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Essays on Race and Finance

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ESSAYS ON RACE AND FINANCE

DISSERTATION

A dissertation submitted in partial
fulfillment of the requirements for
the degree of Doctor of Philosophy
in the Gatton College of Business
and Economics at the
University of Kentucky

By
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ABSTRACT OF DISSERTATION

ESSAYS ON RACE AND FINANCE

In my first chapter, I show a positive municipal financing shock has heterogeneous effects on academic achievement. White students show meaningful improvement, but Black and Hispanic students do not. Consequently, the achievement racial gap widens following the shock. Changes in school funding do not explain this phenomenon; rather, it is explained by heterogeneous outcomes in household Socioeconomic Status (SES). These results highlight the possibility that a credit shock-induced increase in government spending could unexpectedly increase the local racial disparity. The second chapter examines the role of race and racial concordance between financial advisors and their local community. There are significant differences in stock market participation based on community racial composition as well as differences in the characteristics of communities served by minority advisors. Notably, minority advisors are more likely to serve racially concordant communities. We find that racial concordance has only a modest relation with local stock market participation. However, while minority advisors are more likely to drop out of the industry, this relation is mitigated among advisors located in more concordant communities.

KEYWORDS: Race, Municipal Bond, Advisors, Education, Household Finance

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Date: April 1, 2023

ESSAYS ON RACE AND FINANCE

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1.1 Introduction

Despite growing national support for civil rights movements, the socioeconomic status (SES) racial gap stubbornly persists in the US (Chetty, Hendren, Jones, and Porter, 2020b; Derenoncourt, Kim, Kuhn, and Schularick, 2022). One in five children in the US are growing up in poverty, and more than 60% of them are Black or Hispanic.[1] This persistent racial gap in household well-being significantly affects children's human capital accumulation (Dahl and Lochner, 2012; Deckers, Falk, Kosse, Pinger, and Schildberg-Hörisch, 2021; Hanushek, 2001; Reardon, Kalogrides, and Shores, 2019; Jang and Reardon, 2019) and has long-lasting impact on their intergenerational mobility (Chetty et al., 2020b; Sylwester, 2002).

As an important factor in the persistent racial disparity, the role of finance has attracted attention in both academic and policy works. Ample evidence suggest racial minorities do not have equal access to financial markets,[2] yet prior literature generally shows positive local financial shocks can benefit the underrepresented populations and reduce racial gaps in various socioeconomic outcomes.[3] Is this always the case? This paper examines this question in the context of municipal financing conditions, the measure of local government's ability to raise funding through municipal bonds. Adelino, Cunha, and Ferreira (2017) provide causal evidence that improvement in public financing conditions positively affects labor market outcomes and household socioeconomic well-being.[4] This paper asks whether these positive effects have an intergenerational impact on human capital accumulation. Further, do households and students from different races benefit equally from an improved public financing condition?

To facilitate causal inference, I follow Adelino et al. (2017) and Cunha, Ferreira, and Silva (2022+) and use Moody's municipal bond rating recalibration in 2010, which corresponds to nearly 70,000 municipal bond issues that are worth $2.2 trillion in total par value, as a positive exogenous shock to the local municipal financing condition.[5] Adelino et al. (2017) show Moody's recalibration significantly increases

[1]According to National KIDS COUNT. See `https://tinyurl.com/27hf863z`.

[2]See for example Begley and Purnanandam (2021); Dougal, Gao, Mayew, and Parsons (2019); Haendler and Heimer (2021); Chu, Ma, and Zhang (2021); Stefan, Holzmeister, Müllauer, and Kirchler (2018); Giulietti, Tonin, and Vlassopoulos (2019); Bartlett, Morse, Stanton, and Wallace (2022); Bayer, Ferreira, and Ross (2016); Bayer, Casey, Ferreira, and McMillan (2017); Bayer, Ferreira, and Ross (2018); Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022); Chu (2019); Charles and Hurst (2002); Butler, Mayer, and Weston (2022+); Blanchflower, Levine, and Zimmerman (2003); Munnell, Tootell, Browne, and McEneaney (1996); Howell, Kuchler, Snitkof, Stroebel, and Wong (2021); Eldemire-Poindexter, Luchtenberg, and Wynter (2022) among many others.

[3]See for example Levine, Rubinstein, and Levkov (2014); Beck, Levine, and Levkov (2010); Chatterji and Seamans (2012) and Stein and Yannelis (2020).

[4]Guiso, Sapienza, and Zingales (2004) provide a more general examination and show a positive effect of local financial development on socioeconomic well-being.

[5]Treated issues include both revenue and general obligation (GO) bonds. More discussion on the

local government borrowing and spending in treated counties and results in various positive spillover outcomes such as increased public and private employment and household income. Using a generalized difference-in-differences (DiD) estimation, I find that, consistent with the economic benefits documented in Adelino et al. (2017), the recalibration also results in positive education outcomes: Students from treated counties exhibit significant improvement in test scores. A back-of-the-envelope calculation suggests the effect of the recalibration on education outcomes is comparable to an $87 increase in school spending per pupil or a $700 million increase in school spending nationwide.[6]

However, this effect is not evenly distributed within treated counties: Results from re-estimating the generalized DiD estimation for each race group suggest strong heterogeneity in the treatment effect. White students showed significant improvement in test scores. However, there is no significant improvement for Hispanic or Black students. This heterogeneity in treatment effect significantly widens the White-Minority academic achievement gap. A decomposition exercise shows this result is largely orthogonal to the recalibration's impact on achievement wealth gap (Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao, 2017). Robustness tests also suggest this result is not driven by alternative explanations such as demographic shifts (Cornaggia, Gustafson, Israelsen, and Ye, 2019; Derenoncourt, 2022), heterogeneity in control county characteristics (Yagan, 2019), or imprecise measurement.

Prior and contemporaneous literature suggests two potential channels that could drive these heterogeneous outcomes in test scores. The first is the school district borrowing and spending channel (Abott, Kogan, Lavertu, and Peskowitz, 2020; Jackson, Johnson, and Persico, 2016; Jackson, Wigger, and Xiong, 2021; Boyson and Liu, 2022). Because school districts are one of the major borrowers in the municipal bond market, the rating recalibration could reduce the issuing costs and incentivize issuance. However, results in this paper show that changes in school funding are unlikely the factor that drives this heterogeneous treatment effect in the setting of this paper: There is no treatment effect on spending per pupil for school districts in treated counties, and the main results on test score racial gap continue to hold for treated school districts that do not increase spending.

The second mechanism for the recalibration to impact test scores is the household well-being channel. Prior literature has extensively documented the importance of household well-being on academic performance (Dahl and Lochner, 2012; Ananat, Gassman-Pines, Francis, and Gibson-Davis, 2017; Deckers et al., 2021; Butler, Demirci, Gurun, and Tellez, 2021). And Adelino et al. (2017) show the recalibration had a significant impact on the real economy, with a fiscal multiplier of 1.9. In other words, the recalibration-induced increase in municipal borrowing and spending generated significant economic gains in the form of employment opportunities and household income. These benefits came at a crucial time for the children: As the country recovers from the Great Recession, parents who were enabled to earn more

nature of the recalibration is provided in the next section.

[6]Based on the effect of school spending on test scores reported in Abott, Kogan, Lavertu, and Peskowitz (2020). Section III provides a more detailed discussion of this economic magnitude.

from the labor market can provide much-needed income and stability for the family (Hussam, Kelley, Lane, and Zahra, 2021). These economic and psychological benefits positively impact children's performance at school and the accumulation of their human capital (Frisvold, 2015; Camacho, Duque, Gilraine, and Sanchez, 2022). Is the heterogeneous treatment effect on test scores a result of uneven distribution of economic gains from the recalibration? Consistent with this channel, there is economically and statistically significant improvement in socioeconomic well-being for treated White households, but not for treated Black or Hispanic households. Corroborating this result, only White households in treated counties show an improvement in employment status and a reduction in reliance on Supplemental Nutrition Assistance Program (SNAP), an important social safety net.

This paper contributes to the literature on the real effects of municipal financing. Cornaggia, Cornaggia, and Israelsen (2018) show that Moody's rating recalibration in 2010 reduces the financing constraints for municipalities and encourages borrowing. Adelino, Cunha, and Ferreira (2017) show this recalibration-induced increase in municipal borrowing significantly increases government spending, which generates positive spillover effects in the local economy. This paper extends Adelino et al. (2017) by studying the cross-sectional distribution of these economic gains and highlighting their intergenerational impact on racial disparities in human capital accumulation. To this end, a closely-related contemporaneous paper is Boyson and Liu (2022), which also studies the relationship between municipal financing and education inequality. This paper differs from Boyson and Liu (2022) in two important aspects. First, these two papers explore different channels that perpetuate disparity in education outcomes. The inequality in Boyson and Liu (2022) stems from differences in school districts' ability and willingness to borrow and spend on education-related investments, whereas this paper shows it could also come from the unequal distribution of economic gains across households within the same community. Second, Boyson and Liu (2022) does not explicitly study racial disparity in human capital accumulation, which is the main focus of this paper.

This paper also contributes to the literature on the interaction between finance and race. There are two main themes in this topic. The first theme focuses on minority individuals' and households' access to financial markets. Chu et al. (2021), Bayer et al. (2017), Bayer et al. (2018), Butler et al. (2022+), and Chu (2019) show racial minorities do not enjoy the same rate in the household financial markets (mortgage and auto loans). Minority entrepreneurs and HBCUs face higher costs of capital to fund their business (Blanchflower et al., 2003; Dougal et al., 2019; Howell et al., 2021). When trying to participate in the finance markets, racial minorities are more likely to be mistreated (Begley and Purnanandam, 2021; Stefan et al., 2018) and have a harder time settling a dispute (Haendler and Heimer, 2021). There is also evidence that the situation may not significantly improve even in the digital era: Bartlett et al. (2022) and Fuster et al. (2022) show that algorithms could continue to make biased decisions even without human interaction.

The literature's second theme, which this paper relates closely to, focuses on the effect of local financial shocks on racial disparities. Research on this topic generally shows a positive effect of finance on reducing racial inequality. For example, Stein and Yannelis (2020) show banking development can directly improve the SES of the historically marginalized populations by facilitating their financial inclusion. Levine et al. (2014) and Beck et al. (2010) show banking deregulation can also indirectly improve the SES for minorities by increasing credit provision to local businesses and boosting labor demand. Chatterji and Seamans (2012) also provide positive evidence, showing state-level financial deregulation facilitates access to credit for racially underrepresented entrepreneurs. These positive effects, however, beg the question: If positive local financial shocks always reduce racial inequality, why do the test score and SES racial gaps persist after centuries of financial development? This paper contributes to the literature by providing an important case highlighting that positive local financial shocks can also negatively affect the human capital racial gap, which perpetuates racial disparities in various socioeconomic outcomes.

Finally, this paper also relates to the literature on how local financial conditions affect education outcomes. Using the shale boom in Texas as a positive economic shock, Marchand and Weber (2020) and Kovalenko (2022+) show improvement in local economic conditions could have negative effects on high school student outcomes. Using bank regulatory reform as positive credit shocks, Hu, Levine, Lin, and Tai (2020) also find a negative effect of local financial development on student outcomes. This paper contributes to this literature in two important aspects. First, in contradiction to Marchand and Weber (2020), Kovalenko (2022+), and Hu et al. (2020), this paper show a positive effect of local financial conditions on education outcomes. This result differs from Marchand and Weber (2020) and Kovalenko (2022+) potentially because the two papers focus on different student groups. Marchand and Weber (2020) and Kovalenko (2022+) focus on high school students, who are drawn into the local labor market due to the shale boom. The focus of this paper is on students in 3^{rd} to 8^{th} grades, an age group where the substitution channel from Marchand and Weber (2020) and Kovalenko (2022+) is largely muted. And this result differs from Hu et al. (2020) in part because the macroeconomic conditions are different for the sample periods used in these two papers. Importantly, Marchand and Weber (2020), Kovalenko (2022+), and Hu et al. (2020) do not focus on the heterogeneous treatment effect of local financial conditions on children of different races. This paper helps fill in this gap and suggests a potential factor that contributed to the stubborn achievement racial gap.

1.2 Data and Institutional Background

1.2.1 Education, SES, Segregation, and School Funding Data

Educational outcomes data in this paper is from the Stanford Education Data Archive (SEDA). Leveraging 45 million test scores each year, SEDA is the first dataset that comprehensively covers academic achievement and achievement racial gaps in school districts and counties across the United States from 2008 to 2017 school year (Reardon, Ho, Shear, Fahle, Kalogrides, Jang, and Chavez, 2022). County-level data is likely more appropriate for this study because neighborhood and school segregation often occur between school districts within a county. In other words, school district-level outcomes can mask the effect of within-county racial segregation. Nonetheless, Appendix Table A8 shows the impact of recalibration on racial disparity continues to hold at the school district level.

The dataset is a panel with observations at the county-year-grade-subject level.[7] Students are from 3^{rd} to 8^{th} grade and subjects include Math and English Literature. The measure of the test scores is in standard deviation units of the national distribution. This dataset is widely used in recent literature to analyze various factors that contribute to education outcomes: For examples, see Abott et al. (2020), Gilpin, Karger, and Nencka (2021), Reardon et al. (2019), Reardon, Weathers, Fahle, Jang, and Kalogrides (2021), and Torrats-Espinosa (2020). The advantage of this dataset (compared to other public use education datasets, such as the Early Childhood Longitudinal Study) is that it allows researchers to identify time-series variations in academic achievement at the county level by student race. SEDA contains academic outcomes for all racial groups. However, this variable is not as well-populated outside of White, Black, and Hispanic students, which are the focus of this study.

The summary statistics for SEDA data are reported in Table 1.1. An average county has about 1,388 students in a given grade in a given year. The mean score for all students is close to zero (-0.04) because the measure is standardized at the national level. And it is not precisely zero because the standardization is based on observations at the student level instead of the county level. White students (0.11) on average have higher test scores than Black (-0.48) and Hispanic (-0.28) students. There are fewer county-year level observations for Black (131,159) and Hispanic (139,241) students compared to White (262,845) students because, to protect student privacy, the test score is not reported if a race-grade-subject-year category of a given county includes less than 20 test-takers.[8]

In addition to test scores, SEDA reports an average household socioeconomic status for each county-year-race group. This SES measure is constructed through a principal component analysis using median household income, mother's education level, unemployment rate, poverty rate, SNAP eligibility rate, and single mother-headed household rate. SEDA's technical documentation shows this measure is monotonically increasing in income and education level and decreasing in the unemployment rate, poverty rate, SNAP eligibility rate, and single mother-headed household rate.[9] An average White household (Mean SES = 0.07) has a higher SES than average Black (-2.31) and Hispanic (-1.17) households.

SEDA also provides a measure for levels of local racial segregation based on minority students' exposure to White students at school. For more insights, Urban Institute provides a high-quality interactive visualization of this measure at the MSA-level.[10] Although available as a panel variable with both cross-sectional and time-series variations, this paper uses the segregation measure from the 2009 school year to avoid

[7]To ensure the results are not driven by outliers, test score observations from counties with less than 100 total tested students are not included in the analysis. Results are unchanged when they are included.

[8]See Reardon et al. (2022) page 37 and their footnote 24.

[9]See Reardon et al. (2022) Table 16 for more detail.

[10]See `https://www.urban.org/features/segregated-neighborhoods-segregated-schools`.

bad controls problem in DiD inference (Angrist and Pischke, 2008). The segregation variable varies little throughout the time series, so the results are unchanged when using the time-varying measure instead.

The last row of the table reports school district-year level spending per pupil data from the Public Elementary-Secondary Education Finance Dataset in the U.S. Census. Consistent with the number reported in Abott et al. (2020), the average spending per pupil by a school district is around 11 thousand dollars in a given year.

1.2.2 Moody's Recalibration Background and Data

Moody's Investor Service is one of the big three credit rating agencies and offers bond ratings for a wide variety of financial products. It had two different rating systems before its rating recalibration in 2010. Its Municipal Rating Scale (for municipal bonds) measured the distance to distress, which calculates a municipality's likelihood of default in the absence of additional funding from the government. On the other hand, its Global Rating Scale[11] is designed to measure expected losses. Due to the more conservative ratings under the dual-standard system, Moody's share in the municipal bond market declined in years prior to the recalibration. In March 2010, as an attempt to increase its competitiveness in the municipal bond market, Moody's announced a recalibration of its Municipal Rating Scale to align it with the Global Rating Scale (Moody's, 2010). Shortly after the initial announcement, Moody's announced specific plans that resulted in upgrades of nearly 70,000 bond ratings in April and May 2010.

This recalibration is at the local government unit level and not all municipal bond issues were upgraded in the recalibration. For instance, a local government is not affected by the recalibration if it receives the same rating under the Municipal Rating Scale and the Global Rating Scale. Municipal bonds with higher ratings were also less likely to be recalibrated than those with lower ratings. Finally, local governments without Moody's ratings or with no outstanding bonds were not subject to recalibration and can also be used in the control group. As demonstrated in Appendix Figure A1, this diversity in treatment intensity provides abundant geographical variation to facilitate causal inference.

Also important for the causal inference in the setting of this paper, Moody's (2010) specifically clarifies that the recalibration is intended solely to enhance the comparability of ratings across asset classes, and is not associated with a change in the credit quality of the issuer. Cornaggia, Gustafson, Israelsen, and Ye (2019) also provide evidence that this recalibration is not correlated with local economic indicators such as household income, poverty rate, population, and net Adjusted Gross Income (AGI) flow.[12] The list of recalibrated bond issues is from Moody's and includes the rating of each bond issue before and after the recalibration. The recalibration covered 69,657 municipal bonds, most of which had an investment-grade rating before the recalibration. State-level bonds are excluded because they are not linked to a specific county in order to examine the test score outcome. Following

[11]For sovereign bonds, corporate bonds, and structured finance products.

[12]See Cornaggia et al. (2019) Figure 2.

Adelino et al. (2017), insured bonds are also excluded because their rating reflects the credit quality of the insurer instead of the issuer.

The impact of this recalibration on local government financing is economically large: Adelino et al. (2017) show 13-14 bps lower issuance cost and 16%-20% increase in issuance amount following the recalibration. According to Adelino et al. (2017), an average treated county issues about $250 million. So the 16%-20% increase corresponds to around $40-$50 million additional issuances. The summary statistics for this recalibration are reported in Table 1.1: 31% of counties (962 out of 3,103) received recalibration in 2010. Following Cunha et al. (2022+), this paper also includes the continuous recalibration intensity variable, measured as the fraction of the county's local government units that is recalibrated, to capture the intensive margin of the treatment effect. Unconditionally, about 3% of an average county's local government units are recalibrated.

1.3 Public Financing and Test Score

1.3.1 Baseline Estimation

This section examines whether municipal financing condition affects academic achievement using the following generalized difference-in-differences estimation:

$$Test\ Score_{c,t,g,i} = \beta * (Post_t \times Recalibration_c) + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i} \qquad (1.1)$$

Where $Test\ Score_{c,t,g,i}$ is the standardized test score in county c, year t, grade g, and subject i. $Post_t = 1$ for the year 2011 and afterward because Moody's recalibration happened in the middle of 2010.[13] As discussed in the previous section, $Recalibration_c$ can be dichotomous (*Recal. Indicator*) or continuously (*Recal. Intensity*) measured, and results for both specifications are reported to explore both the extensive and intensive margin effects. The β coefficient (DiD estimator) on the interaction term will capture the marginal response to municipal bond rating recalibration. County fixed effects (γ_c) are included to control for time-invariant local factors like culture and preference for education. State-year-grade-subject fixed effects ($\gamma_{s\times t\times g\times i}$) are also included to capture any source of state-specific trends and time-varying unobserved state-level heterogeneity, such as changes in transfers from state governments and difficulty of tests. County-level control variables are not included in the main specification to avoid bad controls problem in DiD setting (Angrist and Pischke, 2008).[14]

Results from estimating Eq. (1.1) are reported in Table 1.2. Panel A of the table reports the results using a dichotomous recalibration indicator. The indicator equals one if the county receives recalibration and equals zero otherwise. Column 1 is based on the universe of both Math and English tests. The result suggests test scores improved by 0.013 standard deviations after municipal bond rating recalibration.

[13] Appendix Table A1 show results are unchanged when excluding all observations from the 2010 school year.

