Racial Disparities and Bias in Consumer Bankruptcy*

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Abstract

Using the near universe of US bankruptcy cases linked to filer, trustee, and judge race data, we show that minority filers are significantly more likely to be dismissed without debt relief. To test whether racial bias contributes to these disparities, we formalize new econometric results for a "differences-in-disparities" research design that, in contrast to outcome tests, does not require specifying decision-maker objectives. We find random assignment to White trustees increases dismissal rates for minority filers in Chapter 13 but not in Chapter 7, where trustee discretion is limited. Our test indicates racial bias is an important factor in bankruptcy dismissals.

Keywords: consumer bankruptcy, racial disparities, racial bias, racial concordance, implicit bias

JEL Codes: C21, D63, G51, J15, K35

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1 Introduction

Each year, close to one million US households enter consumer bankruptcy, obtaining debt relief that exceeds the resources given through all state and federal unemployment insurance programs combined (Lefgren et al., 2010). The benefits of bankruptcy extend beyond household balance sheets. Receiving debt relief through bankruptcy increases longevity, earnings, homeownership, and children's eventual adult earnings relative to unsuccessful bankruptcy filers denied debt relief (Dobbie and Song, 2015; Dobbie et al., 2017; Hamdi et al., 2024). Given its scale and impact on households, a first-order policy concern is understanding whether and why the bankruptcy system works less well for different households. In particular, there are signs that minorities may have less access to the debt relief provided by consumer bankruptcy (e.g., Kiel and Fresques, 2017).[1] Disparate access to bankruptcy's debt relief may compound other disparities such as the racial wealth gap (Derenoncourt et al., 2024) and racial disparities in vulnerability to economic shocks (Ganong et al., 2020). However, systematically documenting the existence and causes of racial disparities in bankruptcy has proven difficult, as data on race are not collected as part of bankruptcy records.

This paper presents new facts on racial disparities in consumer bankruptcy and evidence that racial bias contributes to these disparities. We use new data containing the near universe of US bankruptcy cases over the past two decades and link it to a large database of self-reported and imputed race (for filers).[2] We also manually collect race data for thousands of key legal decision-makers (trustees and judges). Studying bias presents identification challenges, as disparities may also be explained by correlations between race and other determinants of bankruptcy case outcomes. As a solution, we develop a decision model and a new formalization of when and how homophily—measured as *differences in disparities* across decision-makers of different races—can signal the presence of racial bias.[3] As we discuss below, our framework can be useful in settings where traditional econometric tools, such as Becker-style outcome tests, are not feasible.

We document large racial disparities in the rate of bankruptcy dismissal (denial of debt relief). Compared to White filers, minority Chapter 13 and 7 filers are, respectively, 12.7 (22%) and 2.3 pp (85%) unconditionally more likely to have their cases dismissed. Disparities are largest for Black and Hispanic filers. We then show that when minority Chapter 13 filers are quasi-randomly assigned to a White bankruptcy trustee, their probability of dismissal rises 2.3 pp. Through the lens of our econometric framework, this non-zero homophily indicates the presence of taste-based and/or inaccurate statistical discrimination. If we further assume that minority trustees are either neutral or biased against minority filers on average, our estimate implies that at least 15% of the 12.7 pp unconditional disparity is due to these two forms of bias.

[1] We use the racial categories White, Black, Asian, and Other to refer to non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and non-Hispanic Other. We use the term race to refer to race and ethnicity. We use the term minority to refer to people with non-White race or Hispanic ethnicity.

[2] Our findings are qualitatively unchanged when we restrict the sample to self-reported filer race data.

[3] In a slight abuse of terminology, we use the term homophily to refer to differences in the treatment of filers when the filer and the legal decision-maker have the same versus different minority status, similar to the concept of racial concordance.

To study the mechanisms driving our results, we provide evidence on the features of Chapter 13 that may enable bias to influence bankruptcy dismissals. We also estimate a precise null effect for differences-in-disparities in Chapter 7, which we argue is plausibly due to its lower degree of trustee discretion and because Chapter 7 entails fewer subjective evaluations of filer intentions. Taken together, our findings indicate that bias has an important influence on racial disparities in Chapter 13 dismissal rates and suggest that features of the bankruptcy process shape the extent to which bias affects case outcomes.

