How Did It Get This Way? Disentangling the Sources of Teacher Quality Gaps Through Agent-Based Modeling

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Contents

Acknowledgments

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Abstract

We use publicly available, longitudinal data from Washington state to study the extent to which three interrelated processes—teacher attrition from the state teaching workforce, teacher mobility between teaching positions, and teacher hiring for open positions—contribute to "teacher quality gaps" (TQGs) between students of color and other students in K–12 public schools. Specifically, we develop and implement an agent-based model simulation of decisions about attrition, mobility, and hiring to assess the extent to which each process contributes to observed TQGs. We find that eliminating inequities in teacher mobility and hiring across different schools would close TQGs within 5 years, while just eliminating inequities in teacher hiring would close gaps within 10 years. On the other hand, eliminating inequities in teacher attrition without addressing mobility and hiring does little to close gaps.

1.   Introduction

There is abundant evidence of "teacher quality gaps" (TQGs) between advantaged and disadvantaged students in U.S. public schools. These TQGs are evident whether teacher quality is measured by degrees, experience, or advanced credentials (e.g., Bruno et al., 2020; Clotfelter et al., 2005; Kalogrides and Loeb, 2013; Lankford et al., 2002) or by "value-added" measures of teacher effectiveness (e.g., Goldhaber et al., 2015; Isenberg et al., 2021; Sass et al., 2012). For example, longitudinal data on public schools from North Carolina and Washington (Goldhaber et al., 2018) demonstrate that TQGs existed in every available year of data in these states for observable measures of student disadvantage (poverty level and being a student of color) and teacher quality (experience, licensure test scores, and value added). These TQGs have been raised as a significant equity concern (e.g., Cardichon et al., 2020; Education Trust, 2020; Mehrotra et al., 2021), which is well-founded as there is evidence that the TQGs matter for student achievement and explaining student outcome gaps (Chetty et al., 2014; Goldhaber et al., in press; Graham & Flamini, 2021).

In this paper, we use data from Washington state to assess the extent to which TQGs between students of color and other students arise and persist because of three different, but interrelated, processes: attrition from the state workforce, teacher mobility between teaching positions, and hiring teachers for open positions. Consistent with prior literature, we document inequitable patterns in each of these processes. Our primary contribution, however, is to disentangle the extent to which each process contributes to overall TQGs and model how changes in a given process would influence future TQGs.

1

We argue that understanding the sources of TQGs is fundamental to closing them.[1] For example, if most of the inequity between advantaged and disadvantaged schools is the result of differential teacher attrition, states and districts might focus on policies to *keep* high-quality teachers in disadvantaged schools. If, on the other hand, discrepancies in teacher hiring explain most of the observed inequities, states and districts might instead prioritize policies to *attract* high-quality teachers to disadvantaged schools.[2]

A key challenge in understanding the formation and persistence of TQGs is that they can best be understood as the result of a complex adaptive system (Kasman et al, 2021; Miller & Page, 2009). The three processes that we focus on are clearly interconnected: teachers who leave a school, district, or the profession in one year generally must be replaced with new hires in the next. And there is also good evidence that teacher hiring, mobility, and attrition are experienced differently across schools and districts (e.g., Boyd et al., 2011; Goldhaber et al., 2020; Goldhaber and Theobald, 2021), and that teacher hiring and mobility decisions are a result of a "two-sided match" between employers and employees (Boyd et al., 2013).

In order to capture multiple, interacting process as well as the potential importance of heterogeneity in the attributes or behaviors of teachers and school administrators in attrition, mobility, and hiring decisions, we develop and deploy an agent-based modeling approach to characterize these aspects of the teacher labor market. We use this model not to simulate the

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[1] Closing TQGs is a policy goal that has received a good amount of attention over the last decade. For instance, 13 states provided timelines for eliminating teacher quality gaps as part of ESSA plans submitted in 2016 (Ross, 2019). These efforts are consistent with a federal directive from the U.S. Department of Education to develop plans to reduce inequity in the distribution of teacher quality across public schools (Rich, 2014).

[2] It is, of course, possible to address TQGs by creating inequity in one process to offset an inequity in another process. For instance, disadvantaged schools might reduce the attrition of high-quality teachers below the level of attrition of high-quality teachers in advantaged schools to offset gaps in the ability of the two types of school to hire high-quality teachers. Assessing the costs of addressing TQGs is outside the scope of this paper, but we also believe that the politics of implementing solutions to TQGs are likely connected to the sources of the gaps, suggesting the need to better understand these.

impact of any specific policy but, rather, to identify important policy levers in states' efforts to close TQGs. Specifically, we use this model to simulate different hypothetical scenarios that allow us to examine the extent to which each of the three processes *independently* or *synergistically* contribute to TQGs between advantaged and disadvantaged students.

We focus on one specific type of TQG—the relative exposure of students of color and white students to novice teachers (those with less than 5 years of experience). We focus on students of color as a measure of student disadvantage given historical and persistent inequities in their educational outcomes (e.g., Betts et al., 2003; Clotfelter et al., 2009; Reardon, 2011), and consider teacher experience as a proxy for teacher quality given the evidence from many different states and time periods that it predicts teacher effectiveness (e.g., Clotfelter et al., 2005; Rockoff, 2004; Rivkin et al., 2005).

Over the course of the 12-year period we study, students of color are three to four percentage points more likely to be assigned to a novice teacher than other students in Washington. Our simulations provide estimates for how much this gap would close if it were possible to eliminate inequities in teacher attrition, mobility, and hiring across schools that serve more and fewer students of color. We find that eliminating these inequities in teacher *hiring* and *mobility*—i.e., ensuring that all schools are equally likely to hire novice teachers or lose them to other schools that have open positions—would nearly close TQGs within 5 years, while just eliminating inequities in teacher *hiring* would close gaps within 10 years. On the other hand, eliminating inequities in teacher *attrition*—i.e., ensuring similar teacher attrition rates across all schools—without addressing mobility and hiring does little to close these gaps. This suggests that policies that seek to retain teachers in disadvantaged schools must be paired with efforts to

recruit teachers to these schools—whether through new teacher hiring or cross-school transfers—to close TQGs in public schools.

The paper proceeds as follows. In Section 2, we discuss our framework for investigating each of the labor market processes discussed above and the prior literature related to each process. We describe our methods in Section 3, discuss results in Section 4, and conclude with implications for policy and directions for future research in Section 5.

2.   Framework and Literature Review

A growing literature documents the existence and magnitude of TQGs in districts and states across the country (see Goldhaber et al. [2018] for a review), but perhaps equally important is how these inequities formed in the first place. A report from the U.S. Department of Education (Reform Support Network, 2015) identifies several processes within the teacher pipeline—the attrition of teachers from different types of schools, the movement of teachers between schools and districts, and the hiring of new teachers into their first jobs—that could contribute to TQGs across U.S. public schools. The literature on the teacher labor market has documented trends in each of these individual processes that may contribute to TQGs.