[14] Appendix Table A2 show results are unchanged after controlling for race-specific household income, mother's education, and family structure.

Columns 2 and 3 report the estimations separately for English and Math, and the improvements are similar between the two subjects.

To put the economic magnitude of these results in context, using the same test score data from SEDA, Abott et al. (2020) estimate a \$1,000 increase in direct investment per pupil is associated with a 0.15 standard deviation increase in test scores. Under the assumption of a linear relationship, the effect captured in this paper is comparable to a \$87 ($= 0.013/0.15 \times 1,000$) increase in spending per pupil. An average county-grade has 1,388 students, and there are six grades in the sample. So this \$87 per pupil translates into \$0.72 million ($= 87 \times 1,388 \times 6$) per treated county.[15] There are 962 treated counties, so the nationwide effect is approximately \$694 ($= 0.72 \times 962$) million.

Panel B of the table reports estimations using a continuously measured recalibration intensity. By definition, this measure takes into account the intensive margin of the treatment. It is reasonable to expect an intensive margin effect because the labor market impact of recalibration is stronger when more units of local government are upgraded and more jobs are created. Compared to students from a county that received no upgrades, those from a county that has all of its local government units upgraded experience a 0.065 standard deviation increase in their test scores. This intensive margin result suggests the effect on test scores is considerably larger for counties that received more boost in public financing conditions through the recalibration. To illustrate this result is not driven by any specific outlier state, Appendix Figure A2 reports a robustness check exercise for the DiD estimator by dropping one state from the sample at a time. All the permutations in the figure are significant at the 5% level, indicating the result is not likely to be driven by outliers.

1.3.2 Event-time Estimation

Event-time results are reported in Panel (a) of Figure 1.1. Specifically, the recalibration indicator variable is interacted with the indicator variables for each school year and the resulting coefficients are tabulated in the figure. The baseline is the 2008 school year, the first year of SEDA data. Effects post-2013 are aggregated to the "2013+" indicator for brevity and symmetry; alternatively, full time-series results are tabulated in Appendix Figure A3. By construction, these coefficients capture the time series of differences in academic achievements between treated and control counties.

There is no significant difference in academic achievement between the recalibrated and control counties in 2008 and 2009, indicating that the parallel trend condition is likely satisfied for the DiD setting. This condition is especially important considering the timing of the Great Recession, which overlaps with the pre-treatment period. Jackson, Wigger, and Xiong (2021) and Shores and Steinberg (2019) show the Great Recession negatively affected student outcomes through the school funding channel. The parallel pre-trends in test scores between treated and control counties alleviates the concern that the effect on education outcomes documented in this paper is due

[15] As a benchmark, calculated using estimates from Adelino et al. (2017), a treated county on average increases issuance amount by about \$40 to \$50 million.

to the heterogeneous impact of the Great Recession. To further address the concern of recession-induced school funding cuts as the confounding factor, Appendix Figure A4 explicitly examines the dynamic of school district funding and shows no difference between school districts in treated and control counties in the pre-treatment period.

Although Moody's recalibration happened in the middle of 2010, Figure 1.1 suggests there is no effect in that year. This lack of immediate response indicates there could be a short delay between the county's increased ability to raise funding and the materialization of the positive effect. There is a 0.009 standard deviation improvement in 2011 and a similar magnitude persists through 2012. Finally, there is a strong and persistent long-run effect in the 2013-2017 period. This long-run effect is sensible because students are in the sample for consecutive years through their 3^{rd} to 8^{th} grades and an impact in one year would have a meaningful chain effect in the following years. For example, a student who falls behind in their 5^{th} grade is likely to also struggle in their 6^{th} through 8^{th} grades.

1.3.3 Accounting for Multiple Hypothesis Testing

Heath, Ringgenberg, Samadi, and Werner (2022+) suggest researchers need to be careful with statistical inference when reusing an experimental setting. To address this concern, a total of 13 outcome variables on Moody's recalibration are gathered to conduct three widely used adjustments for multiple hypothesis testing: Bonferroni, Holm, and Benjamini, Hochberg, and Yekutieli (BHY) following Harvey, Liu, and Zhu (2016).[16] Results are reported in Appendix Table A3. Common parameters in these three tests are the 5% unadjusted significance level ($\alpha_\omega = 5\%$) and the 13 outcome variables ($M = 13$). The Bonferroni method rejects any hypothesis with *p-value* $\leq \frac{\alpha_\omega}{M}$. Here the adjusted *p-value* for 5% statistical significance is 0.38% (= 5% / 13). The Holm method rejects any hypothesis with *p-value* $\leq \frac{\alpha_\omega}{M+1-b}$. Here the t-stat for the academic achievement estimation ranks 8^{th} on the ordered list. Thus, the adjusted *p-value* for 5% statistical significance is 0.83%. Finally, the BHY method rejects any hypothesis with *p-value* $\leq \frac{\alpha_\omega \times b}{M \times c(M)}$. Following Benjamini and Yekutieli (2001), $c(M)$ is set to equal $\sum_{j=1}^{M} \frac{1}{j}$. The t-stat on the academic achievement variable ranks 8^{th} on the ordered list. Hence, the BHY method adjusted *p-value* for 5% statistical significance is 0.97%. The p-value from column (1) of Table 1.2 is 0.20%, comfortably below the thresholds for all three methods. The null hypothesis that municipal financing does not affect education outcomes can be rejected at the 5% level even after adjusting for multiple hypothesis testing.

[16] The 13 variables include the academic achievement from this paper and the 12 variables from other academic papers using the same experimental design.

1.4 Achievement Racial Gaps

1.4.1 Baseline Estimation

Did the recalibration benefit students of all races equally? To analyze the heterogeneous treatment effect of public financing on student outcomes, this section repeats the DiD analysis described in Eq. (1.1) but replaces the dependent variable with test scores by each racial group with the subscript r denoting race:

$$Test\ Score_{c,t,g,i,r} = \beta * (Post_t \times Recalibration_c) + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i,r} \tag{1.2}$$

As well as the White-Minority achievement gap:

$$Score\ Racial\ Gap_{c,t,g,i,r} = \beta * (Post_t \times Recalibration_c) + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i,r} \tag{1.3}$$

The results are reported in Table 1.3. Column (1) of Panel A estimates a 0.022 standard deviation increase in test scores for White students. Columns (2) and (3) indicate the coefficients for Black and Hispanic students are slightly positive but not statistically significant. In other words, it can not be concluded that there is a reliable improvement in academic achievement for racially underrepresented students. Consequently, columns (4) and (5) show the White-Black and White-Hispanic academic achievement gaps widened by 0.017 and 0.018 standard deviations, respectively. The inference is unchanged when the continuous measure of recalibration intensity is used in Panel B. The intensive margin effect suggests the achievement racial gap widens more in counties that have more units of local government recalibrated.

1.4.2 Event-time Estimation

Event-time results by student race are reported in Panel (b) of Figure 1.1. For White students, there was no pre-recalibration trend in the 2009 and 2010 school years. Similar to the full sample result in Panel (a), there is a significant and persistent improvement after recalibration for White students. Hispanic students in treated counties show a statistically insignificant improvement in the pre-recalibration period and a slight decline in the post-recalibration period, but none of the estimates are statistically significant. Black students also display a mild improvement after the recalibration, but the effect is economically small compared to White students and statistically indistinguishable from zero. Full time-series plot in Panel (b) of Appendix Figure A3 reveals more detail on these dynamics. For White students, the effect stabilizes after 2014 and persists through the end of the sample period. For Black and Hispanic students, the small initial positive effect diminishes over the sample period and becomes economically indistinguishable from zero. The positive public financing shock had a persistent effect on White students, but not on racially underrepresented students.

1.4.3 Alternative Explanations

1.4.3.1 Heterogeneity within the Control Counties

For a county to be included in the control group in the previous analysis, it has to either not have ratings from Moody's for its local government units (labeled grey in Appendix Figure A1), or have Moody's ratings that were not affected in the recalibration (labeled the lightest green in Appendix Figure A1). A potential concern is that the post-financial crisis recovery pattern may be different for these two kinds of counties in the control group. To make sure the results are not driven by the no-issuance counties, I re-estimate the regressions from Table 1.2 and Table 1.3 while excluding counties that do not have ratings from Moody's for its local government units and report results in Appendix Table A4. The estimates from Appendix Table A4 is consistent with those from Table 1.2 and Table 1.3, suggesting the effects of recalibration on test score and its racial gaps are not likely to be driven by the no-issuance counties.

1.4.3.2 Is it the Achievement Race Gap or the Achievement Income Gap?

On average, students from more affluent households do better at school (Dahl and Lochner, 2012). There is also a well-documented correlation between the achievement racial gap and the achievement income gap due to the persistent difference in income between White and minority households (Reardon et al., 2021; Card and Rothstein, 2007; Chetty, Friedman, Saez, Turner, and Yagan, 2020a). If the recalibration increased the achievement income gap, there could be a mechanical effect on the test score racial gap by its correlation with the income gap. Is the achievement racial gap captured in this paper just a simple manifestation of the test score differences between poor and affluent students? To address this possibility, in the spirit of Reardon et al. (2021), I decompose the β coefficient from Eq. (1.3) into a race component (β_1) and an income component (β_2) using the following system:

$$\begin{cases} \textit{Score Racial Gap}_{c,t,g,i,r} = \beta_1 * (\textit{Post}_t \times \textit{Recalibration}_c) + \textit{Score Income Gap}_{c,t,g,i} + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i,r} \\ \textit{Score Income Gap}_{c,t,g,i} = \beta_2 * (\textit{Post}_t \times \textit{Recalibration}_c) + \textit{Score Racial Gap}_{c,t,g,i,r} + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i,r} \end{cases} \tag{1.4}$$

Where the "Score Income Gap" captures the within-county test score difference between "non-poor" and "poor" students, regardless of student race.[17] The intuition is that if the β coefficient from Eq. (1.3) captures the sum of both the effect on the racial gap and the effect on the income gap, then the first model of Eq. (1.4) partials out the income effect and the β_1 coefficient represents the effect of recalibration on the test score racial gap. Similarly, the second model of Eq. (1.4) partials out the race effect, and the β_2 coefficient represents the effect of recalibration on the test score income gap. And the sum of β_1 & β_2 should be close to the β from Table 1.3.

Results for these estimations are reported in Appendix Table A5. The "Test Score N (Non-poor) - P (Poor) Gap" represents the "Score Income Gap". Panel A

[17] According to SEDA, the categorization of "poor" is done by ED*Facts* and the cutoff varies by state.

(B) reports results from decomposing the White-Black (White-Hispanic) test score gap. Columns (1) & (2) report results using the dichotomous measure of recalibration while columns (3) & (4) use the continuous measure. The results from this table are interpreted in the following way: Take columns (3) & (4) from Panel A, for example, β_1 is 0.032 and β_2 is 0.012 and they sum up closely to the β coefficient (0.046). This result suggests that, in this model, about three quarters $[= 0.032/(0.032 + 0.012)]$ of the effect captured in Table 1.3 is attributable to the impact of recalibration on the test score racial gap. Across the different models from Appendix Table A5, β_1 is about 50% - 75% the size of β coefficient from Table 1.3. The results from this decomposition suggest Moody's recalibration had a significant impact on the test score racial gap even after accounting for its impact on the test score income gap.

1.4.3.3 Migration/Demographic Change?

Cornaggia et al. (2019) suggest better public financing induced by Moody's recalibration could attract low-wealth households.[18] Are the results captured in this paper driven by migration? The following evidence suggests this is not the case. First, the migration effects captured in Cornaggia et al. (2019) are concentrated in populations nearing retirement age. In other words, the people that the recalibration attracts are not likely to have kids in the 3^{rd} to 8^{th} grade. Indeed, Cornaggia et al. (2019) also find there is no effect on migration in the [0,19] age group. In this case, the change in the test score is unlikely to be driven by migration.

Second, in Appendix Table A6, I re-estimate the DiD effect from Table 1.3 using only the subsample of counties that do not experience any increase in the fraction of Black or Hispanic population between 2009 (pre-recalibration) and 2011 (post-recalibration). Results from this table show that even in counties without demographic shifts, there is still a significant widening of the White-Minority achievement gap and the magnitude is similar to the full sample results. These two pieces of evidence indicate the heterogeneous effect captured in this paper is not likely to be driven by migration or demographic shift.

1.4.3.4 Imprecise Measurement for Minority Students?

There are more observations for White students in the sample than for minority students. Could the insignificant improvement among minority students be driven by a lack of precision in measurement? The following evidence suggests this is not the case. First, aside from statistical insignificance, the economic magnitudes of the coefficients reported in Table 1.3 for Black and Hispanic students are small. This insignificance in magnitude suggests there are no economically meaningful improvements for Black or Hispanic students compared to White students. Second, Appendix Table A7 shows the inference is unchanged (compared to Table 1.3) when re-estimating the impact of recalibration on White students using only the subsample of counties that also have a substantial amount of minority students. Furthermore, the standard error for White students is quantitatively similar to those for Black and Hispanic students.

[18] Yi (2021) arrives at a similar conclusion using a different exogenous shock to public finance.

These results suggest the widening of the achievement gap is not driven by imprecise measurements for minority students.

1.5 Channels

1.5.1 The School Funding Channel

Abott et al. (2020) show increase in school district funding can positively affect student outcomes. As an important component of local government units, school districts' funding could be boosted by the recalibration. Is the school funding a channel for the impact of Moody's recalibration? To explore this possibility, I gather school district-level public school funding data from the Public Elementary-Secondary Education Finance Dataset in the U.S. Census. As a sanity check, I first confirm the main findings on the test score and test score racial gaps continue to hold using school district (SD) level data and report results in Panel A of Appendix Table A8. I then examine whether recalibration resulted in a change in school funding using the following model at the school district-year level:[19]

$$ln(Spending\ per\ Pupil)_{sd,t} = \beta * (Post_t \times Recalibration_c) + \gamma_c + \gamma_{s\times t} + \epsilon_{sd,t} \quad (1.5)$$

Following Abott et al. (2020), I use the natural logarithm of the dollar amount of spending per pupil per school district year as the outcome variable. Results are reported in Table 1.4. The first two columns show there is no significant effect of recalibration on school spending in the full universe of school districts. Event-time estimation from Appendix Figure A4 also confirms the recalibration had little impact on school districts' spending on students.

However, it could still be possible that the statistically "predominantly White" school districts reacted differently to the recalibration. Columns (3) & (4) explore this possibility by focusing on school districts with more than 95% White students and still find no effect on spending. Finally, Panel B of Appendix Table A8 replicates column (1) from Table 1.2 and columns (4) and (5) from Table 1.3 for school districts that do not increase spending from the 2009 to 2011 school year. Estimates for this subsample are quantitatively similar to the full sample results reported in Panel A. Results from the first two columns in this panel show there is a significant improvement in test scores even for school districts that do not show any increase in spending. Results from the last four columns show that achievement racial gaps widen even for school districts that do not show any increase in spending. Taken together, the results in this section suggest a change in school funding is not likely a channel for the main results.

[19] See `https://www.census.gov/programs-surveys/school-finances.html`. The "Individual Unit Tables" for each year contain the school-district level data used in this paper. The merging identifiers are "NCESID" from Census and "sedalea" from SEDA. The Education Finance dataset includes a county identifier (CONUM) that allows merging with recalibration data.

1.5.2 The Household Socioeconomic Well-being Channel

If the various SES benefits documented in Adelino et al. (2017) were primarily captured by White households, it may not be surprising that only White students show improvement on their tests. This section studies the heterogeneous treatment effect of Moody's recalibration on household socioeconomic well-being as a potential explanation utilizing the county-year-race level SES variable provided by SEDA. The test is in a generalized DiD setting similar to Eq. (1.1), but now the unit of observation is at the county-year-race (c,t,r) level:

$$SES_{c,t,r} = \beta * (Post_t \times Recalibration_c) + \gamma_c + \gamma_{s \times t} + \epsilon_{c,t,r} \tag{1.6}$$

Results are reported in Table 1.5. Column 1 shows there is a significant improvement in White households' socioeconomic status. The improvement is also economically meaningful: Based on the coefficient from Panel A, White households in treated counties show a 22% (= 0.02/0.09) improvement from the mean. The recalibration does not have a statistically significant effect on Black households' SES. Consistent with the downward trend in test scores in the post-recalibration period, the socioeconomic status of Hispanic households is negatively affected, although the economic magnitude is small compared to the mean of -1.17.

Are the counties that improve more in SES the ones also improve more in test scores? To further tighten the relationship between SES and test scores, Table 1.6 examines the correlation between changes in SES and test score (gap) for recalibrated counties between 2009 and 2017. Consistent with SES being the channel for the effect of recalibration on test scores, column (1) of Table 1.6 shows more increase in SES is associated with more improvement in test scores. Columns (2) & (3) of Table 1.6 suggest for the treated counties, more increase in SES racial gap is associated with more widening in the test score racial gap.

Adelino et al. (2017) suggest employment is an important aspect of socioeconomic well-being that is improved by the recalibration. Are there heterogeneous treatment effects for White and minority employment status? Table 1.7 provides corollary evidence that there is a significant reduction in the unemployment rate for the White labor force, but not for the Black or Hispanic labor forces. For the White labor force, column (1) in Panel A of Table 1.7 suggests there is 0.12 percentage points decrease in the unemployment rate, or a 1.7% (= 0.12%/7%) decrease from the mean. For the Black labor force, although the magnitude of the coefficient in column (2) is close to that from column (1), it is small relative to the mean unemployment rate (13%) and is statistically insignificant. For the Hispanic labor force, the coefficient in column (3) is also small and insignificant. In short, the recalibration only resulted in positive employment outcomes for White households and not minority households. This employment effect allows the treated White parents to provide a sound family environment for their children to perform well at school.

Importantly, the changes in the extensive margin of labor market participation shown in Table 1.7 do not paint the full picture of the socioeconomic benefits. For instance, an individual who was never unemployed throughout the sample period could still be positively affected by the recalibration if it enabled them to work for longer hours or secure an additional part-time job. To this extent, reliance on the social safety net (such as the food stamp) may be a better measure for the intensive margin effect of labor market outcomes. Table 1.8 examines this effect. Results from this test suggest some White households show reduced reliance on SNAP, but the effects are muted for Black and Hispanic households. Taken together, the tests in this subsection show household SES is likely an important channel for this heterogeneous treatment effect.

1.6 Conclusion

This paper analyzes the heterogeneous effect of local financial shock on students of different races. Following Moody's municipal bond rating recalibration in 2010, only White households in treated counties show significant improvement in their socioeconomic well-being. This heterogeneous treatment effect has an important intergenerational impact on human capital accumulation: White students from treated counties show significant improvement in their test scores but there is no effect for Black or Hispanic students. Consequently, the achievement racial gap widens as a result of a positive county-wide financial shock.

Table 1.1: Summary Statistics

Variable	**N**	**Mean**	**S.D.**	**P5**	**P95**
Academic Achievement	(County-Year-Grade-Subject level observations)				
Number of Tested Students	272,290	1,388	4,056.08	120	5,585
All Students	272,290	-0.04	0.28	-0.52	0.39
White Students	262,845	0.11	0.25	-0.30	0.53
Black Students	131,159	-0.48	0.27	-0.91	-0.03
Hispanic Students	139,241	-0.28	0.26	-0.69	0.17
White - Black Gap	127,554	0.62	0.25	0.22	1.05
White - Hispanic Gap	137,126	0.45	0.26	0.05	0.89
Non-poor - Poor Gap	255,332	0.55	0.20	0.24	0.90
Socioeconomic Status	(County-Year level observations)				
White Household	29,092	0.09	0.56	-0.83	0.97
Black Household	22,732	-2.32	0.89	-3.74	-0.65
Hispanic Household	26,570	-1.17	0.63	-2.15	-0.09
White-Black Gap	22,661	2.44	0.67	1.26	3.59
White-Hispanic Gap	26,540	1.35	0.44	0.64	2.04
Unemployment	(County-Year level observations)				
White Household	29,092	0.07	0.02	0.03	0.11
Black Household	22,732	0.13	0.05	0.04	0.21
Hispanic Household	26,570	0.08	0.03	0.02	0.13
SNAP Rate	(County-Year level observations)				
White Household	29,092	0.10	0.05	0.03	0.18
Black Household	22,732	0.27	0.08	0.12	0.39
Hispanic Household	26,570	0.18	0.07	0.07	0.29
Moody's Recalibration	(County level observations)				
Recal. Indicator	3,103	0.31	0.46	0.00	1.00
Recal. Intensity	3,103	0.03	0.08	0.00	0.18
Racial Segregation	(County level observations)				
White-Black Segregation	2,888	0.09	0.13	0.00	0.38
White-Hispanic Segregation	2,936	0.07	0.10	0.00	0.30
Spending per Pupil	(School District-Year level observations)				
Dollar Amount ($)	104,192	10,932	5,848.30	7,336	17,872

Note: This table reports summary statistics for academic achievement, SES, unemployment rate, SNAP rate, Moody's recalibration, and racial segregation. Measures of achievement are in standard deviation units of the national distribution.

