.0542	0.0038	0.6604	0.0125
slow-demand	0.1663	0.0493	0.0012	0.0441	0.0033	0.7235	0.0124
slow supply	0.1599	0.0487	0.0011	0.0432	0.0032	0.7315	0.0123