To measure racial disparities in bankruptcy outcomes, we assemble a nationwide dataset of detailed bankruptcy outcomes with self-reported and hand-collected measures of filer, trustee, and judge race. Our bankruptcy data comes from LexisNexis and contain over 26 million consumer bankruptcy cases, constituting the near universe of consumer bankruptcy cases filed since electronic records began in the early 2000s. Using names and addresses for filers, we merge these data to race data from L2. We hand-collect race data for trustees and judges from a variety of public sources. We also merge in detailed filer and case characteristics, such as income, assets, and leverage from the Federal Judicial Center's (FJC) Integrated Bankruptcy Database.[4]

To assess the role of bias among legal decision-makers (trustees and judges) we use a differences-in-disparities ("diff-in-disp") estimator. This estimator compares how racial disparities in dismissal rates change with the race of the decision-maker (DM). To interpret our estimates, we develop a general decision model and econometric results relating our estimator to bias. We formalize conditions that are necessary and sufficient for the diff-in-disp estimator to identify the difference in racial bias across DMs of different races, yielding a test for the presence of bias. The generality of our framework makes it readily usable to study bias in other contexts, such as lending, negotiations, jury decisions, and hiring.

Our diff-in-disp approach has two advantages that make it better-suited than a Becker-style outcome test (e.g., Becker, 1957, 1993; Arnold et al., 2018) to detect bias in settings like bankruptcy. First, the diff-in-disp approach does not require that the researcher observes (or even knows) the outcomes over which potentially biased DMs optimize. Instead, because the necessary data are the race of the DMs and their decisions, our test may be used in situations where outcome tests are infeasible due to either a lack of outcome data or DM objectives being abstract (and hence difficult to measure). For example, in our setting, bankruptcy trustee and judge objectives can include approving "reasonable" expenses for filers on payment plans, approving only "feasible" payment plans, discerning whether financial misreporting was intentional fraud or an honest mistake, determining whether filer hardship is "beyond their control," and maximizing payments to creditors. The subjective nature of these evaluations simultaneously makes it difficult to measure DM objectives and makes bankruptcy especially vulnerable to bias.

Second, when DMs optimize over multiple objectives that feature trade-offs (which may vary by examinee race), scenarios can arise that make the interpretation of outcome tests vulnerable

[4]The FJC data report *final* case characteristics. As such, they reflect the influence of trustees and judges on financial reporting (if these parties disagree with the filer's initial reporting).

to the criticism of Canay et al. (2023). Even an unbiased DM who equates the expected marginal benefit and cost of each decision can apply different rules for dismissing filers by race if the expected costs and benefits covary differently within different racial groups of filers.[5] We discuss such scenarios in Section 5.4. While plausible in the context of bankruptcy, such scenarios do not generally affect the interpretation of our diff-in-disp estimator.

Under an assumption analogous to parallel trends that we term "parallel disparities," we show that the diff-in-disp estimand identifies the difference in bias between White and minority DMs. In the bankruptcy context, parallel disparities requires that the differences in disparities between minority and White filers assigned to White trustees would be the same as the disparities for those assigned to minority trustees if minority filers were counterfactually White (but kept all other non-race characteristics). If this assumption holds, the difference in disparities across filers assigned to different-race DMs is due to bias, rather than differences in either (1) the population of filers assigned to different-race DMs or (2) the influence of non-race characteristics on DM preferences or beliefs.

Without further assumptions, the type of bias identified by diff-in-disp includes statistical discrimination (both accurate and inaccurate) and taste-based bias. If we further assume that, in the absence of taste-based and inaccurate statistical bias, White and minority trustees would on average make decisions resulting in the same disparities for White and minority filers, differences in disparities instead reflect only taste-based and inaccurate statistical discrimination. If this assumption holds, the diff-in-disp estimand differences out the influence of accurate statistical discrimination. Despite our use of the terms accurate or inaccurate statistical discrimination, we stress that any statistical discrimination is potentially problematic, especially given that the non-race characteristics used in statistical discrimination models are themselves often the product of historical discrimination (Spriggs, 2020).

Our framework motivates two falsification tests. In practice, a potential threat to identification would be if filers could manipulate their assignment to DMs. To evaluate this, we recommend a standard balance test. For our empirical analysis, this entails verifying that filer race and non-race characteristics do not predict the race of the assigned trustee. The second is an "interactions" test that tests for potential heterogeneity in DM preferences or beliefs that may be conflated with bias. For this test, we augment our baseline analysis to include a suite of interactions of trustee race with non-race case characteristics. In our setting, we find that our diff-in-disp estimate is unchanged after including these interactions, suggesting that any such heterogeneity is not confounding the diff-in-disp estimand's ability to identify differences in racial bias.

We apply this framework to interpret our estimates of racial homophily between bankruptcy filers and trustees using the random and quasi-random assignment of trustees to cases and our falsification exercises to support the necessary identification assumptions. Under our framework's assumptions, the non-zero homophily we find for Chapter 13 indicates that bias among

[5]For example, if the likelihood of fraud and required plan payments covary differently across filers of different races, marginal White and minority filers may have different plan payments even when facing an unbiased DM.

trustees is influencing bankruptcy dismissals. However, without additional assumptions, we cannot say where the bias is coming from—whether from anti-minority/pro-White bias among White trustees or from anti-White/pro-minority bias among minority trustees. If we assume that minority trustees on average are either unbiased or biased against minority filers, we obtain a sharp lower bound quantifying the role of bias from White trustees in dismissal disparities.[6] Under this additional assumption, our diff-in-disp estimate implies that at least 15% of the 12.7 pp dismissal disparity between minority and White Chapter 13 filers—and 53% of the 3.6 pp conditional disparity—is due to taste-based or inaccurate statistical bias. For Black filers, the share is 20% of their unconditional 13.4 pp disparity; it is 17% for Hispanic filers. Unlike Chapter 13, we find a precise null diff-in-disp effect in Chapter 7, consistent with our discussion below of the more limited scope for trustee bias to impact Chapter 7 cases.