Table 1.2: Effect of Municipal Financing on Academic Achievement

Panel A: Dichotomous Recalibration Measure

	(1) Score **All**	(2) Score **English**	(3) Score **Math**
Post × Recal. Indicator	0.013***	0.014***	0.012***
	(0.003)	(0.003)	(0.004)
County FE	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	-	-
State-Year-Grade FE	-	Yes	Yes
R^2	0.804	0.828	0.804
Observations	272,179	140,744	131,396

Panel B: Continuous Recalibration Measure

	(1) Score **All**	(2) Score **English**	(3) Score **Math**
Post × Recal. Intensity	0.067***	0.069***	0.066***
	(0.023)	(0.022)	(0.028)
County FE	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	-	-
State-Year-Grade FE	-	Yes	Yes
R^2	0.804	0.828	0.804
Observations	272,179	140,744	131,396

Note: This table reports regression results from estimating equation (1.1). The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Column (1) in both panels use full sample that combines English and Math test scores. Columns (2) and (3) analyze English and Math test scores separately. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table 1.3: Effect of Municipal Financing on Racial Gap in Academic Achievement

Panel A: Dichotomous Recalibration Measure

	(1) Score **White**	(2) Score **Black**	(3) Score **Hispanic**	(4) Gap **W - B**	(5) Gap **W - H**
Post × Recal. Indicator	0.022***	0.010	0.001	0.017***	0.018***
	(0.004)	(0.006)	(0.006)	(0.005)	(0.004)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes
R^2	0.735	0.641	0.631	0.636	0.654
Observations	262,728	130,686	139,029	127,075	136,911

Panel B: Continuous Recalibration Measure

	(1) Score **White**	(2) Score **Black**	(3) Score **Hispanic**	(4) Gap **W - B**	(5) Gap **W - H**
Post × Recal. Intensity	0.112***	0.044	-0.005	0.046**	0.099***
	(0.020)	(0.032)	(0.031)	(0.020)	(0.021)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes
R^2	0.735	0.641	0.631	0.636	0.654
Observations	262,728	130,686	139,029	127,075	136,911

Note: This table reports the changes in academic achievement by race and changes in White-Minority achievement gaps. “W - B”(“W - H”) stands for “White - Black”(“White - Hispanic”). The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table 1.4: The (Lack of) Response in School District Spending

	(1)	(2)	(3)	(4)
	ln(Spending)	ln(Spending)	ln(Spending)	ln(Spending)
	All School Dist.	**All School Dist.**	**>95% White**	**>95% White**
Post × Recal. Indicator	0.000		0.004	
	(0.002)		(0.003)	
Post × Recal. Intensity		-0.012		0.019
		(0.010)		(0.031)
School District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
R^2	0.938	0.938	0.929	0.929
Observations	103,710	103,710	27,436	27,436

Note: This table studies the change in school district funding as a potential channel for the effect of recalibration on test scores. Columns (1) and (2) use the full universe of school districts. Columns (3) and (4) uses the subsample of districts with more than 95% White students. The unit of observation is a school district-year and school district and state-year fixed effects are included. Standard errors reported in parentheses are clustered at the school district level. *** p<0.01, ** p<0.05, * p<0.1

Table 1.5: Effect of Municipal Financing on Household's Socioeconomic Well-being

Panel A: Dichotomous Recalibration Measure

	(1) SES **White**	(2) SES **Black**	(3) SES **Hispanic**	(4) SES Gap **W - B**	(5) SES Gap **W - H**
Post × Recal. Indicator	0.020***	-0.005	-0.069***	0.037**	0.080***
	(0.006)	(0.019)	(0.017)	(0.017)	(0.014)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.959	0.845	0.733	0.797	0.704
Observations	29,078	22,722	26,558	22,651	26,528

Panel B: Continuous Recalibration Measure

	(1) SES **White**	(2) SES **Black**	(3) SES **Hispanic**	(4) SES Gap **W - B**	(5) SES Gap **W - H**
Post × Recal. Intensity	0.105***	-0.075	-0.221*	0.217***	0.322***
	(0.035)	(0.080)	(0.119)	(0.073)	(0.103)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.959	0.845	0.733	0.797	0.704
Observations	29,078	22,722	26,558	22,651	26,528

Note: This table reports the change in socioeconomic status (SES) by race. The unit of observation is a county-year and county and state-by-year fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table 1.6: The Relationship between Changes in SES and Test Score (Gap)

	(1) $\Delta Score_{(2017-2009)}$ **All**	(2) $\Delta Gap_{(2017-2009)}$ **W - B**	(3) $\Delta Gap_{(2017-2009)}$ **W - H**
$\Delta SES_{(All,\,2017-2009)}$	0.071***		
	(0.026)		
$\Delta SES\ Gap_{(W-B,\,2017-2009)}$		0.026**	
		(0.013)	
$\Delta SES\ Gap_{(W-H,\,2017-2009)}$			0.026**
			(0.011)
Grade-Subject FE	Yes	Yes	Yes
R^2	0.014	0.020	0.039
Observations	9,734	5,838	5,987

Note: This table analyzes the relationship between changes in SES and test score (gap) for recalibrated counties between 2009 and 2017. Column (1) examines the relationship between changes in SES for all households in the county and the change in test score for all students. Columns (2) & (3) examine the relationship between changes in White-Minority SES gap and changes in White-Minority test score gap. The unit of observation is a county-grade-subject and grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Effect of Municipal Financing on Unemployment

Panel A: Dichotomous Recalibration Measure

	(1) Unemployment **White**	(2) Unemployment **Black**	(3) Unemployment **Hispanic**
Post × Recal. Indicator	-0.0012***	-0.0010	-0.0007
	(0.0004)	(0.0018)	(0.0011)
County FE	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
R^2	0.863	0.626	0.629
Observations	29,078	22,722	26,558

Panel B: Continuous Recalibration Measure

	(1) Unemployment **White**	(2) Unemployment **Black**	(3) Unemployment **Hispanic**
Post × Recal. Intensity	-0.0048**	0.0045	0.0025
	(0.0023)	(0.0067)	(0.0058)
County FE	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
R^2	0.863	0.626	0.629
Observations	29,078	22,722	26,558

Note: This table reports the change in unemployment rate by race. The unit of observation is a county-year. County and state-by-year fixed effects are included. Standard errors reported in parentheses are clustered at the county level. The results in this table are reported to four decimal places in order to avoid reporting 0.000 for the standard error in column(1) of Panel A due to rounding. *** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Effect of Municipal Financing on SNAP Rate

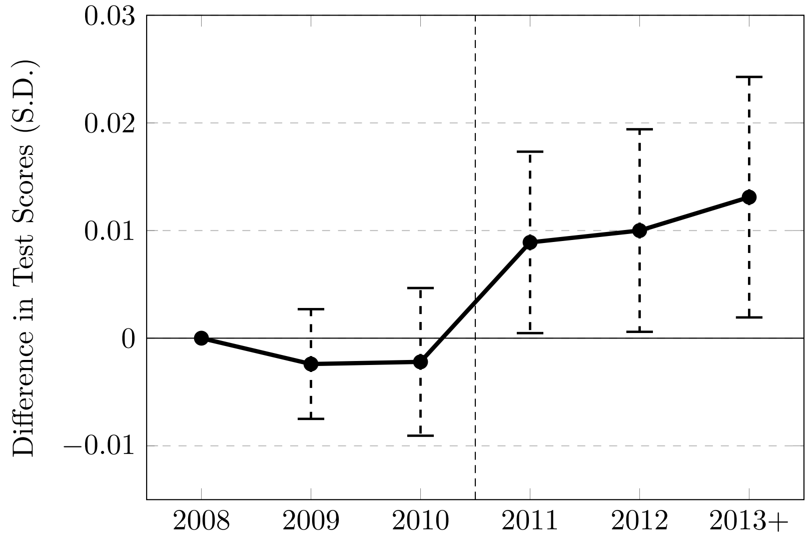
Panel A: Dichotomous Recalibration Measure

	(1) SNAP Rate **White**	(2) SNAP Rate **Black**	(3) SNAP Rate **Hispanic**
Post × Recal. Indicator	-0.003***	0.003*	0.009***
	(0.001)	(0.002)	(0.002)
County FE	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
R^2	0.937	0.785	0.699
Observations	29,078	22,722	26,558

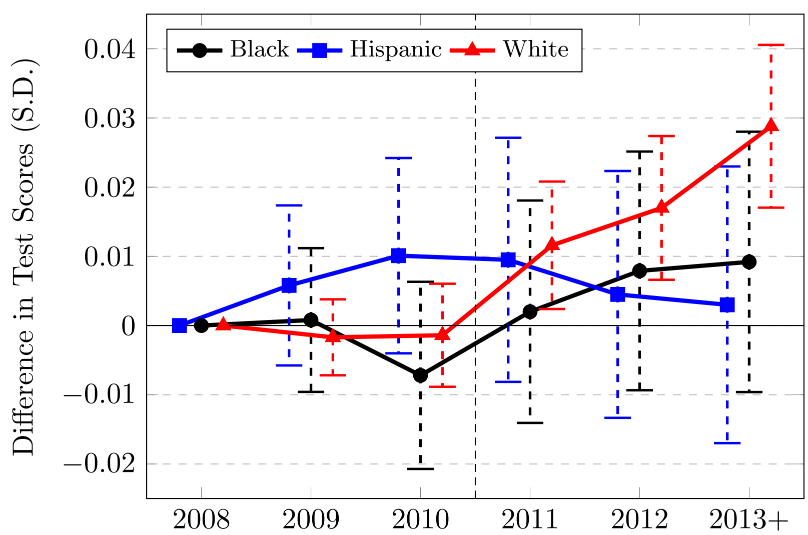
Panel B: Continuous Recalibration Measure

	(1) SNAP Rate **White**	(2) SNAP Rate **Black**	(3) SNAP Rate **Hispanic**
Post × Recal. Intensity	-0.015***	0.014	0.029**
	(0.003)	(0.009)	(0.015)
County FE	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes
R^2	0.937	0.785	0.699
Observations	29,078	22,722	26,558

Note: This table reports the change in SNAP rate by race. The unit of observation is a county year. County and state-by-year fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1



(a) Full Sample



(b) By Race

Figure 1.1: **Effect of Recalibration on Test Scores**
This figure plots coefficients of β_j from the following regression of education achievement on the interaction of recalibration in event time, with 2008 being the benchmark school year. The sample includes counties with full time-series data. County and state-year-grade-subject fixed effects are included. Standard errors are clustered at the county level. Dashed lines represent 95% CI. The point estimates are staggered for ease of reading.

$$Test\ Score_{c,t,g,i} = \sum_j \beta_j (Recal\ Inicator \times Year\ Indicator) + \gamma_c + \gamma_{s \times t \times g \times i} + \epsilon_{c,t,g,i}$$

Chapter 2 Racial Concordance in the Market for Financial Advice

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2.1 Introduction

In the United States, there exists considerable racial disparities in stock market participation. Using data from the Survey of Consumer Finances, Bhutta, Chang, Dettling, Hsu, and Hewitt (2020) show that White households are two to three times more likely to participate in retirement accounts such as 401k's and IRAs, and Hou and Sanzenbacher (2021) show that the average Black or Hispanic household has about half as much retirement wealth as the average White household. While income, intergenerational wealth transfers, and housing stock play a role (Aladangady and Forde, 2021; Bhutta, Chang, Dettling, Hsu, and Hewitt, 2020; Devlin-Foltz, Henriques, and Sabelhaus, 2016), these characteristics cannot fully explain the gap. A study by the Social Security Administration (Choudhury, 2002) found that even within the same income quartile, White households were twice as likely to invest in financial markets than Black and Latino households.[1]

Given that the racial composition of a firm's clientele can have a significant impact on the race of who gets hired, particularly in sales or service occupations (Holzer and Ihlanfeldt, 1998), it is not surprising that minority advisors are underrepresented in the financial advisory industry, which provides services to the majority of the investing households (Survey of Consumer Finances, 2019). A 2018 survey by the Certified Financial Planner (CFP) board of hiring managers found that the majority believed that advisors have an advantage with the clientele of their own racial and ethnic background. Such beliefs appear to echo findings in Stolper and Walter (2019) which showed that advisor-client concordance in gender and family status affects current clients' willingness to follow their advisors' financial advice. Even compared to other white-collar service professions like medicine and legal services, the financial advising industry has low minority representation. While Blacks make up 12% of the labor force in general, they make up only 3% of financial advisors.[2] Similarly, Hispanics make up 18% of the labor force, but only 5% of financial advisors. Against this backdrop, FINRA has made a push for greater diversity and inclusion across the industry, with the goal of better engaging traditionally underinvested communities and representing the needs of all investors.[3] Individual firms have instituted similar initiatives to promote diversity hiring (e.g. Edward Jones, one of the largest firms in

[1] A study by Ariel Investments found that 86% of White households with income of at least $50,000 owned stocks or mutual funds, while only 67% of Black households with similar income did.

[2] Data come from the Bureau of Labor Statistics (BLS) and our estimates are similar to those found in Egan, Matvos, and Seru (2019).

[3] `https://www.finra.org/about/responsible-citizenship/racial-justice`

the U.S, announced a 2025 target of 15% representation of “people of color” among its brokers, up from its current 8% representation).

In our paper, we seek to understand the potential role of race and racial concordance in the market for financial advice. The impact of racial concordance between financial advisors and the community they serve may be particularly pernicious. Black and Hispanic households are underrepresented among the highest income households. Due to various fixed cost of investing, these high-income (generally more White) households are the ones that are most likely to seek out investment advice (Vissing-Jorgensen, 2003). Homophilic preferences by customers may drive the uptake of services based on the existing stock of employees, which then in turn drive labor market decisions.

We exploit a rich dataset with characteristics of financial advisors at the individual advisor level along with public data on stock market participation and sociodemographic characteristics at the community level. We document that the fractions of Black (3.0%), Asian (5.4%), and Hispanic (4.9%) advisors are all lower than their national averages across all occupations (12.3%, 6.5%, and 17.6%, respectively). Further, while the fractions of Asian and Hispanic advisors have nearly doubled since 2000, the fraction of Black advisors has shown no growth over the past two decades. We show differences in the socioeconomic characteristics in which advisors of different races serve: On average, minority advisors work in communities with 6%-9% higher unemployment rate. Compared to an average White advisor, Black and Hispanic advisors work in communities with a lower median household income and a lower fraction of college-educated residents. Asian advisors, on the other hand, work in communities with a higher median household income and more educated residents. While there is some evidence of sorting, i.e. Black advisors are more likely to work in communities with a larger Black population, at the aggregate level, financial advisors serve a population that is racially representative of the entire nation.

We then move to understand how racial concordance between local advisors and the community is related to stock market participation. This relationship is *ex-ante* unclear. Racial concordance may lead to enhanced participation if it enables greater stock market participation for clients due to trust. Trust in the financial market is one of the most important factors when individuals decide whether to participate in the stock market (Guiso, Sapienza, and Zingales, 2008; Burke and Hung, 2021). In an experimental setting, Stolper and Walter (2019) show that concordance on gender, age, and family structure increases the uptake of financial advice. Racial concordance may enhance communication (Redding, 2019) between the advisor and client, leading to productivity increases in the relationship. On the other hand, racial concordance might lead to lower participation due to negative within-group effects (e.g. individuals of certain races may reject minority advisors that “act White” (Austen-Smith and Fryer Jr, 2005)).

Studying this issue empirically presents several challenges. In an ideal setting, we would hold the demand for financial advice constant, randomly change the supply of advisors of different races to communities of different racial makeups, and observe how racial concordance affects household-level participation rates. Our setting deviates from this ideal setting along several dimensions. First, while we observe changes in the supply of financial advisors to a given community, we cannot rule out these shifts did not occur due to firm- or advisor-level changes in the expected demand for financial services. Second, we do not observe individual household level stock market participation decisions. Rather, using IRS data at the community level, we examine the relation of localized stock market participation to the presence of financial advisors of various racial backgrounds.

With these constraints in mind, our results suggest that, on net, there is limited evidence that racial concordance impacts local participation. While there is some evidence of concordance in the cross-section, it is largely nonexistent when we control for unobservable community effects in a fixed effects estimation.

In light of the recent emphasis on diversity hiring and given that we find only limited evidence of a positive effect of racial concordance on participation, we then study how race and racial concordance may affect the advisor's career. Unconditionally, we find that minority advisors tend to leave the industry faster than White advisors. Specifically, minority advisors are 36% more likely than White advisors to quit in the first two years of their career. In racially concordant communities, however, minority advisors exit at a lower rate than those located in non-concordant ones. For example, a one-standard-deviation increase in the local Hispanic population is associated with a modest 5% reduction in the Hispanic advisors' quit rate, suggesting that advisor-client racial matching is a factor in maintaining minority representation in the financial advisory industry.

Despite increasing regulatory and media attention, historically, there has been little academic research on minority representation in the financial services industry. A notable exception is Egan, Matvos, and Seru (2022), which studies the "racial punishment gap" following an incident of misconduct and highlights the potential disadvantages and obstacles for minorities in this industry. Frame, Huang, Mayer, and Sunderam (2022) and Jiang, Lee, and Liu (2021) both document minority representation in mortgage lending and find that the racial matching between mortgage borrowers and loan officers improves borrowers' access to credit. Our study is similar to Frame, Huang, Mayer, and Sunderam (2022) and Jiang, Lee, and Liu (2021) in that we contribute to the literature by being the first to systematically document the characteristics of the minority financial advisors, the firms they work for, the communities they serve, and factor that impact their career success. This knowledge is an important first step toward understanding minority representation in the industry.

We also contribute to the literature that studies agent-customer racial concordance, which generally finds that concordance is positively correlated with customers' willingness to follow agents' advice. For instance, Shen, Peterson, Costas-Muñiz, Hernandez, Jewell, Matsoukas, and Bylund (2018) provides a summary of evidence in the medical setting, and Redding (2019) provides a summary of evidence in the education setting. We contribute to the literature with two new findings. First, we do not find evidence that racial concordance is significantly associated with higher community-level stock market participation rates. Thus, our finding appears to superficially differ from Stolper and Walter (2019), which finds that homophily on gender, age, and marital and parental status is positively correlated with a client's willingness to follow the financial advice of existing customers. This is potentially due to confounding with the fixed monetary cost for participation at the extensive margin. Although racial concordance between the advisor and the household could encourage minority households to participate, on average, many poorer (and disproportionately minority) households may not have the wealth necessary to take action. Second, in addition to examining the impact on clients, we also examine the advisors themselves and find that racial concordance is positively associated with the advisor's career longevity.

From a policy perspective, our findings on racial concordance in the market for financial advice present a mixed picture. Economically, the impact of advisor-client concordance on participation appears to be quite modest in comparison to factors like local wealth. Thus, any advantages that this concordance offers a minority advisor working in a poorer, minority community in their career are likely to be outweighed by the advantages of working in a more affluent area that has more investable wealth. Therefore, hiring practices intended to increase minority representation may not lead to lasting and meaningful access to financial services in those communities.

2.2 Data

2.2.1 Financial Advisors

The data on financial advisors comes from registration data filed on the Form U4 via a series of Freedom of Information Act requests to state regulators and disclosures available through FINRA's BrokerCheck system. Importantly, the Central Registration Depository (CRD) assigns each advisor and firm a unique identification number that remains constant over time, allowing us to carefully track employment movements. FINRA shares much of this information with the public via its BrokerCheck website. Form U4 provides detailed information on advisors' characteristics, employment address histories, and history of misconduct. In the U.S., all registered representatives (the legal term for what we call "financial advisors") must be registered with FINRA by their employer using Form U4. This form must be updated following any material change in the advisor's information (including change in employment or disclosure of misconduct). FINRA and state regulators jointly operate the CRD, which serves as a repository for Form U4 and related regulatory filings. Because we can access both historical filings of U4 and current employment addresses from BrokerCheck, we obtain ZIP code level addresses for the advisors in our dataset. We identify advisors in 16,210 unique ZIP codes. A chief advantage of ZIP code level data is ZIP codes are typically smaller and more homogeneous than counties (e.g. Los Angeles County, California has over 10 million residents and 290 ZIP codes, while Hazard County, KY has around 14 thousand residents and only a single ZIP code).