Teacher Hiring

There is evidence that schools serving more disadvantaged students tend to have less robust applicant pools when hiring for an open position (Boyd et al., 2011; Bruno & Strunk, 2019). There are relatively few studies that focus on the experience level of teachers who are hired into different types of schools, but existing evidence finds that novice teachers tend to have more challenging school placements (e.g., Bruno et al., 2019). Some studies find that there are small to no statistical differences between the value added of teachers in high-poverty schools

relative to low-poverty schools (Isenberg et al. 2021; Sass et al. 2012), while others (Xu et al., 2015) find that novice teachers in high-poverty schools were 0.02 standard deviations lower in terms of value added than teachers at low-poverty schools, and Loeb et al. (2012) find that effective schools are more likely to hire teachers with higher prior estimates of value added.[3]

Teacher Mobility

The empirical evidence on teacher mobility suggests that within-teaching mobility ("transfers") likely contributes to TQGs in two ways. First, teachers who teach in schools with higher proportions of disadvantaged students are more likely to transfer to another school in the same district than those who teach in schools with lower proportions of disadvantaged students (e.g., Cook 2011; Goldhaber et al., 2011; Isenberg et al. 2021; Hanushek et al. 2004; Sass et al. 2012; Scafidi et al., 2007). For example, Isenberg et al. (2021) find that on average, eleven percent of teachers in high-poverty schools transfer to another school in the district compared to five percent in low-poverty schools. This can contribute to TQGs because disadvantaged schools must hire more new teachers each year who, on average, are less experienced and less effective than the average teacher (e.g., Isenberg et al., 2021).

Second, teacher mobility can also contribute to TQGs if experienced teachers are disproportionately more likely to leave disadvantaged schools (or, alternatively, if inexperienced teachers are disproportionately likely to stay in disadvantaged schools). There is some prior evidence of this (e.g., Boyd et al. 2008; Goldhaber et al., 2011; Hanushek and Rivkin 2010; Isenberg et al., 2021); for example, Isenberg et al. (2021) find that experienced teachers are more likely than inexperienced teachers to leave low-poverty schools for high-poverty schools in the same district.

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[3] Importantly, these papers do not focus specifically on teacher hiring, but simply compare the effectiveness of novice teachers in different school settings.

Teacher Attrition

A number of multi-state and national studies demonstrate that teachers in disadvantaged schools are more likely to leave the workforce (e.g., Grissom, 2011; Ingersoll and May, 2012; Kaiser 2011; Keigher 2010; Marvel et al. 2007; Shen, 1997). For instance, in a study of 26 school districts, Isenberg et al. (2021) find that ten percent of teachers leave high-poverty schools in a typical year compared to seven percent of teachers who leave low-poverty schools. Studies that focus on specific schools and districts tend to come to similar conclusions; for example, Barnes et al. (2007) find a six percent difference in turnover between high-poverty and low-poverty schools in Chicago and Illinois Public Schools. These observed patterns are consistent with findings from various individual states like Florida (Ingle, 2009; Feng & Sass, 2017), Georgia (Scafidi et al, 2007), New York (Boyd et al., 2008), Texas (Hanushek et al. 2004), Wisconsin (Imazeki, 2005), North Carolina (Clotfelter et al., 2008; Goldhaber et al., 2011), and in research spanning three decades in our focal state of Washington (Krieg, 2006; Goldhaber et al., 2016; Gritz and Theobald, 1996).

3.   Methods

3.1   Agent-Based Model Design

We use an agent-based model (ABM) model design to study the extent to which three processes—teacher attrition from the state workforce, teacher mobility between teaching positions ("transfers"), and teacher hiring for open positions—contribute to TQGs between advantaged and disadvantaged schools. ABM is a computational modeling approach in which individual entities (i.e., teachers or schools) as well as their interactions with one another over time are explicitly simulated. It is thus well suited for exploring broad questions about educational processes that are driven by the dynamic intersection of individual and

organizational decision making (Kasman & Klasik, 2017; Maroulis et al., 2010). In the following subsections, we discuss the agents and environment of this model, the initialization and dynamics of the model, and the model output.

Agents (Teachers) and Environment (Schools)

The agents in this ABM represent teachers in K–12 public schools in Washington state. Following best practices in the design of complex systems models, we strive for a parsimonious model that has substantial explanatory power for relevant phenomena, capable of representing both relevant agent-level behaviors and the system-level patterns in the outcomes of interest that they produce (Hammond, 2015). Agents in this model have a single attribute: years of experience, with agents having less than 5 years of teaching experience designated as "novice teachers." The environment in which decisions are made that result in hiring, mobility, and attrition is the teacher labor market. We decompose this into two parts: K–12 schools, which are explicitly represented within our simulations, and exogenous, time-dependent factors (e.g., employment opportunities in other professions), which we represent implicitly. For the purposes of model parsimony, schools also have a single attribute: the percentage of students of color that they serve.[4]

Initialization and Dynamics

During the first simulated year of our model, we place a set of teachers in schools; we can initialize the model either "equitably" by doing so at random or "inequitably" by doing so in accordance with observed relationships between teacher experience and school composition in

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[4] Of course, teachers also may have other characteristics correlated with being novices, and schools have other characteristics correlated with the percentage of students of color in the school, all of which are also related to the various processes we investigate. But we select these two characteristics for model parsimony and to connect this simulation to prior documented TQGs that are a function of these two characteristics.

this initial year. In subsequent years in our model, teacher and school interactions follow a serial, three-stage process:

1. *Attrition*. Current teachers decide whether to stop working as public-school K–12 teachers.

2. *Mobility*. Teachers who remain after the previous step decide whether they wish to transfer to an available position in another school.

3. *Hiring*. Finally, schools fill positions from two distinct pools of available applicants, movers and new hires, the latter of whom may have previous teaching experience (e.g., be returning to the profession or entering from elsewhere).

We allow for each of these stages to be characterized either "equitably"—with behavior occurring without any consideration of school composition—or "inequitably," allowing the process to occur differentially across schools serving different types of students. Specifically, when attrition and mobility occur equitably, the probability that teachers leave their current position is a function solely of their experience, while in the inequitable scenario attrition and mobility are also functions of other school-level factors (e.g., the average teacher experience in the school and the percentage of students of color in the school) and interactions with teacher characteristics (see Section 3.2). In the case of teacher hiring, when hiring is equitable, open positions are filled randomly, while under inequitable hiring, open positions are filled based on the level of disadvantage of the school—i.e., schools are probabilistically matched to mover and new hire applicant pools with similar levels of school disadvantage.