We focus on examining homophily between filers and trustees because trustees typically interact more with the filer than judges, and trustees are generally the party that initiates dismissal. Trustees are also relatively understudied in bankruptcy research. However, judges ultimately decide whether to dismiss a case and thus remain an important party. They are also randomly assigned to cases, enabling us to apply our diff-in-disp framework. We also find homophily in judicial decisions. Minority filers randomly assigned to White judges are 1.6 pp more likely to be dismissed in Chapter 13. Judge homophily is largest for Black and Hispanic Chapter 13 filers (1.9 and 2.1 pp, respectively). As with trustees, we also obtain a precise null estimate of judge homophily in Chapter 7.

A universal challenge in racial bias studies, affecting diff-in-disp designs, outcome tests, and rank-order tests (e.g., Anwar and Fang, 2006), is attributing bias to examiners or examinees. There is a possibility that examinees may adapt their behavior in response to interactions with an examiner. In our setting, this could arise if minority filers are biased and modify their behavior when facing a White trustee in a way that increases their dismissal likelihood. If this is the case, the diff-in-disp estimate reflects bias on the part of the filer rather than the DM. This difficulty is pervasive in racial bias studies, with only audit studies or non-interactive settings being plausibly immune to this challenge (e.g., Braucher et al., 2012; Low and Pistaferri, 2024, respectively). Although examiner-examinee interactions create interpretation challenges, such settings are nonetheless important to study, especially because it is often interaction that makes features like race salient and that increases the scope for bias. While empirically disentangling the amount of bias attributable to DMs or filers is beyond our scope, our framework helps clarify the broader empirical challenge. Further, we provide suggestive evidence that anti-minority DM bias is plausibly the mechanism behind our findings rather than anti-White bias among filers. Consistent with these effects arising from trustee bias and not filer behavior, we show that homophily is larger for less experienced trustees and when caseloads are high. We also show that county-level gaps in the Black-White

[6]Social psychology research on implicit bias in the US suggests this assumption is plausible. A regular finding is that Black people on average do not show implicit bias in favor of Black people (Nosek et al., 2002; Livingston, 2002; Sabin et al., 2009; Chan, 2024). Supporting this assumption, we also show that the dismissal disparity correlates with a regional measure of anti-Black bias among White residents but not anti-White bias among Black residents.

Chapter 13 dismissal rate correlate with county-level measures of anti-Black implicit and explicit bias among Whites (but not with anti-White bias among Black residents). Importantly, many of the policy prescriptions we identify to address racial bias remain the same regardless of the source of bias.

Finally, to determine where bias enters the bankruptcy process, we focus on a key feature of Chapter 13: the repayment plan. Unlike Chapter 7, where filers make a one-time payment to creditors at the end of the (typically) 3-month bankruptcy process, Chapter 13 filers are required to make monthly payments over three or five years. We find that Chapter 13 filer-trustee diff-in-disp does not emerge until after the filer has their payment plan confirmed and the filer is responsible for making payments. Leveraging data coding dismissal reasons, we find that Chapter 13 dismissal homophily is driven by dismissal for nonpayment, suggesting that our results are driven by either differences in filers' ability to complete Chapter 13 payments or in how trustees react to missed payments. When a filer misses a payment, trustees have discretion whether and how much time to allow the filer to catch up on missed payments, determine whether a change in filer circumstances merits a plan modification (or a hardship discharge of debt), or seek a dismissal for non-payment. We find significant variation in how trustees exercise this discretion.[7] We find that minority filers assigned to White trustees are on average required to pay $19 more per month, corresponding to an additional $1,000 over five years.[8] However, in a mediation analysis, we show that these larger payments do not explain differences in dismissal disparities, leading us to conclude that trustee discretion in responding to nonpayment is a key reason for dismissal diff-in-disp.