The market for financial advising is typically quite local. For example, regulators and industry groups provide geographically based search tools where the default search is geographically based). We aggregate our data to the community level, which we define as all ZIP codes whose centroid falls within a 10-mile radius around a particular ZIP code's centroid. The median community consists of five adjacent ZIP codes. In the appendix, we replicate our main results at solely the individual ZIP code level.

Panel A of Appendix Table B1 provides a summary of advisor characteristics. An average advisor has 15 years of experience and a total of 4 licenses. 35% of advisors hold a license geared toward the sale of insurance products such as annuities (Series 6), while 74% hold a more general securities license that encompasses the Series 6 but also allows the sale of individual securities (Series 7). 20% of advisors hold the license for supervisory roles (Series 24 or 26), and 51% of advisors hold investment advisory licenses (Series 65 or 66). Finally, about one in eleven advisors have ever committed any misconduct throughout their career.

To determine advisor race, we use the Bayesian Improved First Name Surname Geocoding (BIFSG) algorithm to determine the most likely race of an advisor.[4] BIFSG can be viewed as a refinement of the more widely used Bayesian Improved Surname Geocoding (BISG). These approaches estimate race and ethnicity by combining geocoded address and surname Census data. By using both location and surname data, the techniques significantly outperform methods using only one or the other. The concordance statistic ranges for the BISG methodology are 0.94 for Asian/Pacific Islander, 0.93 for Black, 0.94 for Hispanic, and 0.93 for White, where 0.5 indicates no predictiveness/random and 1.0 indicates perfect predictiveness. While BIFSG has been shown to have a modest improvement in classification over BISG in mortgage lending and voting datasets, the largest improvements occur for Blacks, the group for which the BISG performance is relatively weakest. Based on the BIFSG output, the racial composition of financial advisors in 2019 is 5.4% API, 3.0% Black, 4.9% Hispanic, and 86.7% White. These statistics are consistent with other survey-based data sources. For example, the CFP board reports 4% API, 1.8% Black, and 2.7% Hispanic CFP professionals in 2021.

We track over 600,000 unique advisors across over 10,000 firms between 2011 and 2019. The data give dates and branch locations for individuals employed with member firms. To determine firm characteristics, we aggregate individual advisor information to the firm level to calculate the number of states the firm operates in, the total number of branches, the total number of advisors, and the racial makeup of the advisors working for the firm. Panel B of Appendix Table B1 provides summary statistics on firm-level characteristics. Unconditionally, an average firm operates 13.9 branch offices in 2.7 states and employs 63 advisors. However, the labor concentration at the firm level is highly skewed. On one end, large financial services firms such as Merrill Lynch and Morgan Stanley each employ more than 20,000 advisors and have branches all over the country. On the other end, there are also single-branch firms that dedicate their services to the local community.

2.2.2 Stock Market Participation

We use data from the IRS's Statistics of Income (SOI) and follow Brown, Ivković, Smith, and Weisbenner (2008) to develop our proxy for stock market participation. Our sample ends in 2019 because this is the last year the participation data is available when we ran our analysis. SOI provides annual data on tax returns in a ZIP

[4]See `https://www.tandfonline.com/doi/full/10.1080/2330443X.2018.1427012`.

code, including the number of filers, the average reported salaries and wages, average adjusted gross income (AGI), the number of returns filed, and the number of returns reporting dividends. Following Brown, Ivković, Smith, and Weisbenner (2008), we proxy for stock market participation based on whether a household reported dividend income on their federal tax return in a given year. That is, for ZIP i in year t:

$$Participation_{i,t} = \frac{Number\ households\ reporting\ dividend\ income_{i,t}}{Tax\ returns\ filed_{i,t}} \tag{2.1}$$

Brown, Ivković, Smith, and Weisbenner (2008) note two weaknesses of this measure: (1) dividend income reported on tax returns includes distributions from any mutual fund, including those solely invested in fixed income, and (2) it may not capture those who invest exclusively in non-dividend paying firms, such as growth-oriented stocks. To the extent that we wish to measure individuals' participation in financial markets overall, (1) does not present a serious issue, and (2) is not an issue so long as an investor holds any *one* dividend-paying stock or mutual fund that makes a distribution. Brown, Ivković, Smith, and Weisbenner (2008) additionally show that the correlation between actual equity market participation as reported by the FED's Survey of Consumer Finances across four pooled cross-sections and their measure was 0.62. Lin (2020) finds the correlation between this measure of participation and the measure of participation from the University of Michigan's Health and Retirement Study used in Hong, Kubik, and Stein (2004) is 0.69. We aggregate the ZIP level participation data to the community level using the total number of filings in each ZIP reported in SOI as the population weight.

2.2.3 Local Demographic Data

Finally, we use the American Community Survey (ACS) from the Census Bureau to provide local demographic and socioeconomic data that is likely to affect stock market participation rates. Our sample starts in 2011 because this is the first year the ACS 1-year data became available at the ZIP level. Prior literature shows that local characteristics such as income and education affect capital market participation (van Rooij, Lusardi, and Alessie, 2011; Brown, Cookson, and Heimer, 2019). We control for median household income, education, and unemployment rate. Because our main analysis is at the community level, we aggregate ZIP level data to the community level using population weights. To measure the racial composition, we calculate the percentage of the total population for each race in a community-year. We provide community-level summary statistics of local demographics in Panel C of Appendix Table B1. In an average community, 25% of the population above the age of 25 have a college (or higher) degree, 3% of the population in the labor force are unemployed, and the median household has an annual income of about $60,000. In terms of the racial composition of the residents, an average community is 74% White, 3% Asian/Pacific Islander (API), 9% Black, and 11% Hispanic.[5]

[5]ACS also provides data on the American Indian and Alaska Native (AIAN) population in addition to Asian, Black, and Hispanic populations. However, there are only 86 unique AIAN advisors in

2.3 Descriptive Statistics

2.3.1 Financial Advisors and Underrepresentation

Minority groups tend to be underrepresented in education, healthcare, and legal fields. How this underrepresentation impacts client-provider relationships is an ongoing debate in the literature.[6] In Table 2.1, we examine how the distribution of minorities in the financial advising industry compares to minorities in the labor force in general, as well as these industries where racial concordance has been studied.

Our data come from a cross-section of data from the Bureau of Labor Statistics (BLS) for 2019. As has been shown throughout the literature, we generally find that relative to their proportion in the labor force in general, minorities are underrepresented in these fields, however, some exceptions exist. Hispanics are underrepresented throughout, while Blacks and Asians tend to vary among these professions. For example, we show that Blacks and Asians are overrepresented in healthcare professions, yet underrepresented in education professions.

With respect to our industry of study, financial advisors, we find underrepresentation across all minorities. Further, this underrepresentation is much more severe than that studied in other professions. For example, while Blacks make up 12.3% of the labor force, they represent only 3.0% of financial advisors. While Hispanics make up 17.6% of the labor force, they represent only 4.9% of financial advisors.

Firms have stated a need to grow the number of minority advisors. In an interview with KPMG, the Global Head of Regulatory Relations at Morgan Stanley stated: "It is all of our responsibility to make a more diverse and inclusive workforce and environment a reality at our companies and across the industry." Similarly, many large financial services firms have put in their effort to increase minority representation in the industry.[7] We show in Figure 2.1 that the fraction of Hispanic and API advisors has nearly doubled over our time period of study, while the fraction of Black advisors has remained relatively constant. A study by the U.S. Government Accountability Office also finds a similar trend across these race groups.[8] This suggests that hiring practices intended to grow minority representation are having some impact, but that these gains in representation are not shared by all minority groups.

2.3.2 Advisory Firm Characteristics

In Table 2.2, we describe the characteristics of firms that employ minority advisors using the following regression:

$$Firm\ Char_i = \beta_1\ API\ Advisor_i + \beta_2\ Black\ Advisor_i + \beta_3\ Hispanic\ Advisor_i + Community\ FE \tag{2.2}$$

our sample. Due to the imprecision of statistical inference caused by the small sample size, in this case, we do not include AIAN advisors in our analysis.

[6] See Redding (2019) for a review of the literature in education, Shen, Peterson, Costas-Muñiz, Hernandez, Jewell, Matsoukas, and Bylund (2018) for a review of the literature in healthcare, and Lawton (2016) for a review of the literature in legal services.

[7] See for example Morgan Stanley's Freshman Enhancement Program and JPMorgan Chase &Co.'s Proud to Be Program.

[8] See https://www.gao.gov/products/gao-19-398t.

Our data for firm characteristics (such as number of branches, number of states operating in, and number of advisors) come from aggregating individual advisor information to the firm level. The test sample is a cross-section of advisors from 2019 and the unit of observation is an advisor (i). The advisor race (API, Black, Hispanic) is an indicator equal to one if the advisor is of that corresponding race, and zero otherwise. The benchmark group is White advisors, and the characteristics of the firms they work for are captured in the intercept from the regressions. As such, the coefficients β_1 through β_3 should be interpreted in comparison to White advisors. For each firm characteristic, we test both in the cross-section and within-community.

We find that firms employing minority advisors are generally larger across several dimensions. However, this relationship is not constant across all races and firm characteristics. For example, we find that firms employing Black and Hispanic advisors operate in more states, operate more branch offices, and employ more advisors in general than firms employing White advisors. While firms employing Hispanic advisors also have more assets under management (AUM), firms employing Black advisors have lower AUM.[9] Turning to firms that employ API advisors, we see that the results are even more nuanced. In the cross-section, these firms tend to operate in fewer states and have fewer branch offices, yet within-community we find that they operate more branch offices and manage more assets than the baseline group. This suggests that geographic specialization may play a role in where firms employ minority advisors, a question we examine in the next section.

2.3.3 Communities Where Minority Advisors Work

In aggregate, the communities where financial advisors work closely mirror the racial composition of the nation as a whole. Using advisor-weighed observations, the average community composition is 57.2% White, 17.9% Hispanic, 14.4% Black, and 7.4% API, which is remarkably similar to the entire US average.[10] However, this does not necessarily imply that advisors from one particular race face this average composition because of geographic sorting by the race of households and advisors. The variation in firm characteristics we document in the previous section suggests minority advisors may work in different communities from not only White advisors but from different minority types as well.

In Figure 2.2, we examine the geographic distribution of where minority advisors work. Focusing on minority presence in general, we see that API advisors (fig. a) presence, in general, is less geographically diverse than that of Black advisors (fig. c) and Hispanic advisors (fig. e). When we focus on the fraction of minority advisors serving different geographic areas, the pattern becomes more clear. The concentration

[9]We obtain AUM from Form ADV for a subsample of advisors employed with registered investment advisory firms.

[10]In Appendix Table B2, We also examine the potential differences between communities with and without financial advisors. We find that communities with advisors are on average higher educated, have higher median household income, and are more likely to participate in the stock market. Communities with financial advisors are also more diverse: They have a smaller fraction of White populations and a larger fraction of minority populations from each race group.

of API advisors is dominated by California, the state with the highest population of API residents. Whereas the fraction of Black advisors (fig. d) shows clustering in the Deep South, while the fraction of Hispanic advisors shows clustering in Texas, the Southwest, and California.

We can see this more formally in a regression setting. In Table 2.3, we describe the communities that minority advisors serve. We use community characteristics data obtained from the American Community Survey (ACS) and the following regression:

$$Community\ Char_i = \beta_1\ API\ Advisor_i + \beta_2\ Black\ Advisor_i + \beta_3\ Hispanic\ Advisor_i + Firm\ FE \tag{2.3}$$

The test sample is a cross-section of advisors from 2019. The unit of observation is an advisor (i). The advisor race is an indicator equal to one if the advisor is of that corresponding race, and zero otherwise. As before, the benchmark group is White advisors and the characteristics of their communities are captured in the intercept from the regressions.

In Panel A, the community characteristic we focus on is the racial makeup of the households in that community. We observe evidence of racial matching between advisors and households in the community. For example, API advisors work in communities with roughly 2× more API residents than White advisors.[11] The economic magnitudes are similar for Black and Hispanic advisors. We find modest evidence that API advisors tend to work in communities with more Hispanic households and a similar effect for Hispanic advisors and API households. This effect is likely driven by California which in addition to having the highest population of API households in the U.S., also has the highest population of Hispanic households.

In Panel B, we turn to socioeconomic community characteristics: Unemployment, Income, and Education (fraction of households with a college degree). We again find that the communities that minority advisors serve differ from those served by White advisors and differ from each other. For example, we find that Black and Hispanic advisors work in communities with higher unemployment, lower income, and lower educational attainment than communities served by White advisors. Conversely, API advisors work in communities that have higher incomes and higher educational attainment.

Collectively, our results point to several patterns in the data. First, minority advisors appear to work in areas with more households of similar racial backgrounds. Second, like in many studies of race, the correlations we find are complicated by the fact that not all minority communities (or advisors) are the same and tend to vary geographically and along observable socioeconomic factors.

While this pattern could be driven by firms strategically placing minority advisors into certain communities, this is unlikely to be the only driver. Clifford, Ellis, and Gerken (2021) use childhood residence data for a sample of more than 92,000 financial advisors and show that 40% reside within 50 miles of their childhood home. An additional factor could be that advisors choose to enter the profession when the makeup of the households they serve has a similar racial background to their own. Whether this leads to better career outcomes for the advisor or better financial outcomes for the households in that community, we explore in sections 2.5.2 and 2.5.3.

[11] 6.6-8.4 percentage points compared to the intercept of 7.4-7.5 percentage points.

2.3.4 Minority Financial Advisor Characteristics

Next, we turn to the characteristics of the minority advisors themselves and how they differ from White advisors.

In Table 2.4, we describe the characteristics of minority advisors using the following regression:

$$Advisor\ Char_i = \beta_1\ API\ Advisor_i + \beta_2\ Black\ Advisor_i + \beta_3\ Hispanic\ Advisor_i + FEs \tag{2.4}$$

The test sample is a cross-section of advisors from 2019. The unit of observation is an advisor, i. The advisor race is an indicator equal to one if the advisor is of that corresponding race, and zero otherwise. As before, the benchmark group is White advisors and their characteristics are captured in the intercept from the regressions. Using data from FINRA, we use characteristics that are common in the financial advising literature: years of experience, # of firms worked for, # of professional licenses, insurance, principal, investment advisor, and misconduct.[12] For each advisor characteristic, we test the relation between advisor race in three ways. First, we show simple cross-sectional correlations. Second, to pull out any firm effects for the types of advisors they hire, we include firm fixed effects. Finally, to pull out local geographic effects for the types of areas minority advisors work, we include community fixed effects.

Beginning with Experience, we find that minority advisors tend to have significantly less experience than White advisors. The effect is much stronger for API and Hispanic advisors. As we showed in Figure 2.1, the fraction of API and Hispanic advisors has grown over our sample period, while the fraction of Black advisors has remained constant.

We find that minority advisors generally work for fewer firms, have less licensing in general, are less likely to become supervisors (Principal), less likely to serve as fiduciaries (Investment Advisor), and are generally less likely to commit misconduct. Given the results on experience, this is not surprising as Egan, Matvos, and Seru (2019) show that advisors with less experience tend to work for fewer firms, have less licensing, and are less likely to have committed misconduct.

The notable exception here is the relationship to Insurance. An advisor with a Series 6 license only has the ability to sell securities with a prospectus (typically mutual funds or variable annuity products) while the advisor with a Series 7 license (general securities license) can sell all securities provided by the Series 6 plus individual securities, such as stocks and ETFs. The Series 7 license is typically taken by advisors working at large, wirehouse firms such as UBS and Merrill Lynch, while the Series 6 license is often taken by advisors at insurance-focused firms like State Farm and Northwestern Mutual.

[12] *Insurance* is an indicator variable equal to one if the advisor has a Series 6 license, and zero otherwise. *Principal* is an indicator variable equal to one if the advisor has a Series 24 or 26 license, and zero otherwise. *Investment* advisor is an indicator variable equal to one if the advisor has a Series 65 or 66 license, and zero otherwise. *Misconduct* is an indicator variable equal to one if the advisor has ever committed misconduct, as defined in Egan, Matvos, and Seru (2019), and zero otherwise.

We find that all three minority advisor groups are more likely to have an insurance license than White advisors. Outside of a statistically insignificant relation in the cross-section for API advisors, this relation holds even if they work for the same firm and when they work in the same community. Turning to the within-community results, 34.3% of White advisors have an Insurance license (Series 6). A Black advisor working in the same community as the White advisor is 24.5% more likely to have a Series 6, while a Hispanic advisor in the same community is 31.5% more likely to have a Series 6. Primerica, an insurance firm that also provides clients with mutual fund and variable annuity products, employs the largest percentage of minority advisors in our sample; employing 1 out of every 8 (12) Black (Hispanic) advisors in our sample. Using data from the Survey of Income and Program Participation (SIPP), Harris and Yelowitz (2018) show that due to a higher expected mortality rate, minorities are more likely to buy whole life insurance products, which also have an investment component. If advisors feel that racial concordance improves their expected career success, our insurance finding suggests advisors may choose licensing targeted to the preferences of their potential client base.[13]

2.3.5 Community Selection and Concordance

Our main empirical specifications center around how racial concordance relates to community participation in the stock market and labor market outcomes for the advisor. To better interpret those results, it is first important to understand the effects of selection on the types of advisors (as measured through the same characteristics shown in Table 2.4) that work in communities with more households from the same racial background when compared to minority advisors working in communities with more White households. Advisors endogenously choose which communities they serve and are likely to choose communities in which they expect to be more successful. Minority advisors that choose to target largely White, wealthier communities could be quite different than those advisors that choose to work in communities of similar racial makeup to their own.

In Table 2.5, we test the selection decision of minority advisors using the following regression:

$$\begin{aligned} Advisor\ Char_i = {} & \beta_1 API\ Advisor_i + \beta_2 Black\ Advisor_i + \beta_3 Hispanic\ Advisor_i \\ & + \beta_4 Frac.\ Concordant_{i,t} \\ & + \beta_5 Frac.\ Concordant_{i,t} \times API\ Advisor_i \\ & + \beta_6 Frac.\ Concordant_{i,t} \times Black\ Advisor_i \\ & + \beta_7 Frac.\ Concordant_{i,t} \times Hispanic\ Advisor_i \\ & + FEs + \epsilon_{i,t} \end{aligned} \tag{2.5}$$

[13]Brown, Ivković, Smith, and Weisbenner (2008) and Lin (2020) show a positive correlation between equity market participation data from the IRS (of which we use in this paper) and samples of data that do not require 1099-DIV data. They are silent, however, on how these correlations vary among race. If minority households gain access to equity markets through insurance products like variable annuities (which are non-taxable), the IRS data may underreport participation for minority households.

The test sample is a cross-section of advisors from 2019. The unit of observation is an advisor (i). The advisor race (API, Black, Hispanic) indicators are equal to one if the advisor is of that corresponding race, and zero otherwise. As in Table 2.4, advisor race indicators capture the average effect for each advisor race, whereby White advisors are the benchmark group. To this table, we now add $Frac.\, Concordant_i$, defined as the fraction of the local population that is the same race as the advisor, to capture the general racial concordance effect for advisors of all races, including White. Finally, we also add $Frac.\, Concordant_i \times Race\ Advisor_i$ to capture the incremental effect for minority advisors of a specific race working in communities with differing levels of households with the same race.

We begin by focusing on the main effect of the various $Race\ Advisor_i$ variables. Our results are similar to Table 2.4. For all three groups of minority advisors, we continue to find that they have less experience, work for fewer firms, have less licensing, and are less likely to commit misconduct. Turning to $Frac.\, Concordant_i \times Race\ Advisor_i$, we do find incremental effects for minority advisors, but with little consistent pattern.