3.2   Model Parameterization

Data Sources and Summary Statistics

We use Washington state's S-275 database, which contains information from OSPI's personnel-reporting process and includes school assignment of all certified employees in the state in addition to a measure of teaching experience in the state.[5] S-275 data are available from the 1983–84 school year through the 2020–21 school year, although our analysis in Washington spans 13 years (2001–02 through 2013–14) because these are the same years of data considered in our prior analysis of TQGs (Goldhaber et al., 2018). We consider teachers with a full-time teaching appointment in a single school within a given year. We use the S-275 dataset to quantify each teacher's experience, and specifically whether a teacher has less than 5 years of experience. We then connect these data to publicly available data on the percentage of students of color in each teacher's school from the Washington State Report Card.[6] The final longitudinal dataset in Washington includes 564,296 teacher-year observations (86,241 unique teachers) spanning 13 school years.

In **Figure 1** we provide summary statistics from this dataset that replicate and extend prior work discussed in the previous section about inequities in teacher attrition, mobility, and hiring. Panels A and B illustrate that teacher attrition and mobility are more prevalent in disadvantaged schools in Washington. There is also some evidence of *differential* mobility and attrition that reinforces prior findings; for example, Panel A of Figure 1 illustrates that non-novice teachers are disproportionately likely to leave advantaged schools relative to novice teachers. These findings largely replicate prior trends discussed in Section 2, but more novel are the findings for teacher hiring; in particular, the hiring proportions (Panel C in Figure 1) illustrate

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[5] The S-275 contains the experience that teachers are credited with for pay purposes, which do not include out-of-state teaching, teaching in a private school, or substitute teaching.
[6] Following Goldhaber et al. (2018), we define students of color as American Indian, Black, or Hispanic.

that, conditional on an open position, disadvantaged schools are more likely to hire an inexperienced teacher than an advantaged school.

Statistical Estimation

As described in Section 3.1, inequitable parameterization of the ABMs requires predicted probabilities of teacher attrition, mobility, and hiring for given teachers given characteristics of the school (e.g., the percentage of students of color) and, in the case of attrition and mobility, teacher characteristics (e.g., teacher experience). To generate these inequitable probabilities, we estimate a series of Bayesian models predicting the attrition, mobility, and hiring of teachers between 2002 and 2014. Teacher attrition and mobility are jointly estimated using the mixed-effects multinomial logistic regression model described by equations 1a-1c:

$$\beta_{\cdot,\cdot} \sim N(0, \boldsymbol{I}), \quad \gamma_{\cdot,\cdot} \sim N(0, .1\boldsymbol{I}), \quad \sigma_\tau \sim N(0, \boldsymbol{I}), \quad \sigma_\varsigma \sim N(0, \boldsymbol{I}), \tag{1a}$$

$$\ln\frac{\mathrm{P}(Y_{jst} = \text{Attrit})}{\mathrm{P}(Y_{jst} = \text{Stay})} = \beta_{\mathrm{A},0} + T_{jt}^\top\beta_{\mathrm{A},1} + S_{st}^\top\beta_{\mathrm{A},2} + E_{jst}^\top\beta_{\mathrm{A},3} + \tau_{\mathrm{A},j} + \varsigma_{\mathrm{A},s} + \gamma_{A,t} + \varepsilon_{\mathrm{A},jst}, \tag{1b}$$

$$\ln\frac{\mathrm{P}(Y_{jst} = \text{Move})}{\mathrm{P}(Y_{jst} = \text{Stay})} = \beta_{\mathrm{M},0} + T_{jt}^\top\beta_{\mathrm{M},1} + S_{st}^\top\beta_{\mathrm{M},2} + E_{jst}^\top\beta_{\mathrm{M},3} + \tau_{\mathrm{M},j} + \varsigma_{\mathrm{M},s} + \gamma_{M,t} + \varepsilon_{\mathrm{M},jst}. \tag{1c}$$

T_{jt} is a 4×1 vector of teacher-by-year characteristics including novice status, a novice/year interaction term, and a linear and quadratic term of teaching experience for teacher j and year t. S_{st} is a 3×1 vector of school-by-year characteristics including average experience, proportion of novice teachers, and proportion of students of color in school s and year t. E_{jst} is a 4×1 vector of interactions between the proportion of students of color in school s and individual novice status, individual experience, average experience, and proportion of novice teachers. $\tau_{\cdot,j}$ is a teacher random effect, $\varsigma_{\cdot,s}$ is a school random effect, $\gamma_{\cdot,t}$ is a year fixed effect, and $\varepsilon_{\cdot,jst}$ is a mean-zero error term. For the equitable simulations, we estimate an alternative equitable model

by restricting equations 1a-1c so that only coefficients associated with the linear experience terms and the intercepts are nonzero.

Teacher hiring practices in year t are estimated using the two-stage mixed-effects model described by equations 2a-2c:

$$\beta_{\cdot,\cdot} \sim N(0, \mathbf{I}), \quad \gamma_{\cdot,\cdot} \sim N(0, .1\mathbf{I}), \quad \sigma_\tau \sim N(0, \mathbf{1}), \quad \sigma_\varsigma \sim N(0, \mathbf{I}), \tag{2a}$$

$$\ln \frac{P(M_{st} = 0)}{P(M_{st} > 0)} = \beta_{N,0} + S_{st}^\top \beta_{N,1} + E_{st}^\top \beta_{N,2} + \varsigma_{N,s} + \gamma_{N,t} + \varepsilon_{N,st}, \tag{2b}$$

$$M_{st} = \beta_{H,0} + S_{st}^\top \beta_{H,1} + E_{st}^\top \beta_{H,2} + \varsigma_{H,s} + \gamma_{H,t} + \varepsilon_{H,st}. \quad \text{(for } M_{st} > 0) \tag{2c}$$

M_{st} is the proportion of new hires in year t teaching in a different Washington state school in year $t - 1$. S_{st} is a 4×1 vector of school-year characteristics including the proportion of novice teachers, average teacher experience, the proportion of zero experience teachers, and the proportion of students of color. E_{st} is a 3×1 vector of interaction terms between the proportion of students of color in school s and year t and other school-by-year characteristics. $\varsigma_{\cdot,s}$ is a school random effect, $\gamma_{\cdot,t}$ is a year fixed effect, and $\varepsilon_{\cdot,st}$ is a mean-zero error term. For the equitable simulations, we again estimate an alternative equitable model by restricting equations 2a-2c so that only coefficients associated with the linear experience terms and the intercepts are nonzero.

Prior distributions on each of the coefficients and standard deviation of random effects are chosen to be independently distributed according to a standard normal to remain uninformative. We set the standard deviation of the year fixed effect prior distribution to be 0.1 to reduce the occurrence of unrealistically large year effects having substantial impact on ABM runs. The parameter values used for each ABM run that determine the probabilities of subsequent teacher placements are sampled from the conjugate normal posterior distributions of these estimates.