Related Literature. Our paper contributes to three distinct literatures. First, we contribute a new focus on racial disparities and bias in consumer bankruptcy to the literature on racial disparities in household financial outcomes. Prior work documents large racial disparities in financial outcomes, such as loan approval rates, interest rates, access to funding for entrepreneurial activities, rates of CFPB complaints, eviction rates, and housing returns (Munnell et al., 1996; Reid et al., 2017; Bayer et al., 2018; Blattner and Nelson, 2020; Kermani and Wong, 2021; Cook et al., 2022; Butler et al., 2023; Diamond and Diamond, 2024). To our knowledge, our paper is the first to document racial disparities in consumer bankruptcy for a large (15+ million observations), nationally representative dataset.[9] This is made possible by linking bankruptcy cases to filer race data. Prior work on racial disparities in consumer bankruptcy has largely focused on disparities in filers' chapter choice (e.g., Lefgren and McIntyre, 2009; Kiel and Fresques, 2017; Morrison et al., 2020),

[7] Hand-coding dismissal motions for a random subset of filings, the 10th and 90th percentile nonpayment dismissal filings by trustees occur 1 and 5 months, respectively, after filers stopped making payments, and trustees vary in how many dismissal motions they file in a given case.

[8] This result is driven by Black filers facing White trustees, where Black filers on average pay $36 more per month if assigned a White trustee, corresponding to an additional $2,000 over five years.

[9] Prior work has focused on samples with thousands of observations (Van Loo, 2009; Braucher et al., 2012), individual cities (Morrison et al., 2020), or compared average outcomes across regions with different Black population shares (Kiel and Fresques, 2017).

including finding evidence of attorneys steering Black filers to Chapter 13 (Braucher et al., 2012).[10] A key difference in our paper is that we focus on disparities in *receiving* debt relief, conditional on filing and chapter choice. Moreover, we also examine the role of bias among key legal figures in the bankruptcy process in shaping these disparities.

Second, this paper makes a methodological contribution to the literature on detecting and quantifying racial bias. Our differences-in-disparities framework may be used in situations where a Becker-style outcome test (e.g., Becker, 1957, 1993; Knowles et al., 2001; Arnold et al., 2018; Canay et al., 2023; Hull, 2021) is infeasible due to unobserved or abstract DM objectives. Homophily has been widely used to study bias in many contexts, such as policing (Anwar and Fang, 2006; Antonovics and Knight, 2009; Ba et al., 2021), sports officiating (Price and Wolfers, 2010), and jury convictions (Anwar et al., 2012; Alesina and La Ferrara, 2014).[11] Most recently in finance, Frame et al. (2025) highlight the value of minority-group representation among loan officers using findings that minority borrower mortgage outcomes improve when paired with minority loan officers. However, there is limited prior econometric and theoretical work providing guidance on how and under what conditions homophily relates to racial bias. Notable exceptions are Anwar and Fang (2006) and Alesina and La Ferrara (2014), which propose rank order tests for bias related to homophily, and Antonovics and Knight (2009), which estimates a parametric model of homophily to distinguish taste-based from statistical discrimination. Our decision-model builds on this work by allowing for flexible heterogeneity in DM preferences and inaccurate statistical discrimination. Our econometric results also contribute new identification results that enable separating the influence of accurate statistical discrimination from taste-based and inaccurate statistical bias. We compare our test for bias to other tests in detail in Section 5.4.

Lastly, we build on a law and economics literature exploring the importance of decision-maker characteristics in legal outcomes. Prior work has found evidence of racial bias in bail decisions (Arnold et al., 2018, 2022) and in child protection services (Baron et al., 2024). Additionally, juror race, gender, and political ideology impact conviction rates (Anwar et al., 2012, 2019a,b), and in the context of bankruptcy, caseload and experience affect corporate bankruptcy outcomes (Iverson, 2018; Iverson et al., 2023). By contrast, we highlight the role of trustee and judge bias in shaping disparities in consumer bankruptcy outcomes.

Unlike judges, bankruptcy trustees have received little attention in prior work, and our findings suggest that they have a significant influence on bankruptcy outcomes, similar to that of judges. Recently, Morrison, Pang and Zytnick (2019) find that some lawyers appear to help clients

[10] Despite several potential advantages discussed below, Chapter 13 also has several disadvantages for filers. First, attorney fees are generally higher in Chapter 13 than Chapter 7. Second, Chapter 13 can require filers to make larger repayments to creditors (by statute, no less in Chapter 13 than what creditors would receive in Chapter 7). Third, the Chapter 13 discharge is not received until completion of a three- or five-year repayment plan. Fourth, in large part because so many filers fail to keep up with their payment plans, dismissal rates are much higher in Chapter 13 than Chapter 7 such that Chapter 13 filers are much less likely to receive a discharge at the conclusion of their case. See Section 2 for background on the consumer bankruptcy system.

[11] A parallel literature on racial concordance in healthcare documents how outcomes vary when the race or gender of the patient and provider match (e.g., Cooper-Patrick et al., 1999; Saha et al., 1999; LaVeist and Nuru-Jeter, 2002; Alsan et al., 2019; Takeshita et al., 2020; Jetty et al., 2021; Ye and Yi, 2023).

strategically time their Chapter 7 bankruptcy filings to improve their chances of obtaining a lenient trustee, suggesting that lawyers believe that trustees affect bankruptcy outcomes. Importantly, any such strategic timing is unlikely a source of bias in our empirical analysis. We show that trustee race does not predict filer race nor a variety of case and non-race characteristics. Our regressions also account for trustee differences in overall leniency with trustee fixed effects.