Focusing on years of experience, for example, we find that both in the cross-section and within-firm, API advisors that work in communities with a higher concentration of API households actually have more experience than the API advisor benchmark. To quantify, follow the API advisors example in column (1): Unconditionally, an advisor has 15.4 years of experience. The coefficient on the API advisor indicator is -6.291, suggesting that on average API advisors in communities with no API population have about nine years of experience, six less than the unconditional mean. Serving a community with a higher fraction of API population has two significant effects on an API advisor: the coefficient (-0.808) on the average concordant effect and the coefficient (11.324) on the interaction. In aggregate, API advisors that work in communities with a one-standard-deviation (5 percentage points) higher fraction API population on average have about 0.53 [$= (11.324 - 0.808) \times 0.05$] years more experience, a small number compared to the baseline. In other words, although the estimated coefficients may seem economically meaningful, the actual "selection" effect is small considering small variations in the fraction of minority population. We find no selection effects on experience for Black advisors and only in the cross-section for Hispanic advisors.

Focusing on the other characteristics, we find that API advisors working in communities with a higher fraction of API households are more likely to have more licenses, sell insurance, be investment advisors, and commit misconduct (cross-section only) when compared to the baseline characteristics of the average API advisor. While more licensing and the decision to take on a fiduciary responsibility by becoming an investment advisor may reasonably imply these advisors are of a higher type, the fact that we find some evidence that they are implicated in more misconduct may negate this fact.

When Black advisors work in communities with a higher concentration of Black households we find that they are likely to work for fewer firms and more likely to engage in misconduct. Turning to licensing, we find that Black advisors are more likely to sell insurance, more likely to become a principal, and more likely to become an investment advisor when they work in higher fraction Black communities. Each of these licensing results, however, is not statistically different from zero in our within-firm estimation, suggesting that the types of firms Black advisors choose to work for may be driving the result.

We conclude by examining the effects on Hispanic advisors. We find that Hispanic advisors are more likely to become investment advisors when they work in more Hispanic communities. Further, we find that Hispanic advisors in more Hispanic communities are more likely to become principals (within-firm only) and commit misconduct (cross-section only).

Collectively, our results paint a murky picture on the selection effects of minority advisors. While on the one hand we document evidence of selection, these effects vary in non-obvious ways across advisor characteristics, between the differing minority races, and tend to be small in economic magnitude. We acknowledge that this selection may lead to an omitted variable bias in our main specifications and thus remain cautious in claiming a causal relation throughout.

2.4 Testable Hypothesis

2.4.1 Stock Market Participation

The role that racial concordance between the advisor and household may play is ex-ante unclear. Racial concordance could lead to positive outcomes for households if it enables greater stock market participation for clients. One possible channel for this outcome is trust. Trust in the financial market is one of the most important factors when individuals decide whether to participate in the stock market (Guiso, Sapienza, and Zingales, 2008; Burke and Hung, 2021). Importantly, trust can also reduce investors' perceived riskiness when delegating the portfolio choice to the designated advisor (Gennaioli, Shleifer, and Vishny, 2015). This may be even more important for minorities, who are more likely to be mistreated (Begley and Purnanandam, 2021; Stefan, Holzmeister, Müllauer, and Kirchler, 2018). The literature has shown that concordance on gender, age, and family structure increases the amount of advice people take up (Stolper and Walter, 2019).

Alternatively, racial concordance between the advisor and client could be positive if clients or advisors receive non-pecuniary benefits of working with people of the same race (taste-based discrimination channel; Becker (1957)) or if racial concordance enables better (lower cost) communication between the advisor and client (Redding, 2019), leading to productivity increases in the relationship (informational channel).

Racial concordance between the advisor and the household could have a negative impact as well.[14] In the context of gender, women have been shown to discriminate against other women (Reuben et,al. 2014), while in the context of race individuals may reject minority advisors that "act White" (Austen-Smith and Fryer Jr, 2005) or based on their own level of acculturation may respond better to White advisors (Ogden, Ogden, and Schau, 2004; Tsai and Li, 2012), among others. Further, this

[14] See for example, Harvey, LaBeach, Pridgen, and Gocial (2005), Postmes and Branscombe (2002), and Alexander and Carter (2022).

relationship could be negative if the advisor selection effects we document in Table 2.5 are the result of minority advisors working in communities that are similar on observables but have worse prospects and were rejected by White advisors.

Each of these possible channels is non-mutually exclusive, and while the sign of our estimated concordance coefficients may speak to whether the relation is positive or negative, given our experimental design and data limitations it will be difficult to tease apart the various channels. Formally stated: Similarity in race between households and local financial advisors increases stock market participation by minority households.

2.4.2 Labor Market Outcomes

As stated in the previous section, advisors choose the community they work in. Based on the same arguments for concordance and our stated Hypothesis 1, we posit that racial concordance will also benefit the financial advisor's career outcomes. While we do not have measures of individual success such as assets managed or compensation, we proxy for success by measuring the length of an advisor's career under the assumption that a longer career is more successful than a shorter career. Formally stated: Advisors of similar race to the households they serve survive longer in the advisory labor market.

2.5 Results

2.5.1 Design

We estimate the following models (and precursor versions without various controls and fixed effects):

$$\begin{aligned}
Outcome_{i,t} = {} & \beta_1 API\ Advisor_i + \beta_2 Black\ Advisor_i + \beta_3 Hispanic\ Advisor_i \\
& + \beta_4 Frac.\ Concordant_{i,t} \\
& + \beta_5 Frac.\ Concordant_{i,t} \times API\ Advisor_i \\
& + \beta_6 Frac.\ Concordant_{i,t} \times Black\ Advisor_i \\
& + \beta_7 Frac.\ Concordant_{i,t} \times Hispanic\ Advisor_i \\
& + \gamma \mathbf{X}_{i,t} + FEs + \epsilon_{i,t}
\end{aligned} \tag{2.6}$$

where for Hypothesis 1, the dependent variable ($Outcome_{i,t}$) is community-level stock market participation and for Hypothesis 2, the dependent variable is whether the advisor leaves the industry. Our sample is an annual panel of advisors from 2011 to 2019. The unit of observation is an advisor-year (i,t). As in Table 2.5, $Race\ Advisor_i$ captures the average effect for each advisor race, whereby White advisors are the benchmark group, $Frac.\ Concordant_{i,t}$ captures a general racial concordance effect for advisors of all races, including White, and $Frac.\ Concordant_{i,t} \times Race\ Advisor_i$ captures the incremental effect for minority advisors working in communities with differing levels of households with the same race as the advisor. In all models, we cluster standard errors by community following Abadie, Athey, Imbens, and Wooldridge (2017).

2.5.2 Stock Market Participation

In Table 2.6, we examine the impact of concordance on stock market participation (Hypothesis 1). In the first specification, we examine how the racial composition of the community is related to stock market participation. We find that neighborhood composition is a strong predictor of stock market participation (R^2 of 0.363). The baseline average participation rate is 26.21%. We show that Black and Hispanic populations are associated with lower participation rates, while Asian populations are associated with higher participation rates.

Of course, there are multiple reasons why these populations may be associated with differential participation rates. As suggested in prior literature (van Rooij, Lusardi, and Alessie, 2011; Brown, Cookson, and Heimer, 2019), local characteristics such as income and education affect capital market participation. In specification 2, we add controls for income, education, employment, and year fixed effects. As expected, we find that income and education are highly correlated with participation rates. The R^2 of the model more than doubles to 0.784 indicating the importance of the socioeconomic variables.[15] More interestingly, we find the magnitudes of neighborhood composition drop approximately in half for Black and Hispanic communities, and the sign flips direction for Asian households such that this population is negatively correlated with participation. Yet, even after controlling for socioeconomic factors, we find that communities with higher rates of API, Black, and Hispanic households are less likely to participate in the stock market, all else equal.

We next explore how the relationship changes when we include access to financial advice *# Advisors/Population* and the racial composition of the advisors in the community in specification 3. Including the racial makeup of the advisors also helps to alleviate a simultaneity concern that the race of the advisor may simultaneously correlate with where the advisor chooses to locate. In specification 3 (and all subsequent specifications), we also include standard advisor-level controls (experience, Series 6, Series 7, Investment Advisor, Principal, and Misconduct) but do not report the coefficients for brevity.

We find that access to financial advice increases participation rates. We find a statistically significant, but economically small relation between the presence of an API advisor (+32 bps) and the presence of a Black advisor (-58 bps). We note that the inclusion of these factors does little to change the coefficients on the racial and socioeconomic community factors. Collectively, these results suggest that neighbor composition has explanatory power on participation rates, while advisor racial characteristics are not generally related.

In specification 4, we introduce the variable *Frac. Concordant* which captures the fraction of the neighborhood that shares the same racial background with the advisor. In other words, the coefficient on *Frac. Concordant* is the average effect for racial concordance across all races, including White-White concordance. We find a modest but statistically significant relationship between this variable and participation. This cross-sectional result suggests that, on average, there is a positive correlation between

[15]The addition of the year fixed effects made little difference to the change in R^2.

advisor-clientele racial concordance and stock market participation. But is this the case for all race groups?

As noted previously, there are multiple reasons why we might observe a relation between racial concordance. Moreover, the reasons may apply differently for concordance among the different racial groups. In specification 5, we include the interaction of *Frac. Concordant* with minority advisor race indicator. These coefficients pick up the incremental effect of racial concordance for API, Black, and Hispanic advisors and the estimated effect should be added to *Frac. Concordant* to determine the combined effect of advisor and household racial concordance. We find an overall positive concordance relation for White and Asian advisors and given the insignificance of $Frac. Concordant \times API$, the magnitudes for White and API advisors are similar. We find negative concordance for Black and Hispanic advisors. The incremental effects of -0.0735 and -0.0642, respectively, are statistically different from zero and when combined with the main effect (*Frac. Concordant*), the joint effect is negative and statistically different from zero.

To quantify the economic size of the effect, follow the Black advisors' example in specification (5): Unconditionally, a community has average stock market participation of 17%. The coefficient on the Black advisor indicator is 0.0224, suggesting that on average Black advisors who work in communities with zero Black population are associated with 13% higher participation rates when compared to the unconditional mean. Serving a community with a higher fraction of Black population has two significant effects on a Black advisor: the coefficient (0.0399) on the average concordance effect, and the coefficient (-0.0735) on the interaction, which captures the incremental concordance specific to Black-Black matching. In aggregate, Black advisors that work in communities with a one-standard-deviation (13 percentage points) higher fraction Black population on average have about 0.44 percentage points $[= (0.0399 - 0.0735) \times 13\%]$ lower stock market participation, a 2.6% decrease compared to the baseline.

As stated previously, however, advisors choose where to work and place effects outside of those captured in the socioeconomic factors could explain why selection of certain communities and advisors occurs. One way to limit this impact is to look at time-series changes within a particular community. We take this approach in specification 6 by adding community fixed effects. Consistent with the earlier findings, an increase in income and education are positively related to participation, while the proportion of Black and Hispanic households is negatively related. In this specification, we find very little evidence of advisor race and matching. The coefficient on *Frac. Concordant* effectively drops to zero. The incremental effects for Black and Hispanic communities also fall to zero. We find statistical evidence of positive racial concordance for API advisors and communities, but the effect size is economically small: A one standard deviation increase in the fraction of API populations (5 percentage points) is only associated with about 1 bps $[= (0.0016 + 0.0002) \times 0.05]$ increase in participation as the result of API-API concordance.

For robustness, we redo the above analysis at the ZIP level and report results in Appendix Table B3. By nature of the empirical design, this robustness test empirically restricts the measurement for each variable to a single ZIP-year (instead of a community of ZIPs) and conceptually restricts racial concordance to only exist within-ZIP. We draw similar conclusions from this robustness test as the community-level test. First, controlling for ZIP-level and advisor-level characteristics, minority (API, Black, Hispanic) households are less likely to participate in the stock market. Second, on average, we observe a positive but economically small concordance effect in the cross-section. However, when accounting for ZIP fixed effects, we again find little evidence for racial concordance to matter for stock market participation.

Overall, our evidence is consistent with the idea that community composition is associated with stock market participation rates, even after controlling for observable socioeconomic factors. However, we find little evidence of a concordance effect on participation.

2.5.3 Labor Market

The industry for financial advice is one with relatively high career turnover. A common compensation arrangement in this industry would be a salary or draw for 12 to 24 months and then a shift to a fee/commission only compensation structure. Developing a book of business is a lengthy process and many advisors exit the business early. Here we study the rates at which minority advisors leave the industry and whether racial concordance has any impact on career length. We repeat equation (6), where the dependent variable is now an indicator variable equal to one if the advisor quits the industry that year, and zero otherwise. We report our results in Table 2.7.[16]

As in the previous section, in specification 1 we begin by studying the unconditional quit rates for the racial groups. We find that API, Black, and Hispanic advisors each have a higher rate of leaving the industry. The magnitude is economically large: in a given year, an average Black advisor is almost 30% (=0.0094/0.0325) more likely to leave the profession than an average White advisor; the magnitude is larger for API and Hispanic advisors.

In specification 2, we control for observable advisor characteristics[17] and year fixed effects and see the magnitudes drop by about 30-40%, although the coefficients remain statistically significant: Minority advisors have a higher likelihood of exiting from the industry in a given year even controlling for advisor characteristics and year fixed effects. In specification 3, we see that the addition of community racial and socioeconomic (income, education, and employment) characteristics diminish the magnitudes of the advisor race coefficients. These results suggest that being in a minority community is more important than the race of the advisor in determining career longevity. This finding from specification 3 suggests what we observe in specifications 1 & 2 could partly be due to the racial matching between advisors and households as documented in Panel A of Table 2.3.

In specification 4, we add *Frac. Concordant*. The coefficient on *Frac. Concordant* is negative and statistically significant, suggesting that sharing the racial background

[16]We define quitting as exiting the industry and not returning for the remaining of the sample period.

[17]Including certifications, years of experience, investment advisor status, supervisory status, and misconduct.

with the community leads to a lower likelihood of exiting the industry. In specification 5, we include the interaction of *Frac. Concordant* with the minority advisor race indicator. We find an overall positive concordance relation for all three minority groups. In specification 6, even after the addition of community fixed effects, we find consistent evidence that although minority advisors are more likely to leave the industry, they are less likely to do so in concordant areas. However, the economic magnitude of the coefficients falls meaningfully compared to those from specification 5. To quantify the economic size of the effect, consider the following Hispanic advisor example. The unconditional quit rate in our sample is 3.25% annually. The coefficient on Hispanic advisor indicator is 0.0103, suggesting that in a given year an average Hispanic advisor who works in a community with zero Hispanic population is 31.7% more likely to quit the industry when compared to the unconditional mean. Serving a community with a higher fraction of Hispanic population has two significant effects on a Hispanic advisor: the coefficient (0.0073) on the average concordance, and the coefficient (-0.0217) on the interaction. In aggregate, Hispanic advisors that work in communities with a one standard deviation (15 percentage points) higher fraction of Hispanic population on average is about 0.22% $[= (0.0073 - 0.0217) \times 15\%]$ less likely to quit the industry in a given year, a 5% reduction compared to the baseline quit rate of 4.28% (= 3.25% + 1.03%) for Hispanic advisors. To place the magnitude of the concordance effect into perspective, the incremental reduction in quit rate for a Hispanic advisor that moves to a one standard deviation higher median household income community would be about $2\times$ larger than the reduction from the racial concordance effect.

For robustness, we redo the above analysis at the ZIP level and report results in Appendix Table B4. First, notice that the first two specifications have the exact same results as those in Table 2.7. This is to be expected since these two specifications only include advisor-level information and do not utilize any information from the ZIP or the Community. Moving on to specifications 3 & 4 we continue to find that advisors serving a greater fraction of minority populations are more likely to exit from the industry, while on average the effect is largely negated by the concordance effect as captured by *Frac. Concordant*. Finally, in specifications 5 & 6, we find less consistent evidence for the effect of racial concordance on advisor career longevity across different race groups, although the average effect across all race groups (*Frac. Concordant*) remains negative and statistically significant. This discrepancy with Table 2.7 is potentially due to the stringent geographical definition restricting the ability to capture the totality of the racial composition of the local community.

Collectively, our results suggest that advisor-clientele racial concordance is associated with a lower advisor quit rate, partially negating the higher average quit rate among minority advisors. However, the effect is smaller than the negating effect on the quit rate from serving a more affluent community and is sensitive to the geographical specification of the model.

2.6 Conclusion

Using detailed data on financial advisors and the local communities they serve, we examine the role of race and racial concordance in the market for financial advice. First, we provide a detailed summary of community level attributes such as stock market participation by racial composition. We document the potential role of assortative matching between advisors and the communities they serve. We then examine the relation between financial advisor race and community racial composition, and find only a modest association with community-level stock market participation rates. We do find that minority advisors are more likely to drop out of the industry; however, this relation is mitigated among advisors located in more concordant communities. Our results provide insight into the potential efficacy of diversity hiring in the industry and highlight potential impacts on recently hired minority advisors.

Table 2.1: Minority Representation

This table presents the statistics for the minority representation in the US labor market in 2019. Financial advisor data is from the sample of this paper, the rest statistics are from the Bureau of Labor Statistics.

Profession	Black	Asian	Hispanic
Education, Training, and Library	10.2%	5.3%	11.0%
Healthcare Practitioners and Technical	12.5%	9.6%	9.0%
Legal	8.3%	6.1%	9.5%
Financial Advisors	3.0%	5.4%	4.9%
All Occupations	12.3%	6.5%	17.6%

Table 2.2: Characteristics for Firms with Minority Advisors

This table documents the characteristics of firms that minority advisors work for in 2019. The unit of observation is a financial advisor. API is the abbreviation for Asians and Pacific Islanders. *API Advisor* is an indicator that equals 1 if the advisor is API. *Black Advisor* is an indicator that equals 1 if the advisor is Black. *Hispanic Advisor* is an indicator that equals 1 if the advisor is Hispanic. *# of States* is the total number of states the firm operates in. *ln(# of Branches)* is the natural logarithm of the total number of branches operated by the firm. *ln(# of ADV)* is the natural logarithm of the total number of advisors employed by the firm. *ln(AUM)* is the natural logarithm of the firm's total asset under management (AUM). Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	# of States		ln(# of Branches)		ln(# of ADV)		ln(AUM)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
API Advisor	-2.770***	0.311	-0.235***	0.099***	0.023	0.174***	1.287***	0.314***
	(0.828)	(0.289)	(0.088)	(0.032)	(0.066)	(0.029)	(0.255)	(0.102)
Black Advisor	2.880***	1.734***	0.338***	0.204***	0.389***	0.244***	-0.291***	-0.062*
	(0.531)	(0.192)	(0.053)	(0.021)	(0.039)	(0.021)	(0.077)	(0.035)
Hispanic Advisor	2.240***	2.125***	0.367***	0.344***	0.457***	0.412***	0.248**	0.168***
	(0.460)	(0.229)	(0.057)	(0.024)	(0.052)	(0.026)	(0.123)	(0.053)
Constant	37.019***	36.874***	5.843***	5.825***	7.662***	7.661***	20.078***	20.134***
	(0.496)	(0.020)	(0.056)	(0.002)	(0.043)	(0.002)	(0.119)	(0.006)
Community FE	-	Yes	-	Yes	-	Yes	-	Yes
R^2	0.003	0.300	0.003	0.308	0.003	0.219	0.006	0.361
Observations	527,347	524,481	527,347	524,481	527,347	524,481	419,348	416,380

Table 2.3: Characteristics of Communities with Minority Advisors

This table documents the characteristics of communities where minority advisors serve in 2019. The unit of observation is a financial advisor. API is the abbreviation for Asians and Pacific Islanders. *API Advisor* is an indicator that equals 1 if the advisor is API. *Black Advisor* is an indicator that equals 1 if the advisor is Black. *Hispanic Advisor* is an indicator that equals 1 if the advisor is Hispanic. Panel A reports the racial composition of residents in the community. *Frac. API* is the fraction of populations that are API. *Frac. Black* is the fraction of populations that are Black. *Frac. Hispanic* is the fraction of populations that are Hispanic. Panel B reports the socioeconomic characteristics of the community. *Unemployment* is the unemployment rate among populations in the labor force. *ln(Income)* is the natural logarithm of median household income. *Frac. College* is the fraction of the population over the age of 25 with a bachelor's or higher degree. Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Racial Characteristics