The estimates from the models in equations 1a–2c (provided in Appendix Table A1) strongly comport with the summary statistics discussed in Section 3.2 and the prior literature discussed in Section 2; teachers in schools that serve more students of color are more likely to leave public K–12 schools than teachers in schools with fewer students of color, and schools that serve a high proportion of students of color are more likely to hire a novice teacher when they have an opening than schools that serve fewer students of color. As in the summary statistics, there is also evidence of differential inequity, as experienced teachers are particularly likely to leave schools with higher proportions of students of color.

We use the coefficients from Appendix Table A1 to generate predicted probabilities of attrition, mobility, and hiring for open positions (as described in Section 3.1). Our primary model outputs are distributions of TQG derived from proportions of novice teachers serving students of color and white students in each year across 100 simulation runs in each of sixteen "inequity" configurations (i.e., with each potential combination of inequality present or not for initialization, attrition, mobility, and hiring). Due to our parameterization strategy, this allows us to simultaneously account for both estimation error (i.e., through sampling of parameter values) and model stochasticity, and thus to explore a substantial amount of model sensitivity using our primary analysis data.

4.   Results

4.1   Model Use and Experimentation

In **Figure 2**, we explore the "generative sufficiency" of our model in two key respects (Epstein, 2012). First, when each of our three inequality pathways are active, we expect to generate TQGs similar to those observed in the real world during the years that correspond to our

simulations. The solid lines in the first two panels of Figure 2 plot the simulated probability that

students are assigned to a novice teacher over simulation years for students of color (Panel A)

and other students (Panel B) alongside the true assignment rates (dotted lines) and 90 percent

confidence intervals for these estimates (dashed lines) that, as described in the previous section,

account for both estimation error from the models in equations 1a–2c in Section 3 *and* simulation

error across 100 iterations of each simulation. As shown in these figures, the simulated

probability that both groups of students are assigned to a novice teacher tracks very closely with

the observed probabilities, and well within the margin of error for these estimates across

simulation years. As a result, and as shown in Panel C of Figure 2, the simulated TQG tracks the

observed TQG (documented for these same years of data in Goldhaber et al. [2018]) very closely

across simulations years and, again, well within the margin of error for these estimates.[7]

Second, when each of the inequity pathways is inactive, we expect that TQGs will be

functionally non-existent. This will establish the degree to which our characterizations of teacher

labor market processes—and only these characterizations—are capable of broadly explaining

TQGs. In Panel D of Figure 2, we show that—when all of the inequity pathways are set to be

equitable across schools—the TQG goes to zero within about 8 simulation years, on average. So,

the figures in Panels C and D showing the simulated TQG when all processes are inequitable

(Panel C) and equitable (Panel D) represent bounds on the simulated TQGs discussed in the next

section that turn on and off these inequity pathways one at a time.

4.2   *Simulation Results*

We begin by providing an overview of the most straightforward simulations that turn off

(i.e., set to "equitable") one inequity pathway at a time. The intuition behind these simulations is

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[7] In Appendix Figure A1, we also show that rates of attrition, mobility, hiring, and overall proportions of novice teachers in these simulations track the true rates quite closely.

that, if only one process in the teacher labor market becomes equitable while the others remain inequitable, then any subsequent reductions in the overall TQG (relative to the TQG when all processes are inequitable) provides an estimate of how much that specific process contributes to TQGs. Alternatively, these exercises provide an estimate of how much we might expect TQGs to decrease in response to a hypothetical intervention that manages to remove all inequity in one of the three processes we investigate.

In **Figure 3**, we first repeat in Panel A the figure showing the evolution of the simulated TQG across simulation years when all inequity pathways are on. We then present analogous figures for simulations in which the attrition (Panel B), mobility (Panel C), and hiring (Panel D) inequity pathways are turned off. Panel B shows that, perhaps contrary to expectation, turning off *only* the attrition inequity pathway—i.e., ensuring that the probability of teacher attrition is the same for teachers across all school settings in the state—does little to reduce TQGs. In fact, the TQG from the "all inequitable" simulation is within the confidence interval for the estimated TQG under this simulation in each of the 12 simulation years. In other words, eliminating inequities in teacher attrition without addressing mobility and hiring does little in the short run to close these gaps.

In contrast, Panels C and D both show substantial reduction in the simulated TQG when the mobility or hiring inequity pathways are turned off. In the case of mobility, the TQG reduces to about half of the observed TQG by the fifth year of the simulation and stays at about half of the observed TQG for the remainder of the simulation years. The reduction in the TQG as a result of turning off the hiring inequity pathway is less rapid but larger over time, reduced all the way to close to zero by year 8 of the simulation. This simulation suggests that, even under observed rates of attrition and mobility from different schools by experienced and inexperienced

14

teachers, TQGs could be eliminated in less than 10 years if the probability of *replacing* these teachers with an experienced teacher was the same across advantaged and disadvantaged schools.

Finally, and as discussed in the introduction, this simulation represents a complex adaptive system (Kasman et al., 2021; Miller et al., 2009) in which all three processes are dynamically interconnected. It is therefore important to consider how these different processes might *interact* to better understand how policies that affect more than one process—e.g., incentives to keep teachers in their current school that might affect both attrition and mobility, or interventions to recruit teachers to disadvantaged schools that might affect both mobility and hiring—might affect TQGs. We therefore plot in **Figure 4** the estimated TQG and associated confidence intervals after 5 simulation years (Panel A) and after 10 simulation years (Panel B) for the simulation associated with *each combination* of inequity pathways. The estimates for "1 Attrition," "2 Mobility," and "3 Hiring" correspond exactly with the corresponding estimates in Panels B–D of Figure 3, but the simulations that turn off multiple inequity pathways lead to additional conclusions; for example, the simulation that turns off both the mobility and hiring inequity pathways results in a TQG after just 5 years that is indistinguishable from zero. This suggests that interventions that target teacher recruitment to disadvantaged schools, whether through new teacher hiring or transfers from other schools, could close TQGs even faster than interventions that target just one of these processes.

5.   Conclusions

We believe that the results from these simulations can inform both recommendations for policymakers seeking to close TQGs and provide a framework for considering the extent to

which specific interventions might be expected to affect them. Of particular interest is the finding that teacher mobility and hiring play outsized roles in contributing to TQGs, and teacher attrition *from the workforce* contributes relatively little to observed TQGs, at least when other processes (mobility and hiring) are still inequitable. That teacher attrition appears to play a relatively minor role in TQGs is notable given that it has been the focus of many efforts to close TQGs (e.g., Carver-Thomas & Darling-Hammond, 2017; Mehrotra et al., 2021).

To make this concrete, an oft-cited example an intervention to make teacher retention more equitable is a bonus policy implemented in North Carolina in the early 2000s in which certified math, science, and special education teachers working in disadvantaged schools received an annual bonus of $1800. Clotfelter et al. (2008) found strong evidence that the policy reduced the combined attrition and mobility of teachers from disadvantaged schools, and importantly, found that experienced teachers demonstrated the greatest response to the policy. Our simulations suggest that *even such a successful intervention* will only have a substantial impact on TQGs if: a) patterns of mobility (not just overall rates of retention) follow similar patterns; and b) patterns of hiring to replace departing teachers are made more equitable as well.