The rest of the paper proceeds as follows. Section 2 presents relevant institutional background on consumer bankruptcy in the US. We describe our data in Section 3. Section 4 then presents our results describing racial disparities in dismissal rates. We formalize our decision model and econometric results in Section 5, contrasting our approach with other tests for bias. We then estimate differences in disparities and apply our conceptual framework to relate our results to racial bias in Section 6. We discuss mechanisms in Section 7. Section 8 concludes.

2 Background: Consumer Bankruptcy in the US

One in ten Americans seek debt relief by filing for bankruptcy under Chapter 7 or 13 at some point in their life (Stavins, 2000; Keys, 2018). Bankruptcy can help households cope with financial distress—for example, stemming from job loss or medical expenses—by reducing required debt payments and preventing wage garnishment. In doing so, bankruptcy offers households an implicit form of insurance that can help them better smooth consumption across states of the world (Livshits et al., 2007; Chatterjee et al., 2007; Dávila, 2020; Indarte, 2023). The scale of the debt relief offered under Chapters 7 and 13 is substantial, totaling $187 billion in a typical year.[12] During the Great Recession, the annual debt write-downs provided by bankruptcy were similar in size to the annual transfers from unemployment insurance and were larger than those of measures like the Home Affordable Modification Program (Auclert et al., 2019).

Discharging debt through bankruptcy can benefit filers on many dimensions. Financially, filers typically see better credit scores and credit access in the years after filing compared to insolvent non-filers (Albanesi and Nosal, 2018). Auclert et al. (2019) find that access to bankruptcy increased aggregate employment by nearly 2% during the Great Recession, suggesting that bankruptcy discharges smooth and stabilize consumption. Conversely, filers whose cases are *dismissed* (versus those who receive debt discharge) experience lower earnings, higher foreclosure rates, lower homeownership rates, and higher mortality rates (Dobbie and Song, 2015; Dobbie et al., 2017). Hamdi et al. (2024) find that the children of bankruptcy filers whose filings are dismissed ultimately earn less income as adults relative to the children of filers whose debts are forgiven in bankruptcy.

However, filing for bankruptcy also entails a variety of costs. Court fees typically range from $300 to $500, and attorney fees are around $1,250 to $2,200 for Chapter 7 and $3,125 to $6,250 for Chapter 13 (DeNicola, 2024). Additionally, filers can be required to make payments to creditors out of assets (Chapter 7) or out of disposable income (Chapter 13). Non-monetary costs like stigma may also be an important deterrent to filing (Indarte, 2023). In the long-term, the "bankruptcy

[12] See Tables 1A and 1D of the Administrative Office of the United States Courts' Annual BAPCPA Report.

flag" that appears on a filer's credit report for seven to ten years can depress credit access (Musto, 2004; Dobbie et al., 2020; Gross et al., 2020; Herkenhoff et al., 2023). Filing also costs filers the option to file in the near future, as discharges can only be granted every two to eight years.[13] When filers' petitions are dismissed, not only do they not receive any debt relief, but they still bear many of the costs of bankruptcy, including the bankruptcy flag on their credit report.

2.1 The Bankruptcy Process

To initiate bankruptcy proceedings, filers (also referred to as petitioners) submit schedules thoroughly detailing their assets, liabilities, income sources, and expenses, along with proof of recently completing a credit counseling course.[14] Filers then participate in a meeting with their lawyer (if retained), the bankruptcy trustee, and their creditors (referred to as the Meeting of Creditors or the 341 Meeting). Filers must attend this meeting and are sworn in by the trustee; creditors most often do not attend. This meeting is either in-person or virtual, includes verification of photo identification, and is an important step for the trustee to form a recommendation to the judge and to detect fraud.[15]

The trustee compares a filer's submitted schedules to financial documents (tax returns, bank statements, auto titles, etc.) to assess a filing's accuracy. Trustees may also gather additional evidence (e.g., from real property records, tax collectors, and individuals close to the debtor) and may question the filer about the reasonability of asset valuations, expenses, and income forecasts. This subjective judgment includes determining whether any misreporting reflects intentional fraud or an innocent mistake.[16] For Chapter 7, the trustee must verify that the filer passes the Chapter 7 eligibility means test (income below the state median) and gains the power to sell the filer's assets that are in excess of state or federal exemption limits. For Chapter 13, trustees assess (and potentially object to) debtors' repayment plans including their forecast of their disposable income for the next three or five years and their necessary expenses. Within 60 days after the Meeting of Creditors, the filer must complete another financial education course, which emphasizes budgeting and rebuilding credit after bankruptcy.