	Frac. API		Frac. Black		Frac. Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)
API Advisor	0.084***	0.066***	-0.010*	-0.016***	0.092***	0.053***
	(0.007)	(0.008)	(0.005)	(0.003)	(0.006)	(0.005)
Black Advisor	-0.009***	-0.005***	0.105***	0.096***	-0.001	0.002
	(0.002)	(0.001)	(0.005)	(0.004)	(0.004)	(0.003)
Hispanic Advisor	0.014***	0.010**	-0.013***	-0.014***	0.177***	0.150***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.021)	(0.015)
Constant	0.074***	0.075***	0.141***	0.142***	0.171***	0.174***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.006)	(0.004)
Firm FE	-	Yes	-	Yes	-	Yes
R^2	0.073	0.233	0.028	0.208	0.092	0.283
Observations	497,868	494,719	497,868	494,719	497,868	494,719

Panel B. Socioeconomic Characteristics

	Unemployment		ln(Income)		Frac. College	
	(1)	(2)	(3)	(4)	(5)	(6)
API Advisor	0.002***	0.000	0.103***	0.093***	0.026***	0.022***
	(0.000)	(0.000)	(0.015)	(0.012)	(0.005)	(0.004)
Black Advisor	0.003***	0.003***	-0.064***	-0.055***	-0.015***	-0.010***
	(0.000)	(0.000)	(0.007)	(0.006)	(0.004)	(0.003)
Hispanic Advisor	0.002***	0.002***	-0.028	-0.028*	-0.028***	-0.024***
	(0.000)	(0.000)	(0.021)	(0.016)	(0.004)	(0.004)
Constant	0.033***	0.034***	11.182***	11.182***	0.400***	0.400***
	(0.000)	(0.000)	(0.008)	(0.007)	(0.003)	(0.003)
Firm FE	-	Yes	-	Yes	-	Yes
R^2	0.009	0.196	0.011	0.170	0.006	0.170
Observations	497,857	494,708	497,792	494,642	497,857	494,708

Table 2.4: Advisor Characteristics

This table presents the characteristics of minority advisors in 2019. The unit of observation is a financial advisor. API is the abbreviation for Asians and Pacific Islanders. *API Advisor* is an indicator that equals 1 if the advisor is API. *Black Advisor* is an indicator that equals 1 if the advisor is Black. *Hispanic Advisor* is an indicator that equals 1 if the advisor is Hispanic. *Years of Exp.* is the advisor's total years of experience starting from the first year of their career. *# of Firms* is the total number of firms the advisor has worked for. *# of Licenses* is the total number of licenses the advisor holds. *Insurance* is an indicator variable equal to one if the advisor has a Series 6 license. *Principal* is an indicator variable equal to one if the advisor has a Series 24 or 26 license. *Inv. Advisor* is an indicator variable equal to one if the advisor has a Series 65 or 66 license. *Misconduct* is an indicator variable equal to one if the advisor has ever committed misconduct, as defined in Egan, Matvos, and Seru (2019). Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Years of Exp.			# of Firms			# of Licenses			Insurance			Principal			Inv. Advisor			Misconduct		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
API Advisor	-4.738***	-3.397***	-4.123***	-0.173***	-0.127***	-0.231***	-0.367***	-0.276***	-0.328***	-0.023	0.024***	0.038***	-0.056***	-0.061***	-0.075***	-0.181***	-0.066***	-0.089***	-0.043***	-0.024***	-0.028***
	(0.168)	(0.100)	(0.112)	(0.021)	(0.013)	(0.016)	(0.020)	(0.010)	(0.012)	(0.020)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)	(0.016)	(0.010)	(0.005)	(0.003)	(0.002)	(0.002)
Black Advisor	-1.153***	-0.826***	-0.904***	-0.076***	0.040***	-0.034**	-0.168***	-0.100***	-0.121***	0.141***	0.033***	0.084***	0.004	-0.014***	-0.005	-0.091***	-0.041***	-0.063***	-0.023***	-0.016***	-0.017***
	(0.182)	(0.116)	(0.108)	(0.021)	(0.013)	(0.016)	(0.018)	(0.015)	(0.016)	(0.010)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.011)	(0.005)	(0.006)	(0.003)	(0.002)	(0.002)
Hispanic Advisor	-4.325***	-3.417***	-4.180***	-0.110***	-0.034***	-0.133***	-0.355***	-0.276***	-0.334***	0.124***	0.075***	0.108***	-0.046***	-0.049***	-0.060***	-0.113***	-0.054***	-0.086***	-0.031***	-0.023***	-0.040***
	(0.122)	(0.081)	(0.098)	(0.021)	(0.011)	(0.010)	(0.014)	(0.010)	(0.011)	(0.022)	(0.008)	(0.006)	(0.005)	(0.004)	(0.004)	(0.015)	(0.009)	(0.007)	(0.004)	(0.002)	(0.002)
Constant	15.883***	15.765***	15.822***	1.946***	1.932***	1.950***	4.025***	4.014***	4.022***	0.345***	0.349***	0.343***	0.203***	0.203***	0.205***	0.533***	0.521***	0.525***	0.092***	0.091***	0.092***
	(0.118)	(0.059)	(0.009)	(0.012)	(0.005)	(0.001)	(0.010)	(0.006)	(0.001)	(0.010)	(0.003)	(0.001)	(0.003)	(0.002)	(0.000)	(0.010)	(0.005)	(0.001)	(0.003)	(0.001)	(0.000)
Firm FE	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Community FE	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
R^2	0.019	0.162	0.106	0.001	0.198	0.086	0.006	0.132	0.070	0.006	0.411	0.232	0.002	0.091	0.059	0.009	0.321	0.178	0.002	0.072	0.063
Observations	527,146	523,974	524,282	527,194	524,012	524,330	527,194	524,012	524,330	524,120	521,102	521,255	527,194	524,012	524,330	527,194	524,012	524,330	527,194	524,012	524,330

Table 2.5: Advisor-Community Selection

This table presents the effects of selection on the types of advisors that work in communities with more households from the same racial background. API is the abbreviation for Asians and Pacific Islanders. *API (Black, Hispanic) Advisor* is an indicator that equals 1 if the advisor is API (Black, Hispanic). *Frac. API (Black, Hispanic) in Community* ranges from 0 to 1 and is the fraction of populations in the community that are API (Black, Hispanic). *Frac. Concordant* is the fraction of populations in the community that are the same race as the advisor. *Frac. Concordant* × *API (Black, Hispanic)* is the interaction of *Frac. Concordant* and the advisor race indicator. Outcome variables are the same as described in Table 2.4. Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Years of Exp.		# of Firms		# of Licenses		Insurance		Principal		Inv. Advisor		Misconduct	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Frac. Concordant	-0.808	-0.247	-0.256***	-0.149***	-0.367***	-0.241***	0.049	0.049**	-0.055***	-0.081***	-0.191***	-0.101***	-0.011	0.003
	(0.705)	(0.417)	(0.079)	(0.043)	(0.080)	(0.048)	(0.076)	(0.024)	(0.019)	(0.017)	(0.053)	(0.034)	(0.014)	(0.010)
API Advisor	-6.291***	-4.128***	-0.370***	-0.216***	-0.620***	-0.411***	-0.044	0.019	-0.076***	-0.091***	-0.328***	-0.134***	-0.062***	-0.026***
	(0.535)	(0.297)	(0.057)	(0.029)	(0.055)	(0.030)	(0.063)	(0.019)	(0.013)	(0.011)	(0.040)	(0.030)	(0.009)	(0.007)
Frac. API in Community	-4.229***	-0.582	0.792***	0.514***	-0.201	-0.067	-0.660***	-0.158***	0.119***	0.072**	-0.596***	-0.159*	-0.119***	-0.041*
	(1.552)	(0.892)	(0.186)	(0.092)	(0.166)	(0.094)	(0.146)	(0.041)	(0.039)	(0.031)	(0.130)	(0.086)	(0.033)	(0.022)
Frac. Concordant × API	11.324***	4.444***	0.093	-0.004	0.883***	0.361***	0.840***	0.249***	-0.090*	-0.013	1.022***	0.316***	0.169***	0.022
	(2.622)	(1.561)	(0.241)	(0.114)	(0.235)	(0.136)	(0.242)	(0.080)	(0.048)	(0.042)	(0.171)	(0.120)	(0.043)	(0.030)
Black Advisor	-1.788***	-1.021***	-0.052	0.044	-0.264***	-0.160***	0.117**	0.058***	-0.031**	-0.048***	-0.163***	-0.079***	-0.031***	-0.019**
	(0.465)	(0.310)	(0.057)	(0.035)	(0.057)	(0.040)	(0.050)	(0.016)	(0.015)	(0.013)	(0.034)	(0.021)	(0.010)	(0.008)
Frac. Black in Community	-2.446**	-1.459**	0.161	0.055	-0.487***	-0.342***	-0.405***	-0.087***	0.000	0.001	-0.499***	-0.220***	-0.101***	-0.062***
	(1.008)	(0.629)	(0.115)	(0.061)	(0.112)	(0.068)	(0.108)	(0.030)	(0.026)	(0.025)	(0.078)	(0.056)	(0.020)	(0.017)
Frac. Concordant × Black	2.210	0.975	-0.491***	-0.233**	0.078	0.047	0.320**	-0.006	0.078*	0.041	0.207**	0.092	0.054*	0.039*
	(1.410)	(1.033)	(0.169)	(0.105)	(0.167)	(0.133)	(0.146)	(0.044)	(0.046)	(0.038)	(0.094)	(0.062)	(0.027)	(0.023)
Hispanic Advisor	-5.442***	-3.641***	-0.231***	-0.108***	-0.495***	-0.364***	0.144**	0.097***	-0.077***	-0.091***	-0.290***	-0.154***	-0.064***	-0.031***
	(0.521)	(0.349)	(0.060)	(0.036)	(0.058)	(0.039)	(0.067)	(0.021)	(0.016)	(0.014)	(0.039)	(0.030)	(0.014)	(0.010)
Frac. Hispanic in Community	-1.894**	0.319	0.144	0.164***	-0.260**	-0.095	-0.296**	-0.032	0.040*	-0.003	-0.488***	-0.167**	-0.029	0.031*
	(0.962)	(0.653)	(0.109)	(0.057)	(0.107)	(0.071)	(0.115)	(0.030)	(0.023)	(0.022)	(0.092)	(0.069)	(0.020)	(0.017)
Frac. Concordant × Hispanic	3.484**	0.245	0.082	0.043	0.275*	0.138	0.150	-0.030	0.028	0.082**	0.614***	0.282***	0.100**	0.005
	(1.559)	(1.029)	(0.190)	(0.105)	(0.159)	(0.111)	(0.209)	(0.064)	(0.043)	(0.037)	(0.130)	(0.098)	(0.044)	(0.031)
Firm FE	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes	-	Yes
R^2	0.020	0.163	0.008	0.202	0.007	0.133	0.034	0.413	0.004	0.094	0.025	0.323	0.004	0.072
Observations	507,999	504,854	508,045	504,891	508,045	504,891	505,029	502,032	508,045	504,891	508,045	504,891	508,045	504,891

Table 2.6: Racial Concordance and Stock Market Participation

This table documents the correlation between advisor-household racial match and stock market participation. The unit of observation is an advisor-year. API is the abbreviation for Asians and Pacific Islanders. *API (Black, Hispanic) Advisor* is an indicator that equals 1 if the advisor is API (Black, Hispanic). *Frac. API (Black, Hispanic) in Community* ranges from 0 to 1 and is the fraction of populations in the community that are API (Black, Hispanic). *Frac. Concordant* is the fraction of populations in the community that are the same race as the advisor. *Frac. Concordant* $\times$ *API (Black, Hispanic)* is the interaction of *Frac. Concordant* and the advisor race indicator. The outcome variable is the stock market participation rate which ranges from 0 to 1. In columns (2) to (6), we control for community characteristics as described in Table 2.3. In columns (3) to (6), we control for advisor characteristics including certifications, years of experience, investment advisor status, supervisory status, and misconduct. Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Frac. API in Community	0.3635***	-0.0517***	-0.0568***	-0.0445***	-0.0267	0.1319***
	(0.0342)	(0.0176)	(0.0165)	(0.0159)	(0.0198)	(0.0367)
Frac. Black in Community	-0.1874***	-0.1074***	-0.1127***	-0.1011***	-0.0755***	-0.1939***
	(0.0127)	(0.0082)	(0.0078)	(0.0075)	(0.0093)	(0.0214)
Frac. Hispanic in Community	-0.2378***	-0.1175***	-0.1250***	-0.1147***	-0.0885***	-0.2293***
	(0.0124)	(0.0070)	(0.0064)	(0.0055)	(0.0086)	(0.0220)
ln(Income)		0.0854***	0.0911***	0.0916***	0.0913***	0.0976***
		(0.0068)	(0.0075)	(0.0075)	(0.0076)	(0.0080)
Frac. College		0.3496***	0.3090***	0.3094***	0.3121***	0.1413***
		(0.0126)	(0.0151)	(0.0151)	(0.0151)	(0.0141)
Unemployment		0.0553	0.0350	0.0509	0.0554	0.0349
		(0.0754)	(0.0744)	(0.0752)	(0.0750)	(0.0238)
# Advisor/Population			2.5843***	2.6256***	2.5848***	-0.6722
			(0.6658)	(0.6626)	(0.6636)	(0.5815)
API Advisor			0.0032***	0.0074***	0.0151***	-0.0001
			(0.0008)	(0.0014)	(0.0036)	(0.0001)
Black Advisor			-0.0058***	-0.0020	0.0224***	0.0001
			(0.0010)	(0.0014)	(0.0036)	(0.0001)
Hispanic Advisor			0.0004	0.0020*	0.0260***	0.0000
			(0.0011)	(0.0012)	(0.0039)	(0.0001)
Frac. Concordant				0.0141***	0.0399***	0.0002
				(0.0029)	(0.0055)	(0.0001)
Frac. Concordant×API					-0.0013	0.0016***
					(0.0173)	(0.0006)
Frac. Concordant×Black					-0.0735***	-0.0001
					(0.0109)	(0.0002)
Frac. Concordant×Hispanic					-0.0642***	0.0003
					(0.0120)	(0.0003)
Constant	0.2621***					
	(0.0042)					
Year FE	-	Yes	Yes	Yes	Yes	Yes
Advisor Controls	-	-	Yes	Yes	Yes	Yes
Community FE	-	-	-	-	-	Yes
R^2	0.363	0.784	0.792	0.793	0.794	0.995
Observations	4,090,086	4,081,858	4,059,870	4,059,870	4,059,870	4,059,620

Table 2.7: Racial Concordance and Advisor Quitting

This table documents the advisor-household racial match and advisor career longevity. The unit of observation is an advisor-year. API is the abbreviation for Asians and Pacific Islanders. *API (Black, Hispanic) Advisor* is an indicator that equals 1 if the advisor is API (Black, Hispanic). *Frac. API (Black, Hispanic) in Community* ranges from 0 to 1 and is the fraction of populations in the community that are API (Black, Hispanic). *Frac. Concordant* is the fraction of populations in the community that are the same race as the advisor. *Frac. Concordant* × *API (Black, Hispanic)* is the interaction of *Frac. Concordant* and the advisor race indicator. The outcome variable is an indicator that equals 1 if the advisor leaves the industry in that year. In columns (2) to (6), we control for community characteristics as described in Table 2.3. In columns (3) to (6), we control for advisor characteristics as described in Table 2.6. Standard errors reported in parentheses are clustered at the community level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
API Advisor	0.0225***	0.0153***	0.0075***	0.0026	0.0247***	0.0151***
	(0.0024)	(0.0019)	(0.0014)	(0.0016)	(0.0047)	(0.0030)
Black Advisor	0.0094***	0.0054***	0.0025**	-0.0020*	0.0217***	0.0136***
	(0.0012)	(0.0012)	(0.0010)	(0.0012)	(0.0038)	(0.0028)
Hispanic Advisor	0.0143***	0.0080***	0.0010	-0.0009	0.0239***	0.0103***
	(0.0013)	(0.0010)	(0.0012)	(0.0011)	(0.0042)	(0.0028)
Frac. API in Community			0.0472***	0.0329***	0.0722***	0.0177
			(0.0103)	(0.0095)	(0.0141)	(0.0631)
Frac. Black in Community			0.0245***	0.0110***	0.0410***	0.1456**
			(0.0042)	(0.0041)	(0.0074)	(0.0581)
Frac. Hispanic in Community			0.0399***	0.0278***	0.0564***	-0.0215
			(0.0046)	(0.0041)	(0.0078)	(0.0412)
Frac. Concordant				-0.0163***	0.0156***	0.0073**
				(0.0023)	(0.0050)	(0.0036)
Frac. Concordant×API					-0.0899***	-0.0390***
					(0.0206)	(0.0115)
Frac. Concordant×Black					-0.0624***	-0.0348***
					(0.0105)	(0.0075)
Frac. Concordant×Hispanic					-0.0645***	-0.0217***
					(0.0122)	(0.0076)
Constant	0.0325***					
	(0.0011)					
Year FE	-	Yes	Yes	Yes	Yes	Yes
Advisor Controls	-	Yes	Yes	Yes	Yes	Yes
Community Controls	-	-	Yes	Yes	Yes	Yes
Community FE	-	-	-	-	-	Yes
R^2	0.001	0.011	0.013	0.013	0.013	0.028
Observations	3,592,902	3,573,890	3,565,771	3,565,771	3,565,771	3,565,353

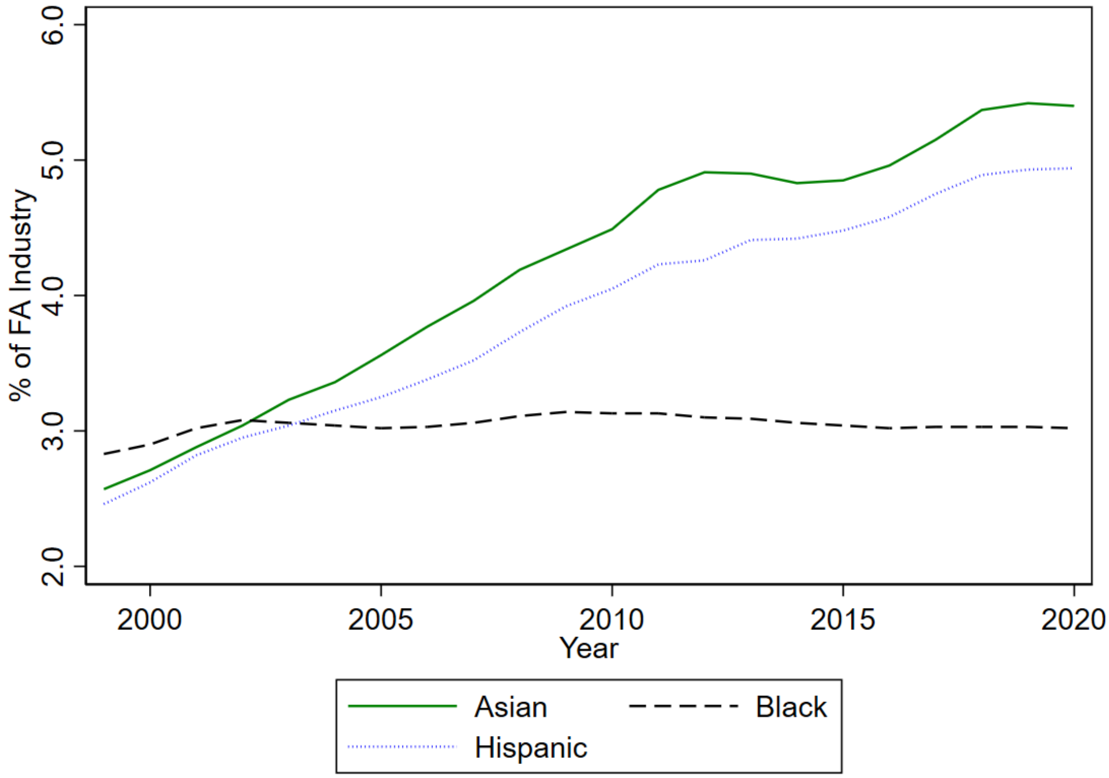
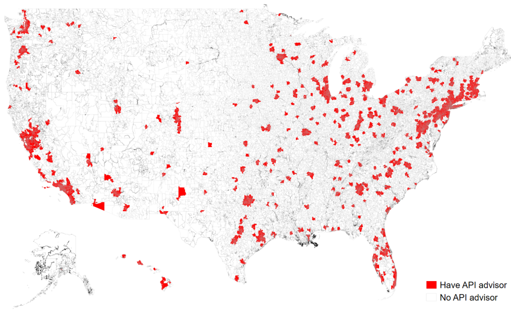
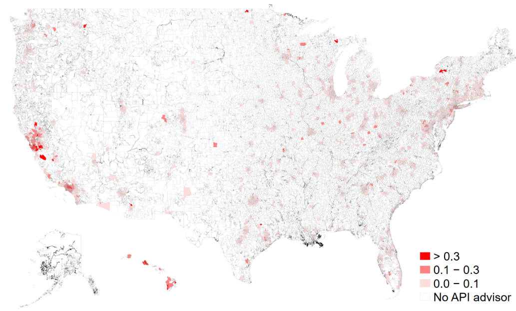


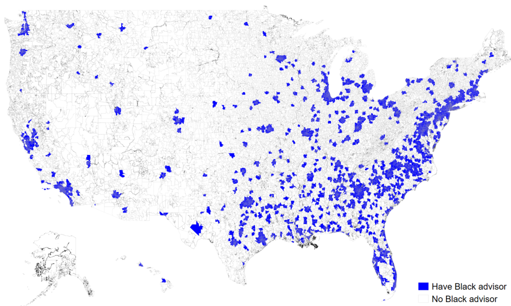
Figure 2.1: **Time-Series of Minority Representation**
This figure documents the time-series of minority representation in the financial advisor industry. The solid green, dashed black, and dashed purple lines represent Asian, Black, and Hispanic advisors, respectively. The x-axis represents each calendar year and the y-axis is the fraction of the total number of financial advisors (in percentage points).