These findings suggest that we need to learn more about what affects recruitment to and transfers from disadvantaged schools. There is only a small literature on these issues. For instance, there is evidence that transfer provisions in collective bargaining agreements increase the inequity in the distribution of teacher experience by providing more senior teachers advantages within districts when schools downsize or new slots open in a district (Anzia & Moe,

2014; Goldhaber et al., 2016). But there is very little quantitative evidence about the factors that affect the equity of teacher quality related to recruitment and hiring processes.[8]

More generally, our framework for evaluating teacher quality gaps points to work in two future directions. The first is to study whether the patterns we observe for inequities measured by teacher experience are reflective of other measures of teacher quality. While experience is arguably an important teacher qualification, and certainly the easiest to observe for policy purposes, it would be useful to know whether the findings are robust to alternative measures. The second direction is to use this framework to evaluate the impact of policies designed to impact the processes we simulate. For example, if a given intervention is shown to reduce the movement of teachers from advantaged to disadvantaged schools by a given amount or increase the probability that a disadvantaged school is able to hire an experienced teacher, then this framework can be used to simulate the downstream consequences of these changes in terms of subsequent TQGs. We view this as an important line of future research that can inform future efforts to close TQGs in K-12 public schools.

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[8] The cost of any intervention is also an important consideration. Indeed, it is conceivable that the most cost-effective means of closing TQGs is to make a process inequitable (in favor of disadvantaged schools) to offset inequities in another process that may be harder to address.