Bankruptcy cases terminate in one of three ways: discharge, dismissal, or conversion from one bankruptcy chapter to another. For filers who succeed in receiving a discharge at the conclusion of their cases, their debts are forgiven after they have made any required payments to creditors. Common reasons for case dismissal include fraud, failure to complete mandatory educational classes, failure to file forms or submit documents, failure to pay court fees, missing the Meeting of Creditors, perceived infeasibility of the Chapter 13 payment plan, and missed Chapter 13 payments.

[13] Chapter 7 filers must wait eight years to file again under Chapter 7 and four years to file under Chapter 13. Chapter 13 filers must wait two years to file again under Chapter 13 and six years to file under Chapter 7.

[14] Argyle et al. (2021) find that the total debt reported on these schedules averages 7% more than the total amount of liabilities visible on credit reports.

[15] Trustees may delegate a 341 Meeting to their staff attorneys.

[16] Nagel (2024) finds evidence that Chapter 13 trustees provide oversight that results in fewer material misstatements on bankruptcy filing schedules.

Differences Between Chapters 7 and 13. Under Chapter 7, debtors receive forgiveness of all of their debts after forfeiting all non-exempt assets.[17] By contrast, debtors under Chapter 13 retain their assets and receive debt forgiveness of their unsecured debts after completing a three- or five-year repayment plan.[18] Typically, Chapter 7 cases have a final ruling (i.e., discharge of debt or dismissal) within three months of filing. At this point, filers make any required payments out of non-exempt assets and have their debt discharged.[19] In Chapter 13, the next step after the Meeting of Creditors is confirmation of a three- or five-year payment plan. Trustees have the legal responsibility to challenge the repayment plan, including objecting to expenses. Trustees or creditors may also object to any payment plan that does not allocate all of the filer's disposable income—defined as income minus "necessary" expenses—toward repayment such that most plan payments closely align with a filer's predicted disposable income. Statute requires that the sum of Chapter 13 payments be at least as high as what the creditor would have received under Chapter 7 (the value of non-exempt assets); Chapter 13 debt relief cannot be more generous than what Chapter 7 would have provided.

Because trustees must assess filers' predicted income and necessary expenses when reviewing filers' proposed payment plans, trustees exercise more discretion in Chapter 13 relative to Chapter 7. Trustees can disagree with filer forecasts; disagreements can be especially large for filers with irregular income. Trustees also have discretion when deciding whether to object to the reasonableness of an expense (for example, whether a filer's high rent is reasonable or justifiable). Trustees may object to plans they do not consider meeting the statute's "feasible" requirement, often leading to either payment plan modifications or dismissal.

Chapter 13 trustees also have discretion when it comes to how to respond to missed plan payments. Trustees may allow the filer time to cure such delinquencies. They may also file a motion to dismiss the case without debt relief or to modify the repayment plan. If the reason for nonpayment is for severe financial hardship—for example, due to job loss or serious illness—the trustee may recommend to the judge that the filer qualifies for a hardship discharge. In a limited sample of hand-coded trustee motions for nonpayment dismissal, we find evidence of discretion, with some trustees filing for dismissal immediately after nonpayment and some trustees waiting up to 14 months.

In addition to the greater subjectivity in Chapter 13, the financial incentives facing trustees differ across chapters. Because Chapter 7 cases rarely have assets in excess of exemption limits, Chapter 7 trustees typically receive a flat fee for administering the case (currently set at $60 by statute). When there are non-exempt assets, Chapter 7 trustees also receive a portion of the liquidation proceeds. Although there is wide variation across districts, Chapter 7 trustees typically do not depend on Chapter 7 consumer cases as a significant source of their income. Rather, the bulk

[17] Chapter 7 filers can reaffirm a secured debt, such as an auto loan, that they wish to survive bankruptcy and can also use their exempt assets to purchase their non-exempt ones if sufficient.

[18] Chapter 13 also allows debtors to pay delinquent tax debt and domestic support obligations and extends an automatic stay to co-borrowers.

[19] Roughly 95% of Chapter 7 cases have no non-exempt assets, in which case filers do not make any payments beyond court and attorney fees.

of the income of most Chapter 7 trustees tends to come from working as a bankruptcy attorney or corporate bankruptcy trustee. In contrast, being a Chapter 13 trustee is a full-time job and typically the primary source of income for these trustees. Chapter 13 trustees retain up to 10% of the filer's monthly payments to administer their office (28 USC § 586).