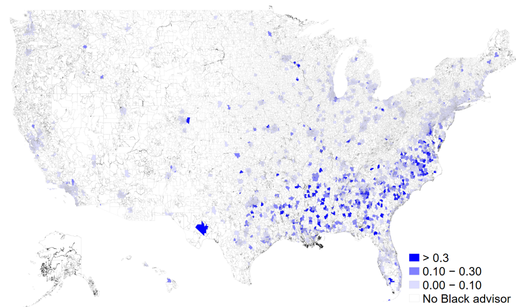
(a) API Advisor Presence



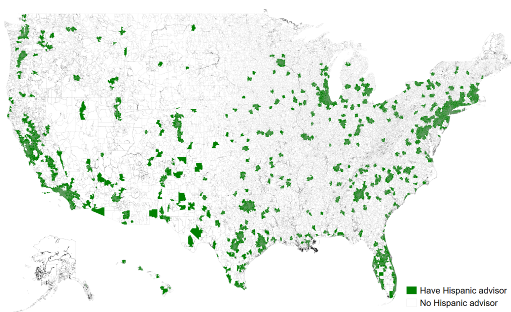
(b) API Advisor Fraction



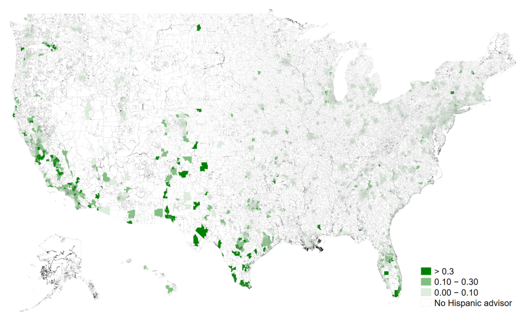
(c) Black Advisor Presence



(d) Black Advisor Fraction



(e) Hispanic Advisor Presence



(f) Hispanic Advisor Fraction

Figure 2.2: **Cross-Section of Minority Representation**
This figure documents the geospatial nature of minority representation in the financial advisor industry in 2019 at the community level. The colors red, blue, and green represent Asian, Black, and Hispanic advisors, respectively. The subfigures on the left (a,c,e) indicate whether there is any minority advisor presence in the community. And the subfigures on the right (b,d,f) indicate the fraction of minority advisors in the community. Darker shades represent a higher fraction of minority advisors in the local market.

Appendices

Appendix A: Additional Tables and Figures for Chapter 1

The following section includes additional evidence (in the form of tables and figures) for Chapter 1.

Table A1: Robustness to Excluding the 2010 School Year

	(1) Score **All**	(2) Score **All**	(3) Score **White**	(4) Score **White**	(5) Score **Black**	(6) Score **Black**	(7) Score **Hispanic**	(8) Score **Hispanic**
Post × Recal. Indicator	0.014***		0.023***		0.007		0.003	
	(0.004)		(0.004)		(0.007)		(0.006)	
Post × Recal. Intensity		0.070***		0.114***		0.034		0.013
		(0.025)		(0.023)		(0.034)		(0.036)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.805	0.805	0.736	0.736	0.645	0.645	0.630	0.630
Observations	242,827	242,827	234,590	234,590	116,559	116,559	124,525	124,525

Note: This table replicates results from Table 1.2 and Table 1.3 but exclude the 2010 school year. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Robustness to Controlling for Local Demographics

	(1) Score **All**	(2) Score **All**	(3) Score **White**	(4) Score **White**	(5) Score **Black**	(6) Score **Black**	(7) Score **Hispanic**	(8) Score **Hispanic**
Post × Recal. Indicator	0.011***		0.020***		0.009		0.001	
	(0.003)		(0.003)		(0.006)		(0.006)	
Post × Recal. Intensity		0.058**		0.101***		0.038		-0.006
		(0.023)		(0.020)		(0.032)		(0.031)
ln(Median Income) (All)	-0.026	-0.028						
	(0.023)	(0.023)						
Bachelor Education Rate (All)	0.370***	0.375***						
	(0.074)	(0.073)						
Single Mom Rate (All)	-0.042	-0.043						
	(0.065)	(0.065)						
ln(Median Income) (White)			-0.046*	-0.047*				
			(0.024)	(0.024)				
Bachelor Education Rate (White)			0.340***	0.349***				
			(0.071)	(0.072)				
Single Mom Rate (White)			-0.099	-0.097				
			(0.081)	(0.081)				
ln(Median Income) (Black)					0.015	0.015		
					(0.012)	(0.012)		
Bachelor Education Rate (Black)					0.127**	0.128**		
					(0.054)	(0.054)		
Single Mom Rate (Black)					0.002	0.002		
					(0.036)	(0.036)		
ln(Median Income) (Hispanic)							-0.013	-0.013
							(0.011)	(0.011)
Bachelor Education Rate (Hispanic)							-0.000	0.001
							(0.047)	(0.047)
Single Mom Rate (Hispanic)							-0.025	-0.025
							(0.033)	(0.033)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.802	0.802	0.736	0.736	0.641	0.641	0.631	0.631
Observations	271,990	271,990	262,728	262,728	130,686	130,686	139,029	139,029

Note: This table replicates results from Table 1.2 and Table 1.3 but adds county-year-race level control variables including the natural logarithm of median household income, the proportion of adults with a bachelor's degree or higher, and the proportion of households with children that are headed by a single mother. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Robustness to Adjusting for Multiple Hypothesis Testing

Variable	**Source**	**t-stat**	**Order**	**Holm threshold**	**BHY threshold**
Trading volume	Cornaggia et al. (2018)	11.52	1	0.38%	0.12%
Tax return	Cornaggia et al. (2019)	6.20	2	0.42%	0.24%
Household income	Adelino et al. (2017), Cornaggia et al. (2019)	5.52	3	0.45%	0.36%
Moody's rating	Adelino et al. (2017), Cornaggia et al. (2018)	4.32	4	0.50%	0.48%
Issuance	Adelino et al. (2017), Cornaggia et al. (2018)	3.59	5	0.56%	0.60%
Pvt. employment	Adelino et al. (2017)	3.47	6	0.63%	0.73%
Yield	Adelino et al. (2017), Cornaggia et al. (2018)	3.24	7	0.71%	0.85%
Education outcome	**This paper**	**3.13**	**8**	**0.83%**	**0.97%**
Election outcome	Cunha et al. (2022+)	3.07	9	1.25%	1.09%
Gini	Cornaggia et al. (2019)	2.41	10	1.67%	1.21%
AGI net flow	Cornaggia et al. (2019)	2.18	11	2.50%	1.33%
Gov. spending	Adelino et al. (2017)	2.10	12	1.00%	1.45%
Gov. employment	Adelino et al. (2017)	1.70	13	5.00%	1.57%

Note: This table reports results for two adjustments for multiple hypothesis testing. Outcome variables are collected from Adelino et al. (2017), Cornaggia, Cornaggia, and Israelsen (2018), Cornaggia et al. (2019), and Cunha et al. (2022+). In cases that an outcome variable is tested in two papers, the larger t-stat is used.

Table A4: Robustness to Excluding Counties without Moody's Rating

	(1) Score **All**	(2) Score **All**	(3) Score **White**	(4) Score **White**	(5) Score **Black**	(6) Score **Black**	(7) Score **Hispanic**	(8) Score **Hispanic**
Post × Recal. Indicator	0.014***		0.023***		0.012		0.003	
	(0.004)		(0.004)		(0.008)		(0.008)	
Post × Recal. Intensity		0.056**		0.100***		0.032		-0.006
		(0.027)		(0.023)		(0.038)		(0.036)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.820	0.820	0.768	0.767	0.682	0.682	0.658	0.659
Observations	179,577	179,379	174,882	174,882	92,844	92,844	105,054	105,054

Note: This table replicates results from Table 1.2 and Table 1.3 but excludes counties that did not have a Moody's rating prior to 2010. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Decomposition of the Score Racial Gap and the Score Income Gap

Panel A: Test Score White-Black Gap

	(1) Score Gap **W - B**	(2) Score Gap **Income**	(3) Score Gap **W - B**	(4) Score Gap **Income**
Post × Recal. Indicator	0.009**	0.010***		
	(0.005)	(0.004)		
Post × Recal. Intensity			0.032**	0.012
			(0.016)	(0.020)
Test Score Income Gap	0.450***		0.450***	
	(0.010)		(0.010)	
Test Score W - B Gap		0.267***		0.268***
		(0.007)		(0.007)
β from Table 1.3	**0.017**		**0.046**	
County FE	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes
R^2	0.685	0.686	0.685	0.686
Observations	119,457	119,457	119,457	119,457

Panel B: Test Score White-Hispanic Gap

	(1) Score Gap **W - H**	(2) Score Gap **Income**	(3) Score Gap **W - H**	(4) Score Gap **Income**
Post × Recal. Indicator	0.013***	0.007**		
	(0.004)	(0.003)		
Post × Recal. Intensity			0.073***	0.028
			(0.019)	(0.019)
Test Score Income Gap	0.424***		0.424***	
	(0.009)		(0.009)	
Test Score W - H Gap		0.237***		0.237***
		(0.006)		(0.006)
β from Table 1.3	**0.018**		**0.099**	
County FE	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes
R^2	0.688	0.697	0.688	0.697
Observations	130,652	130,652	130,652	130,652

Note: This table reports results for decomposing the DiD coefficient from Table 1.3 into a race effect and an income effect. "Test Score Income Gap" captures the difference in test scores between non-poor and poor students. "β from Table 1.3" reports the point estimates from columns (4) & (5) from Table 1.3. Panel A (B) reports results related to White-Black (White-Hispanic) test score gap. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Robustness to Controlling for Demographic Change

Panel A: Dichotomous Recalibration Measure

	(1) Score **White**	(2) Score **Black**	(3) Score **Hispanic**	(4) Gap **W - B**	(5) Gap **W - H**
Post × Recal. Indicator	0.031***	0.003	-0.003	0.033***	0.023**
	(0.008)	(0.011)	(0.012)	(0.012)	(0.010)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes
R^2	0.741	0.618	0.623	0.641	0.702
Observations	80,727	39,576	31,275	37,529	30,564

Panel B: Continuous Recalibration Measure

	(1) Score **White**	(2) Score **Black**	(3) Score **Hispanic**	(4) Gap **W - B**	(5) Gap **W - H**
Post × Recal. Intensity	0.178***	0.041	0.024	0.119**	0.144**
	(0.049)	(0.062)	(0.072)	(0.048)	(0.056)
County FE	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes
R^2	0.741	0.618	0.623	0.640	0.702
Observations	80,727	39,576	31,275	37,529	30,564

Note: This table reports the changes in academic achievement by race and changes in White-Underrepresented achievement gaps for subsample of counties that do not have increase in fraction of Black or Hispanic population between 2009 and 2011. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Robustness to Controlling for Imprecise Measurement

	(1) Score **White**	(2) Score **White**	(3) Score **White**	(4) Score **White**
Post × Recal. Indicator	0.022***		0.016***	
	(0.005)		(0.004)	
Post × Recal. Intensity		0.071***		0.075***
		(0.022)		(0.023)
County FE	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes
R^2	0.732	0.732	0.726	0.726
Observations	127,075	127,075	136,911	136,911

Note: This table reports the change in academic achievement for White students, but only focus on counties with available estimates for Black (Hispanic) students. The unit of observation is a county-year-grade-subject and county and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

Table A8: School District Level Results on Test Score

Panel A: All School Districts

	(1) Score **All**	(2) Score **All**	(3) Gap **W - B**	(4) Gap **W - H**	(5) Gap **W - B**	(6) Gap **W - H**
Post × Recal. Indicator	0.014***		0.038***	0.024***		
	(0.003)		(0.005)	(0.005)		
Post × Recal. Intensity		0.090***			0.133***	0.120***
		(0.016)			(0.024)	(0.022)
School District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.738	0.738	0.298	0.317	0.298	0.317
Observations	1,117,508	1,117,508	473,891	524,077	473,891	524,077

Panel B: School Districts with No Increase in Spending

	(1) Score **All**	(2) Score **All**	(3) Gap **W - B**	(4) Gap **W - H**	(5) Gap **W - B**	(6) Gap **W - H**
Post × Recal. Indicator	0.009**		0.039***	0.026***		
	(0.004)		(0.008)	(0.007)		
Post × Recal. Intensity		0.092***			0.115***	0.113***
		(0.022)			(0.031)	(0.029)
School District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Grade-Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.752	0.752	0.337	0.389	0.337	0.389
Observations	408,676	408,676	184,889	204,513	184,889	204,513

Note: This table reports the test score results at the school district (SD) level. Panel A uses the full universe of school districts. Panel B uses the subsample of districts that do not increase spending per pupil between 2009 and 2011. For both Panels, the first two columns replicate column (1) from Table 1.2 while columns (3) through (6) replicate columns (4) & (5) from Table 1.3. The unit of observation is a SD-year-grade-subject and SD and state-year-grade-subject fixed effects are included. Standard errors reported in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1

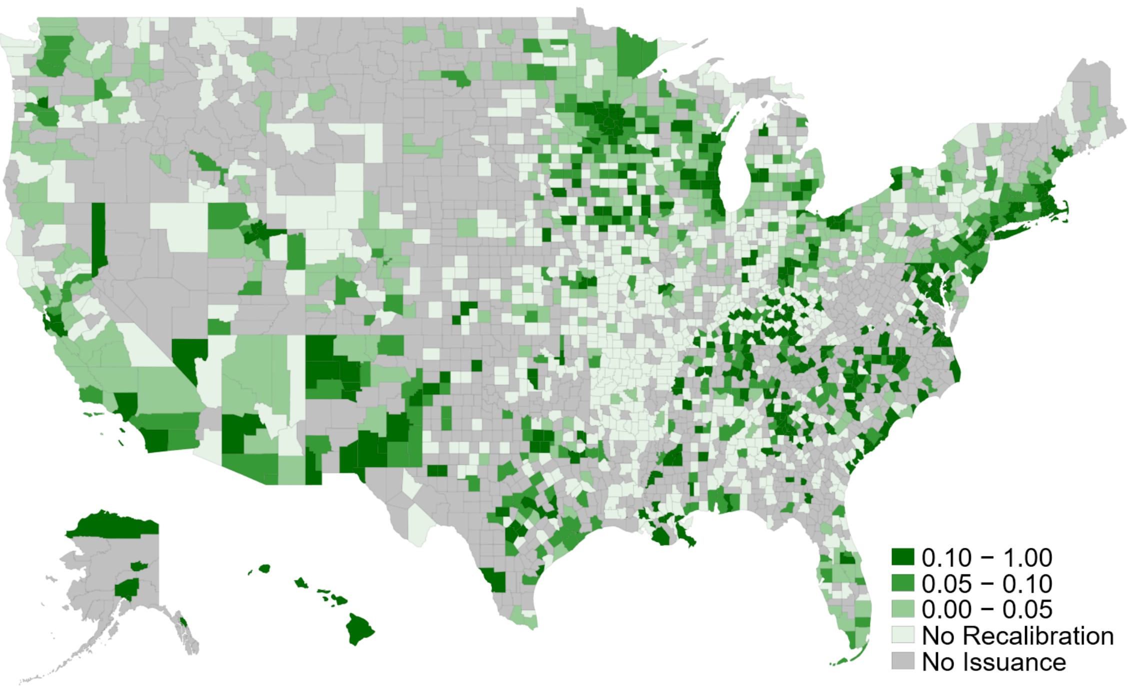
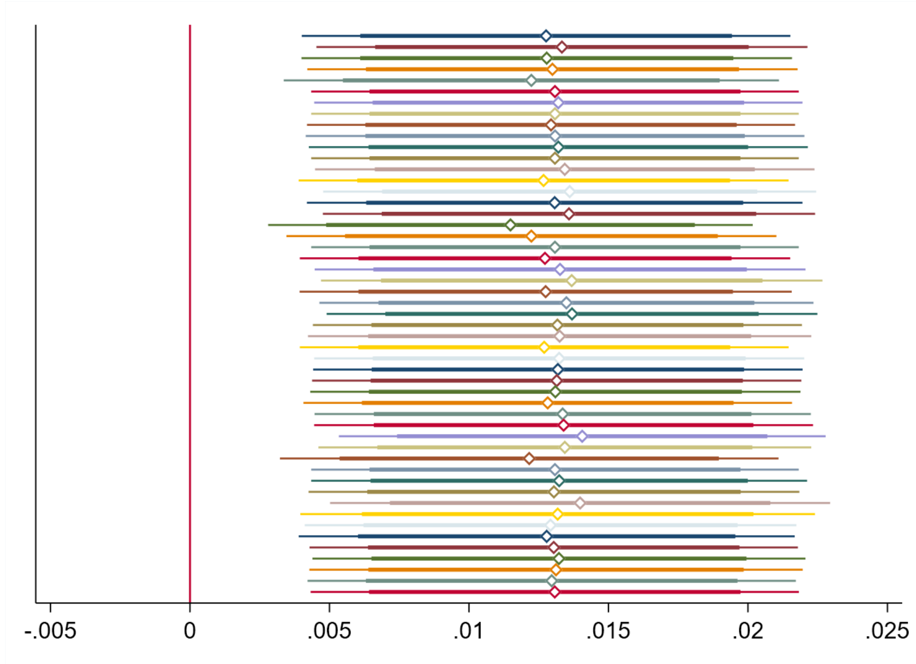
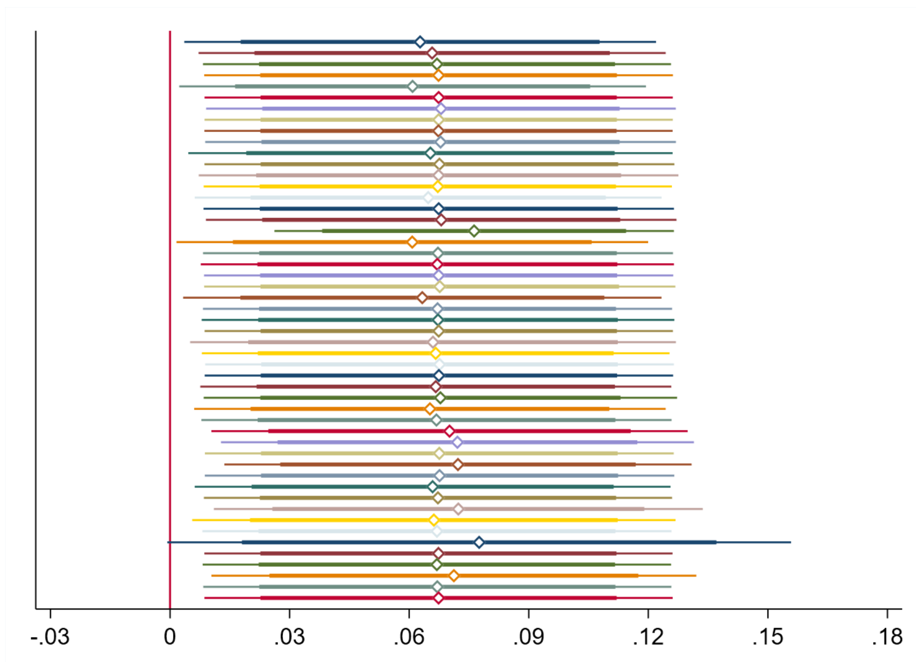


Figure A1: **Geographic Distribution of Moody's Recalibration**

This map demonstrates the geographic distribution of Moody's municipal bond rating recalibration. Variations in color shades represent the fraction of treated local government units in a county. Grey colored counties either do not have local government bonds issued in the three years prior to recalibration or do not have a rating from Moody's.