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Figure 1. Teacher attrition, mobility, and hiring by quartile of school percent students of color (SOC) and teacher experience
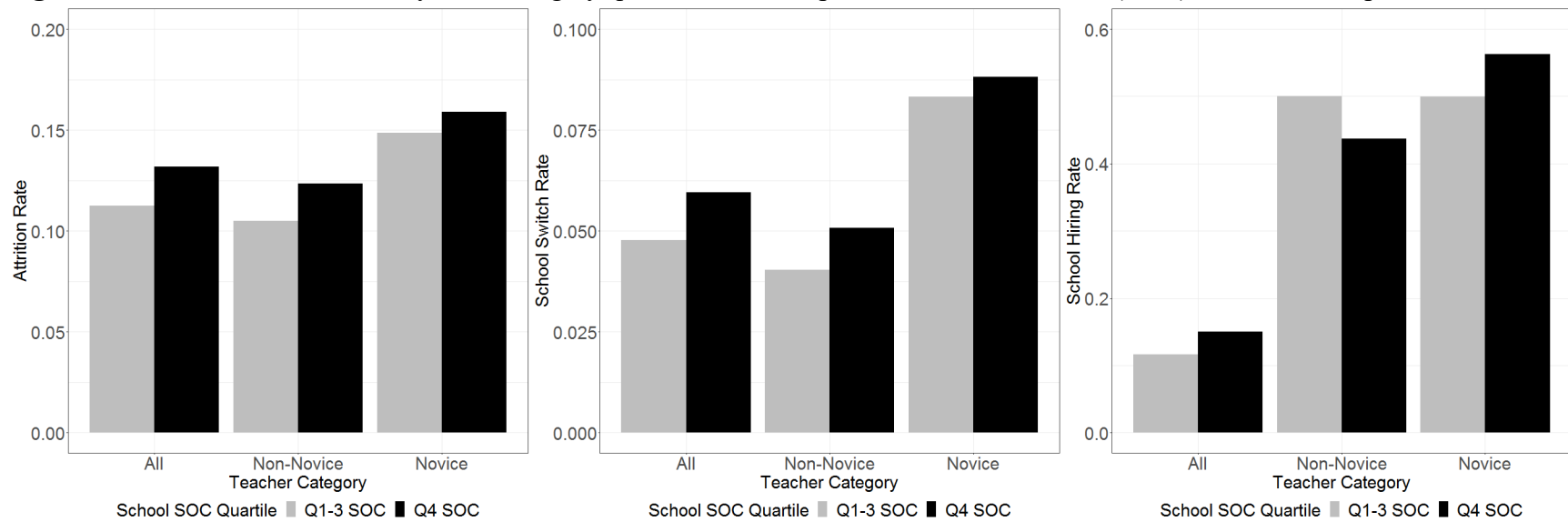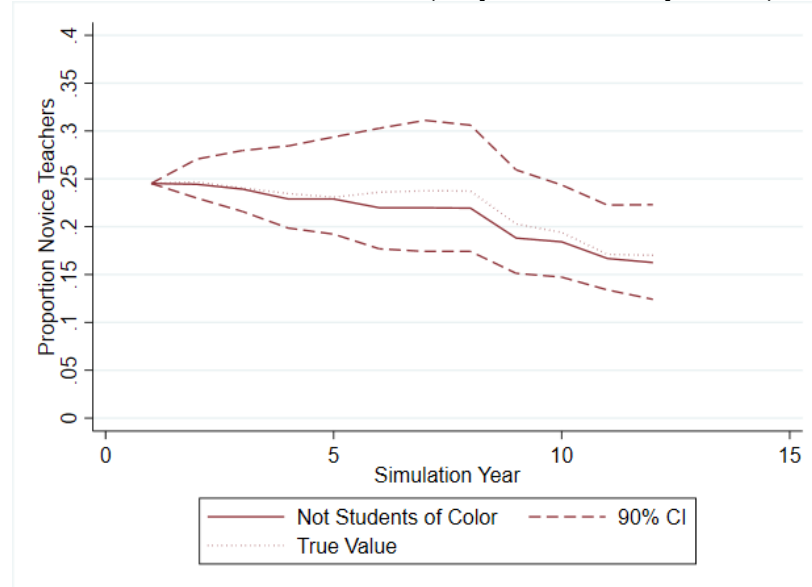
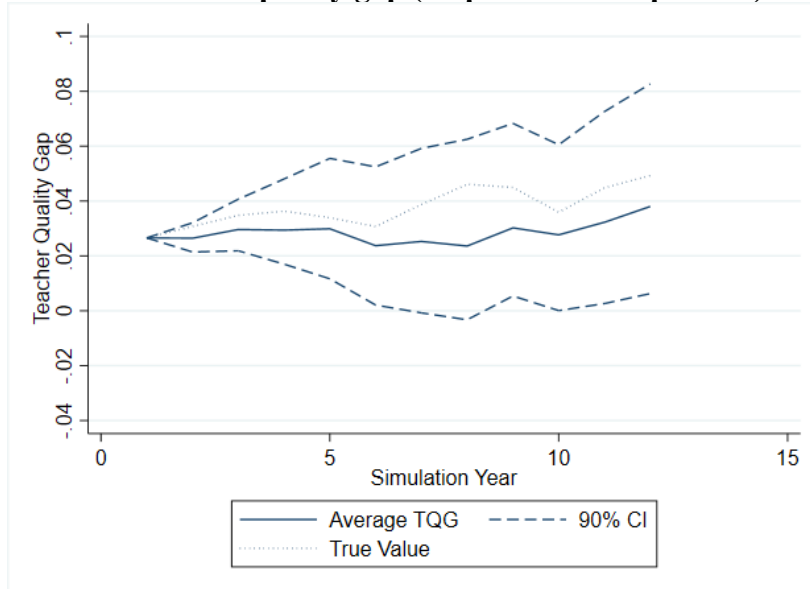**Figure 2. Simulated novice teacher exposure and teacher quality gaps, by simulation year**
Panel A. Students of color (all processes inequitable)   **Panel B. Not students of color (all processes inequitable)**
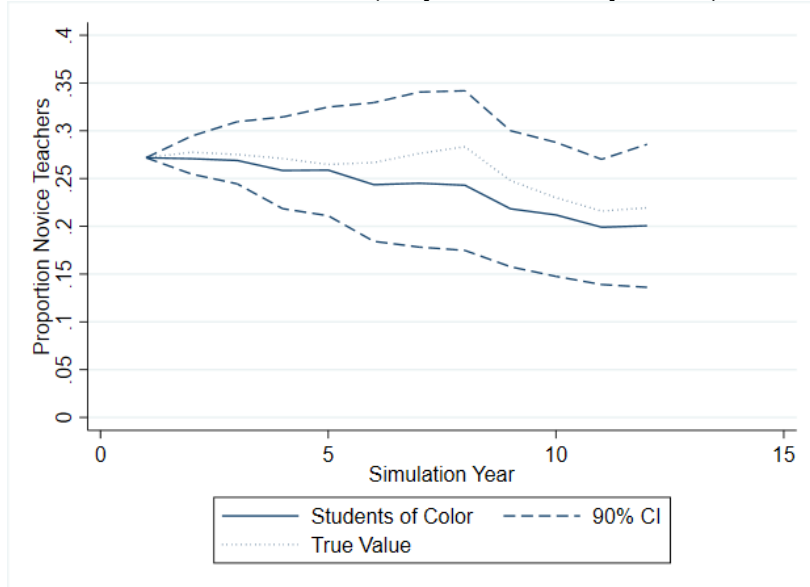
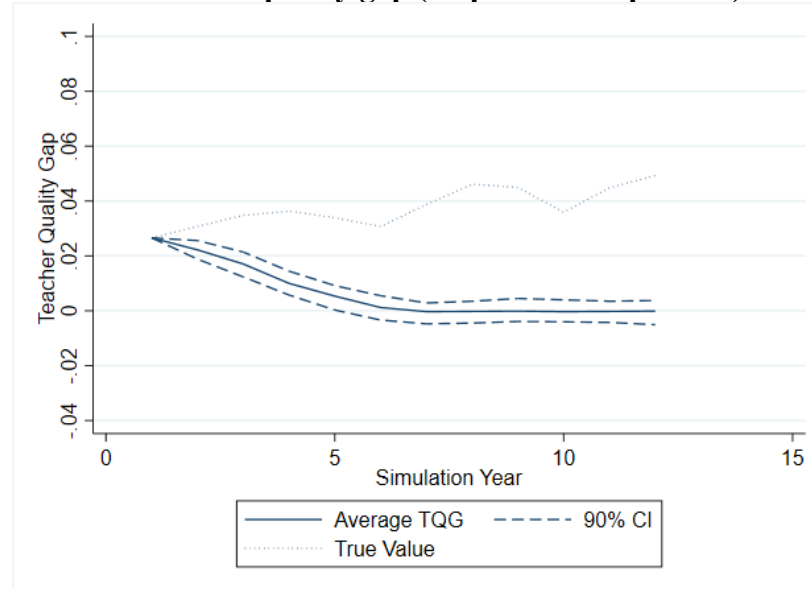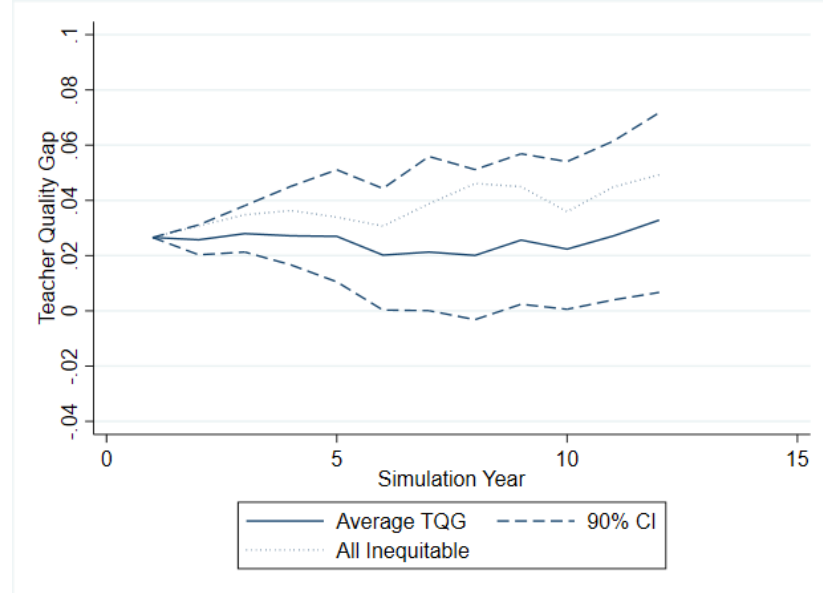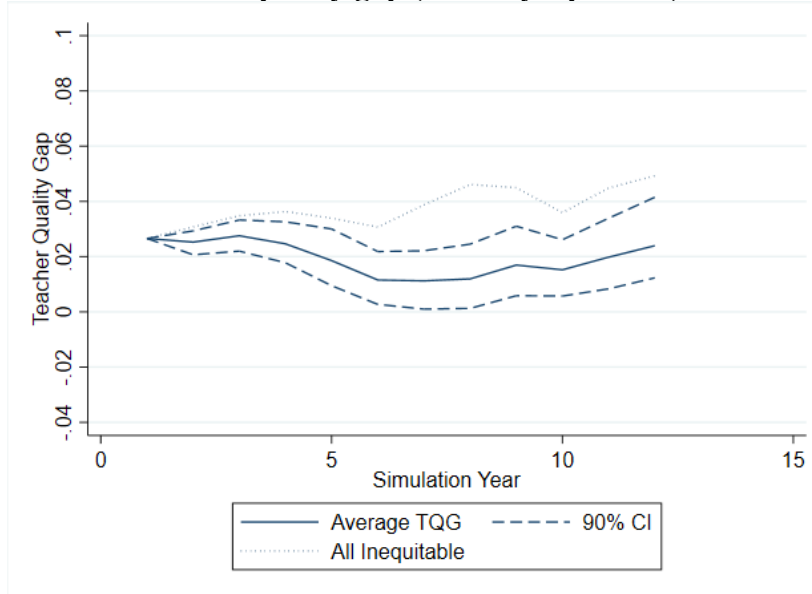**Panel C. Teacher quality gap (all processes inequitable)**   **Panel D. Teacher quality gap (all processes equitable)**