Filer Interactions with Trustees and Judges. Typically, Chapter 7 filers do not appear before the judge unless seeking to reaffirm a secured debt or if there is an objection from the trustee necessitating a court appearance. Depending on the district, Chapter 13 filers may appear before the judge for the confirmation of their repayment plan. Afterward, trustees and their staff interact with the filer during the repayment period. During the payment phase, the trustee is the first party to respond to nonpayment. The trustee may also opt to monitor the filer to detect changes in income that the filer may not report to the trustee (e.g., by monitoring their subsequent tax returns). Typically, the filer only ever interacts with the judge again if the trustee files a motion to the court for dismissal, a plan modification, or an early discharge. While judges ultimately make final decisions on whether to dismiss a case or discharge debt, the trustee is often the party that brings reasons for dismissal to the judge's attention; judges rarely initiate dismissal proceedings themselves. In our conversations, bankruptcy trustees, judges, and attorneys regularly describe both chapters as a "trustee-driven" process.

The Observability of Filer Race by Trustees. Department of Justice guidance instructs filers to send their assigned trustee a copy of their photo identification in advance of their 341 Meeting of Creditors (see also 11 USC § 521(h)). Filer race is directly observable again by trustees when swearing in filers at the 341 Meeting of Creditors. When trustees delegate this meeting to a staff attorney, trustees may still observe filer race directly from a copy of this identification. Moreover, even in cases where trustees do not personally meet filers or see their identification, they may infer filer race from a variety of characteristics. A substantial social sciences literature finds that decision-makers' implicit biases can be triggered by other markers of identity. For example, Bertrand and Mullainathan (2004) find that, even without face-to-face interactions or photos, employers were more likely to respond to otherwise identical resumes submitted by fictitious applicants with White-sounding names than with Black-sounding names. Perhaps most relevantly, Braucher et al. (2012) find that bankruptcy attorneys were more likely to steer unseen and otherwise-identical borrowers to Chapter 13 when debtors' names and churches suggested they were Black.

Scope for Racial Bias. Bankruptcy trustees and judges make a variety of subjective evaluations when choosing whether to dismiss a bankruptcy case. If racial bias influences their perceptions of the filer's honesty, hardship, and ability to pay, trustees and judges may dismiss cases at different rates for otherwise-similar filers of different races. Scope for racial bias seems particularly large in Chapter 13 given both the amount of discretion in evaluating repayment plans and responding to missed payments.

3 Data and Descriptive Facts

The backbone of our dataset is court docket header information from the universe of consumer bankruptcy filers in the LexisNexis Public Records database from 1990-2022. The filing header data includes the identity of the filer, trustee, and bankruptcy judge for nearly 30 million bankruptcy proceedings. These data allows us to merge our bankruptcy cases with the Federal Judicial Center (FJC) Integrated Database of all bankruptcy cases filed since Fiscal Year 2008 by case number, court district, and filing date. The FJC data add detailed information sourced from bankruptcy cases beyond the simple header information from LexisNexis. The FJC data are regularly updated so that they reflect any financial information that is changed over the course of the case. For example, if a trustee uncovers additional assets or income, our data would reflect this influence of the trustee.[20]

Our bankruptcy case data do not initially contain any information on race. Recent research has found that standard imputation algorithms used to predict race can err by coding non-White individuals as being White, and can thus bias estimates of racial disparities to zero (Derby et al., 2024; Greenwald et al., 2024) To obtain these data for filers, we use the filer's name and residential address to merge bankruptcy data with reported race from L2. L2's race data are self-reported when available (approximately 21% of individuals), and imputed using proprietary methods otherwise.[21] L2 procures this information from sources such as voter and product registration records and surveys. To mitigate possible measurement error from imputed race, we verify robustness of our results to restricting to subgroups for which the source is voter registration records. The residential addresses of judges and trustees are not reported in the bankruptcy data, limiting our ability to precisely identify race via L2. Instead, we manually infer their race from publicly available images.[22] To the extent that this approach may occasionally misclassify the race of a trustee or judge, we note that, similar to potential race imputation mistakes, any such measurement error should bias our results away from finding homophily, making our estimates, if anything, conservative.[23]

3.1 Summary Statistics

Panel A of Table 1 reports summary statistics for bankruptcy outcomes and characteristics. We observe dismissal and chapter status for 26 million cases.[24] After merging in self-reported filer race data from L2, we have 15.3 million observations. The rate of filing Chapter 13 versus 7 and the within chapter rates of dismissal are similar in both the full sample and subsample with known filer race, suggesting that there is unlikely significant sample selection related to dismissal in the

[20] The FJC data are archived annually. Since most cases finish within three months, we cannot observe revisions in the data for most cases and only observe the final information for the case.

[21] For recent uses of L2 data in economics research, see Allcott et al. (2020); Billings et al. (2021); Dahl et al. (2023); Billings et al. (2024).

[22] Our research assistants hand-collected race data for trustees and judges from public websites and independently cross-checked each classification decision. See Greenwald et al. (2024) for a similar method.

[23] See a detailed related argument in Goldsmith-Pinkham and Shue (2023).