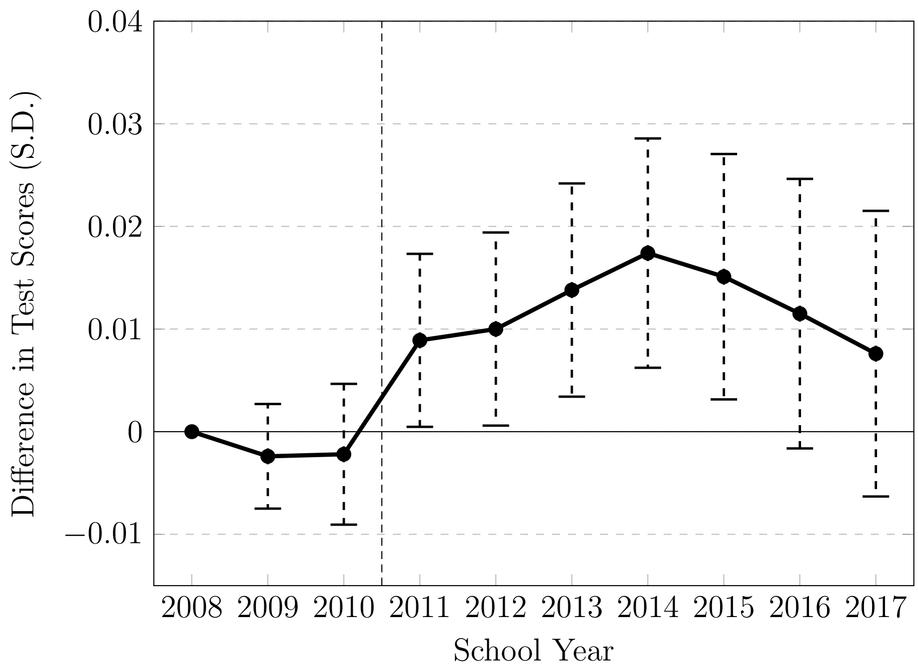
(a) Dichotomous Recalibration Measure



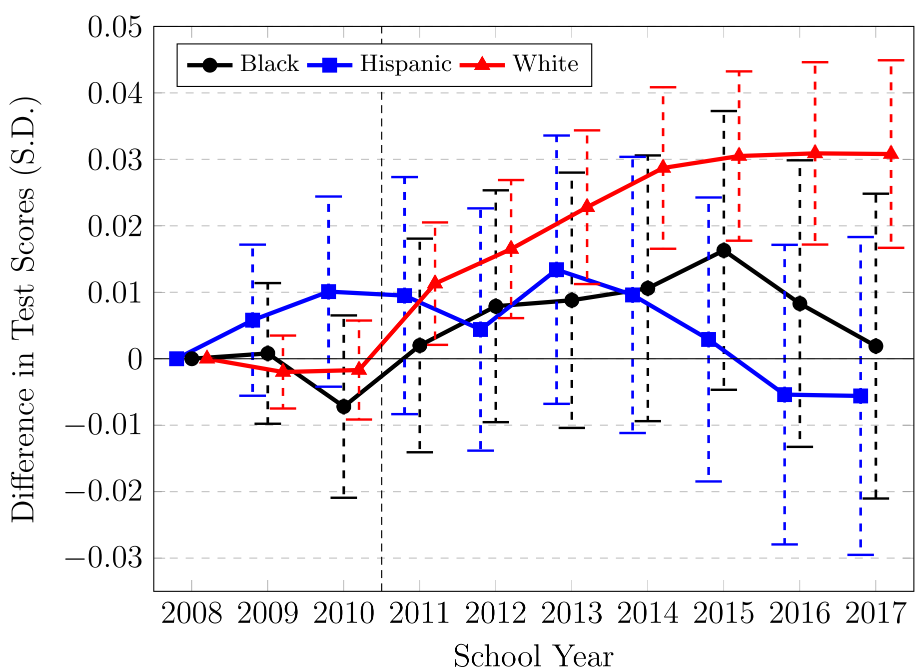
(b) Continuous Recalibration Measure

Figure A2: **Robustness of Result to Removing One State at a Time**

This figure plots coefficients of β_j from column (1) of Table 1.2, but remove one state from the sample at a time. The coefficients are alphabetically ordered based on state name abbreviation and legends are omitted due to space constraints. The Diamonds are point estimates and the thicker (thinner) lines represent the 95% (99%) CIs.



(a) Full Sample



(b) By Race Group

Figure A3: **Full Time-Series Event-Time Estimation**
This figure replicates the estimation from Figure 1.1 using full time-series indicators instead of aggregating post-2013 effects to the "2013+" indicator, with 2008 being the benchmark school year. The sample includes counties with full time-series data. County and state-year-grade-subject fixed effects are included. Standard errors are clustered at the county level. Dashed lines represent 95% CI. The point estimates are staggered for ease of reading.

$$Test\ Score_{c,t,g,i} = \sum_j \beta_j (Recal\ Inicator \times Year\ Indicator) + \gamma_c + \gamma_{s\times t\times g\times i} + \epsilon_{c,t,g,i}$$

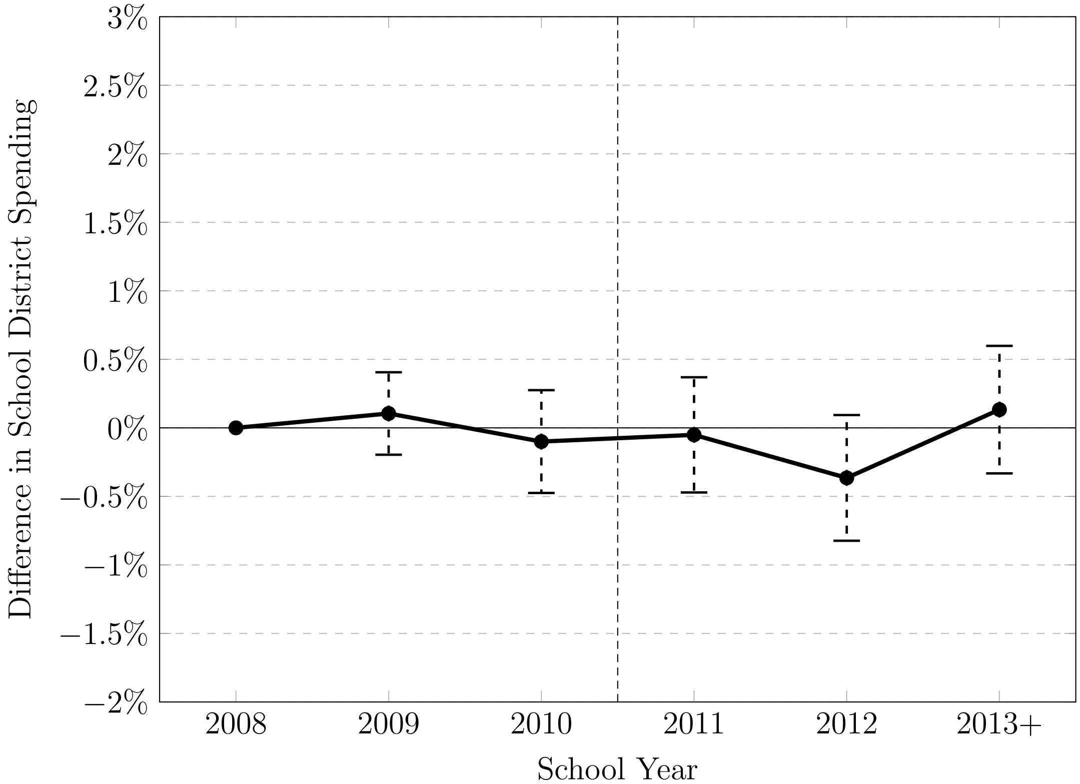


Figure A4: **Effect of Recalibration on School District Spending per Pupil**
This figure plots coefficients of β_j from the following regression of the natural logarithm of school districts' annual spending per pupil on the interaction of recalibration in event time, with 2008 being the benchmark school year. The sample includes school districts with full time-series data. School District and state-by-year fixed effects are included. Standard errors are clustered at the School District level. Dashed lines represent 95% CI.

$$ln(Spending\ per\ Pupil)_{sd,t} = \sum_j \beta_j(Recal\ Inicator \times Year\ Indicator) + \gamma_s d + \gamma_{s\times t} + \epsilon_{sd,t}$$

Appendix B: Additional Tables for Chapter 2

The following section includes additional evidence (in the form of tables) for Chapter 2.

Table B1: Summary Statistics

This table presents the summary statistics at the advisor (Panel A), firm (Panel B), and community (Panel C) level. API is the abbreviation for Asians and Pacific Islanders. *Years of Exp.* is the advisor's total years of experience starting from the first year of their career. *# of Licenses* is the total number of licenses the advisor holds. *Insurance* is an indicator variable equal to one if the advisor has a Series 6 license. *Principal* is an indicator variable equal to one if the advisor has a Series 24 or 26 license. *Inv. Advisor* is an indicator variable equal to one if the advisor has a Series 65 or 66 license. *Misconduct* is an indicator variable equal to one if the advisor has ever committed misconduct, as defined in Egan, Matvos, and Seru (2019). *Frac. API (Black, Hispanic)* is the fraction of populations that are API (Black, Hispanic). *Unemployment* is the unemployment rate among populations in the labor force. *Frac. College* is the fraction of the population over the age of 25 with a bachelor's or higher degree.

Panel A: Advisor-Level

	Mean	SD	25%	50%	75%
Years of Exp.	15.38	10.08	7.00	14.00	21.00
Total Licenses	3.98	1.40	3.00	4.00	5.00
Insurance	0.35	0.48	0.00	0.00	1.00
Management	0.20	0.40	0.00	0.00	0.00
Inv. Advisor	0.51	0.50	0.00	1.00	1.00
Misconduct	0.09	0.28	0.00	0.00	0.00

Panel B: Firm-Level

	Mean	SD	25%	50%	75%
# of States	2.69	5.76	1.00	1.00	2.00
# of Branches	13.91	139.38	1.00	1.00	2.00
# of Advisors	63.05	708.21	1.00	2.00	8.00
# of Minority Advisors	8.46	118.96	0.00	0.00	1.00
Fraction of API Advisors	0.04	0.15	0.00	0.00	0.00
Fraction of Black Advisors	0.02	0.11	0.00	0.00	0.00
Fraction of Hispanic Advisors	0.03	0.13	0.00	0.00	0.00

Panel C: Community-Level

	Mean	SD	25%	50%	75%
Frac. College	0.26	0.12	0.17	0.23	0.33
Unemployment	0.03	0.01	0.02	0.03	0.04
Median Household Income	60594.66	18357.37	48576.37	57143.00	68817.98
Stock Market Participation	0.17	0.08	0.11	0.16	0.21
Frac. White	0.74	0.22	0.61	0.81	0.93
Frac. API	0.03	0.05	0.00	0.01	0.03
Frac. Black	0.09	0.13	0.01	0.03	0.12
Frac. Hispanic	0.11	0.15	0.02	0.05	0.13

Table B2: Community Summary Statistics by Advisors Coverage

This table reports community summary statistics included in Panel B of Table B1 but separately for communities with and without advisor coverage.

Panel A. Communities with Advisors

	Mean	SD	25%	50%	75%
Frac. College	0.28	0.12	0.19	0.26	0.36
Unemployment Rate	0.03	0.01	0.02	0.03	0.04
Median Household Income	63553.02	18560.22	51033.68	59506.27	72045.34
Stock Market Participation	0.18	0.07	0.13	0.17	0.22
Frac. White	0.72	0.22	0.59	0.78	0.91
Frac. API	0.03	0.05	0.01	0.02	0.04
Frac. Black	0.10	0.12	0.01	0.04	0.13
Frac. Hispanic	0.12	0.14	0.03	0.06	0.15

Panel B. Communities without Advisors

	Mean	SD	25%	50%	75%
Frac. College	0.17	0.08	0.12	0.16	0.21
Unemployment Rate	0.03	0.02	0.02	0.03	0.04
Median Household Income	50042.78	12951.95	41008.29	49283.56	57438.00
Stock Market Participation	0.12	0.08	0.07	0.11	0.17
Frac. White	0.80	0.22	0.71	0.90	0.96
Frac. API	0.01	0.02	0.00	0.00	0.01
Frac. Black	0.07	0.16	0.00	0.01	0.03
Frac. Hispanic	0.08	0.15	0.01	0.02	0.06

Table B3: Racial Concordance and Stock Market Participation (ZIP level)

This table documents the correlation between advisor-household racial match and stock market participation. The unit of observation is an advisor-year. API is the abbreviation for Asians and Pacific Islanders. *API (Black, Hispanic) Advisor* is an indicator that equals 1 if the advisor is API (Black, Hispanic). *Frac. API (Black, Hispanic) in ZIP* ranges from 0 to 1 and is the fraction of populations in the ZIP that are API (Black, Hispanic). *Frac. Concordant* is the fraction of populations in the ZIP that are the same race as the advisor. *Frac. Concordant* × *API (Black, Hispanic)* is the interaction of *Frac. Concordant* and the advisor race indicator. The outcome variable is the stock market participation rate which ranges from 0 to 1. In columns (2) to (6), we control for ZIP characteristics as described in Table 2.3. In columns (3) to (6), we control for advisor characteristics including certifications, years of experience, investment advisor status, supervisory status, and misconduct. Standard errors reported in parentheses are clustered at the ZIP level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Frac. API in Zip	0.2882***	-0.0899*	-0.1403***	-0.1241***	-0.1295***	0.0517
	(0.0446)	(0.0516)	(0.0368)	(0.0345)	(0.0415)	(0.0325)
Frac. Black in Zip	-0.4833***	-0.1562***	-0.1434***	-0.1258***	-0.1234***	-0.0451*
	(0.0284)	(0.0243)	(0.0225)	(0.0227)	(0.0317)	(0.0254)
Frac. Hispanic in Zip	-0.4412***	-0.2054***	-0.1999***	-0.1858***	-0.1845***	-0.0802***
	(0.0307)	(0.0194)	(0.0184)	(0.0202)	(0.0272)	(0.0270)
Log(Income)		0.0924***	0.1107***	0.1106***	0.1109***	0.0472***
		(0.0146)	(0.0095)	(0.0095)	(0.0095)	(0.0058)
% with Bachelor Degree		0.3667***	0.3391***	0.3409***	0.3419***	0.0015
		(0.0278)	(0.0263)	(0.0267)	(0.0269)	(0.0275)
Unemployment Rate		-0.3480	-0.1599	-0.1432	-0.1377	0.0006
		(0.2476)	(0.1970)	(0.1973)	(0.1971)	(0.0468)
# Advisor/Population			0.0240***	0.0241***	0.0242***	-0.0050
			(0.0031)	(0.0031)	(0.0032)	(0.0098)
API Advisor			0.0109***	0.0200***	0.0144	-0.0014
			(0.0034)	(0.0045)	(0.0134)	(0.0009)
Black Advisor			-0.0054***	0.0031	0.0070	-0.0008
			(0.0018)	(0.0036)	(0.0135)	(0.0009)
Hispanic Advisor			0.0044	0.0118**	0.0130	-0.0010
			(0.0036)	(0.0056)	(0.0141)	(0.0009)
Frac. Match				0.0231***	0.0233	-0.0012
				(0.0077)	(0.0187)	(0.0012)
Frac. Concordant×API					0.0300	0.0057**
					(0.0413)	(0.0028)
Frac. Concordant×Black					-0.0190	0.0015
					(0.0358)	(0.0021)
Frac. Concordant×Hispanic					-0.0046	0.0026
					(0.0441)	(0.0020)
Constant	0.3744***					
	(0.0095)					
Year FE	-	Yes	Yes	Yes	Yes	Yes
Advisor Controls	-	-	Yes	Yes	Yes	Yes
ZIP FE	-	-	-	-	-	Yes
R^2	0.368	0.753	0.773	0.774	0.774	0.993
Observations	4,088,382	4,081,858	4,059,870	4,059,870	4,059,870	4,059,620

Table B4: Racial Concordance and Advisor Quitting (ZIP level)

This table documents the advisor-household racial match and advisor career longevity. The unit of observation is an advisor-year. API is the abbreviation for Asians and Pacific Islanders. *API (Black, Hispanic) Advisor* is an indicator that equals 1 if the advisor is API (Black, Hispanic). *Frac. API (Black, Hispanic) in ZIP* ranges from 0 to 1 and is the fraction of populations in the ZIP that are API (Black, Hispanic). *Frac. Concordant* is the fraction of populations in the ZIP that are the same race as the advisor. *Frac. Concordant* × *API (Black, Hispanic)* is the interaction of *Frac. Concordant* and the advisor race indicator. The outcome variable is an indicator that equals 1 if the advisor leaves the industry in that year. In columns (2) to (6), we control for ZIP characteristics as described in Table 2.3. In columns (3) to (6), we control for advisor characteristics as described in Table 2.6. Standard errors reported in parentheses are clustered at the ZIP level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
API Advisor	0.0225***	0.0153***	0.0090***	0.0045***	0.0120**	0.0034
	(0.0024)	(0.0019)	(0.0015)	(0.0016)	(0.0050)	(0.0032)
Black Advisor	0.0094***	0.0054***	0.0034***	-0.0008	0.0051	0.0014
	(0.0012)	(0.0012)	(0.0010)	(0.0012)	(0.0046)	(0.0029)
Hispanic Advisor	0.0143***	0.0080***	0.0034***	-0.0003	0.0028	-0.0056*
	(0.0013)	(0.0010)	(0.0012)	(0.0014)	(0.0047)	(0.0029)
Frac. API in Zip			0.0243***	0.0162**	0.0250**	-0.0461***
			(0.0080)	(0.0079)	(0.0103)	(0.0160)
Frac. Black in Zip			0.0111**	0.0025	0.0090	-0.0347**
			(0.0049)	(0.0048)	(0.0082)	(0.0154)
Frac. Hispanic in Zip			0.0255***	0.0186***	0.0227***	-0.0306
			(0.0040)	(0.0039)	(0.0076)	(0.0191)
Frac. Concordant				-0.0114***	-0.0050	-0.0100***
				(0.0018)	(0.0060)	(0.0037)
Frac. Concordant×API					-0.0262*	-0.0005
					(0.0149)	(0.0093)
Frac. Concordant×Black					-0.0173	-0.0094
					(0.0116)	(0.0071)
Frac. Concordant×Hispanic					-0.0039	0.0210***
					(0.0129)	(0.0077)
Constant	0.0325***					
	(0.0011)					
Year FE	-	Yes	Yes	Yes	Yes	Yes
Advisor Controls	-	Yes	Yes	Yes	Yes	Yes
ZIP Controls	-	-	Yes	Yes	Yes	Yes
ZIP FE	-	-	-	-	-	Yes
R^2	0.001	0.011	0.012	0.012	0.012	0.028
Observations	3,592,902	3,573,890	3,565,771	3,565,771	3,565,771	3,565,353

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- ◇ **Media Coverage**: *VoxEU; The New York Times; The Washington Post; Marginal Revolution; The Boston Globe; National Affairs Blog; Reform Austin; SafeGraph Blog*

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- ◇ With Chris Clifford and Will Gerken
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Awards and Grants

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AFA Committee on Racial Diversity (CORD) Mentoring Program	2022-2023
EuropeanFA Doctoral Travel Grant	2022
Finance Advisory Board Teaching Assistant of the Year	2021
Graduate Student Fellowships (Luckett, Gatton, Max Steckler)	2017-present
ISFE Summer Research Grant	2019, 2020 (×3)
Gatton College Research Excellence Grant	2020, 2023