Figure 3. Individual simulation results over simulation years

Panel A. Teacher quality gap (all processes inequitable)

Panel B. Teacher quality gap (attrition equitable)

Panel C. Teacher quality gap (mobility equitable)

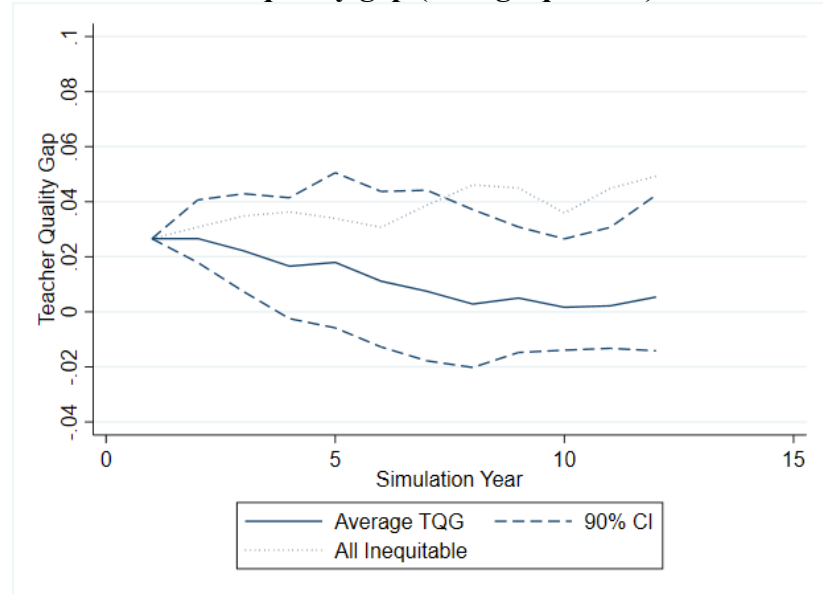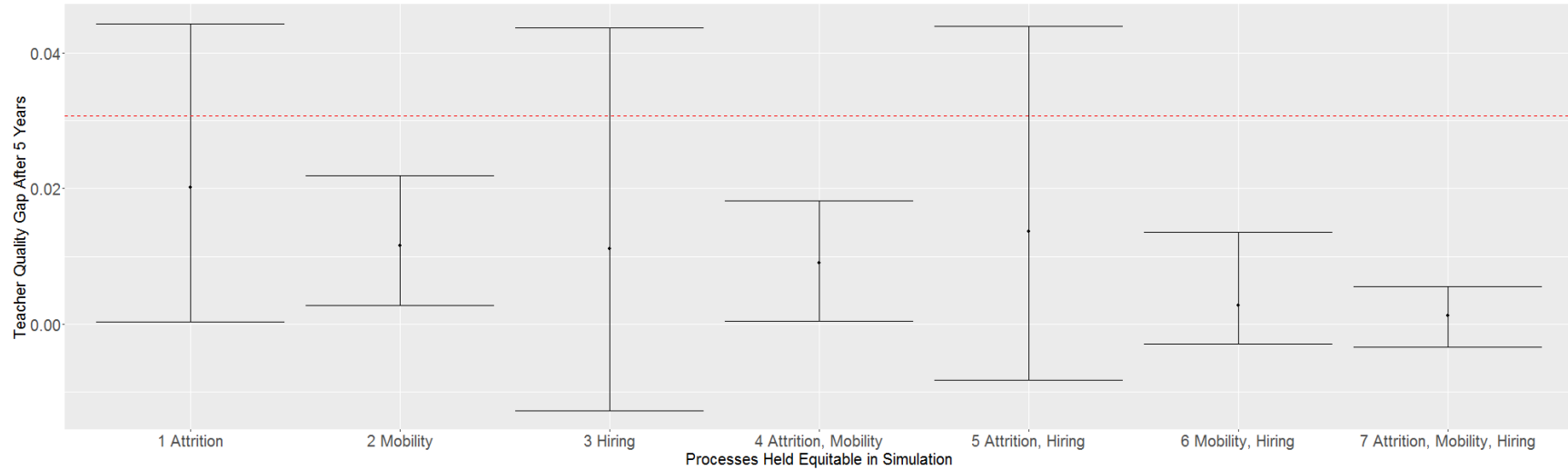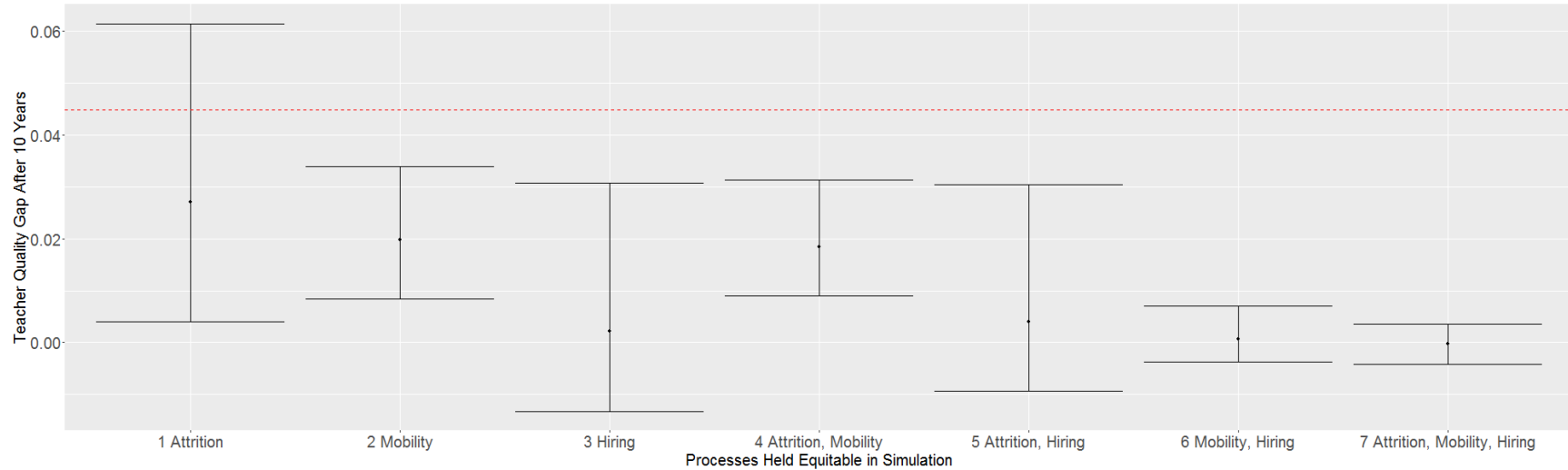**Panel D. Teacher quality gap (hiring equitable)**

Figure 4. Results across simulations, selected simulation years

Panel A. Teacher quality gaps after 5 years (horizontal line = true gap)

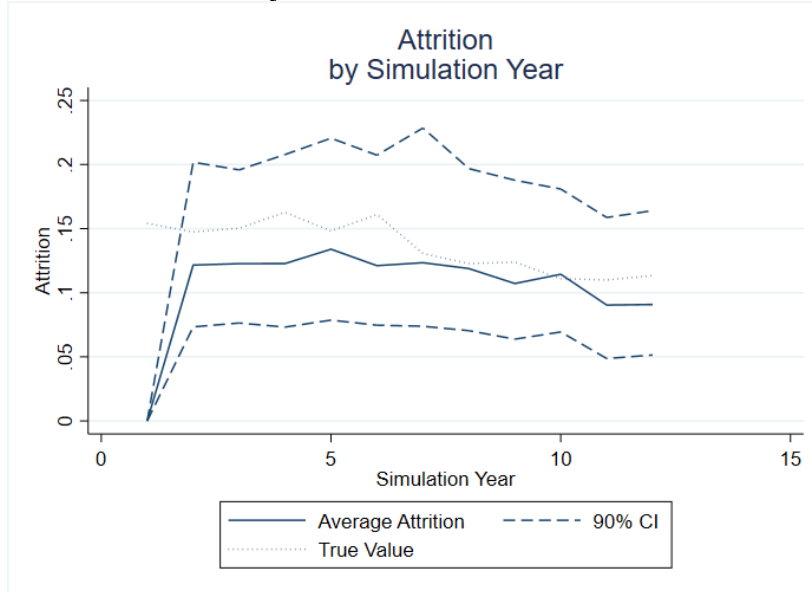## Panel B. Teacher quality gaps after 10 years (horizontal line = true gap)

Appendix Table A1. Selected coefficients from first-stage Bayesian regression models

| Column	(1)	(2)	(3)
Model	Multinomial Logit for Attrition and Mobility		Bernoulli New Hiring Model
Outcome	Teacher Attrition	Teacher Mobility	School Hires New Teacher
Novice Teacher	0.56***	0.14	
	(0.03)	(0.05)	
Teacher Experience	0.02***	-0.04	
	(0.00)	(0.00)	
School Proportion of Novice Teachers	0.15	0.43**	-0.52
	(0.13)	(0.20)	(0.27)
Average Experience in School	0.01	-0.03***	0.05***
	(0.01)	(0.01)	(0.01)
Percent SOC in School	0.77**	-0.67	0.98*
	(0.32)	(0.50)	(0.55)
Novice Teacher * Percent SOC in School	-0.01	-0.10	
	(0.09)	(0.15)	
Teacher Experience * Percent SOC in School	0.02***	0.03***	
	(0.00)	(0.01)	
School Proportion of Novice Teachers * Percent SOC in School	-0.26	0.09	0.14
	(0.37)	(0.55)	(0.64)
Average Experience in School * Percent SOC in School	-0.05**	0.00	-0.05*
	(0.02)	(0.03)	(0.03)
Observations	269,725		12,367

Note. P-values from two-sided t-test: *$p<.10$; **$p<.05$; ***$p<.01$. SOC = students of color.

Appendix Figure A1. Simulation processes at observed values (all processes inequitable)
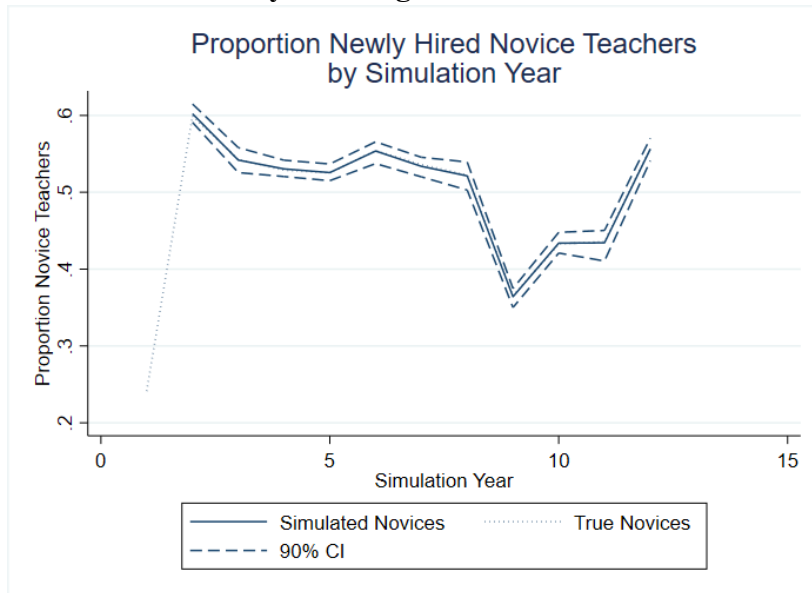**Panel A. Probability of attrition**   **Panel B. Probability of school move**
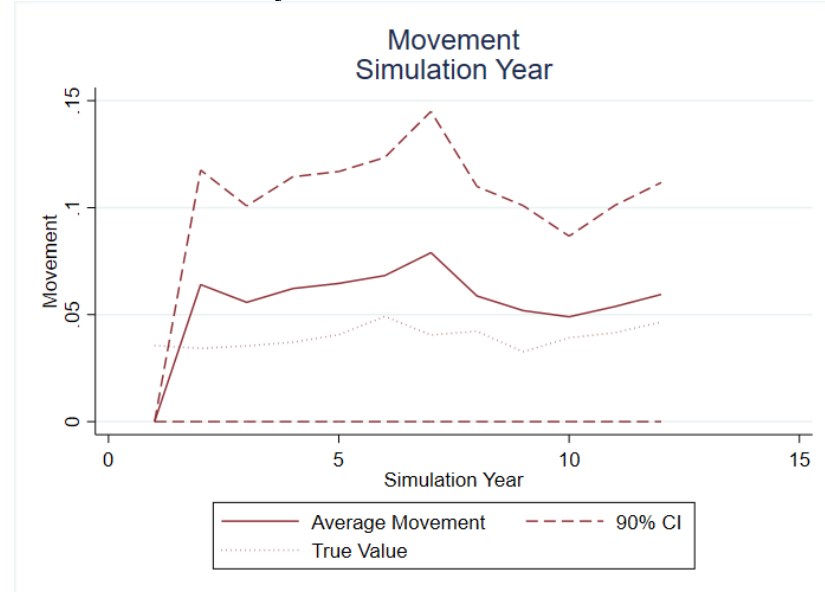
Panel C. Probability of hiring novice teacher   **Panel D. Proportion of novice teachers**