[24] Around 3.5% of all consumer bankruptcy cases are converted from Chapter 7 to Chapter 13 or vice versa. We classify these cases by their final disposition chapter.

subsample where filer race is known. The other case characteristics are observed only for the subset of approximately 6.9 million cases that merge with the FJC data, mostly due to the more limited time period covered by the FJC data.

Overall, 18% of bankruptcy cases are dismissed, meaning that the court terminated the case without allowing any debt relief. However, dismissal is rare for Chapter 7 (2.7% of cases) but it is the modal outcome for Chapter 13 cases (61% of cases). As discussed above, among other differences, Chapter 13 cases involve payment plans, can be dismissed when debtors fail to make the corresponding payments, and are required for filers whose income fails a means test.

Table 2 describes other characteristics of bankruptcy filers.[25] Around 5% of petitioners file *pro se*, meaning they represent themselves instead of being represented by an attorney. About 14% of filers have filed before, especially among Chapter 13 filers (33%). Very few Chapter 7 filers report holding non-exempt assets, whereas almost all Chapter 13 filers report non-exempt assets. Roughly half of filers own a home, and roughly a quarter file jointly with a co-petitioner (usually a spouse). The average petitioner has $3,851 in monthly income, $143,000 in assets and 6 times as much debt as assets, with about half of their debt being secured. Chapter 7 petitioners anticipate having $300 more in monthly expenses than income post-bankruptcy. In contrast, Chapter 13 petitioners anticipate earning $850 more in income each month than their expenses. For Chapter 13 filers, this measure of disposable income corresponds to their required monthly payments.

Filer, Trustee, and Judge Race Composition. Panel A of Table 3 reports race shares for our sample. We find that 64% of US bankruptcy filers are White, 18% are Black, 15% are Hispanic, and roughly equal shares of the remaining 4% are Asian or Other. Comparing across chapters, Chapter 13 filers are more than twice as likely to be Black (31%) than Chapter 7 filers (13%).

Panel B of Table 3 reports the distribution of trustee race. We find that 91% of US bankruptcy trustees are White, 6% are Black, and the remaining 3% are roughly evenly split between Asian and Hispanic. Chapter 13 trustees are slightly more racially diverse. Within Chapter 13, 84% of trustees are White and 13% are Black, with Asian and Hispanic trustees almost equally comprising the remaining 3%. We see a similar race distribution for Judges in Panel C as that of the trustees. Across both chapters, 91% of US bankruptcy judges are White, 6% are Black, and the remainder are roughly evenly split between Asians and Hispanics.

Dismissal and Chapter Choice Disparities. We calculate dismissal rates by racial group in Panel B of Table 1. More than 32% of Black filers have their bankruptcy petitions dismissed, compared with 12% for both White and Hispanic filers, 11% for Other filers, and 10% for Asian filers. One contributor to racial disparities in dismissal rates is chapter choice. Black filers are the most likely to file under Chapter 13 at a rate of 46%. Asian, Hispanic and Other filers select Chapter 13 in roughly 15-19% of cases. White filers file Chapter 13 in 23% of cases.

In Figure 1, we decompose the role of chapter choice in explaining differences in dismissal

[25] See Appendix Tables A1-A5 for descriptive statistics by filer race.

rates across races. To do so, we calculate a counterfactual dismissal rate using each race's within-chapter rate of dismissal, which we then aggregate across chapters using White filers' rate of filing for Chapter 13. This counterfactual dismissal rate is higher for all minorities compared to White filers. For Black filers, moving from filing for Chapter 13 at a rate of 46% to 23% (White filers' rate) would lower their overall dismissal rate from 32% to 17% (assuming their within-chapter rates of dismissal are unchanged).

Prior research points to three possible explanations for the differences in chapter choice by race. First, Braucher et al. (2012) find evidence of attorney steering of Black filers toward Chapter 13 in an audit study. The experimenters present attorneys with bankruptcy schedules and randomly vary the names and churches of the filers to signal the race of the filer. Attorneys are 23-25 pp more likely to recommend Chapter 13 to filers implied to be Black rather than White. Second, attorney and court fees are paid upfront in Chapter 7 whereas they can be rolled into the repayment plan in Chapter 13.[26] As a result, filers facing difficulty affording Chapter 7's upfront costs may opt instead to file for Chapter 13. Lastly, in some jurisdictions, Chapter 13 can prevent repossession of vehicles for debts related to traffic fines. Morrison et al. (2020) argue that this contributes to higher usage of Chapter 13 by Black filers because they have longer commutes on average, such that the loss of a vehicle may be more burdensome.

While chapter choice explains a significant fraction of overall dismissal rates, there are also large within-chapter racial disparities. In order to understand the role of racial bias among trustees and judges in contributing to these disparities, we next focus on within-chapter racial disparities.

4 Dismissal Disparities in Consumer Bankruptcy

This section measures within-chapter racial disparities in dismissal rates and examines the extent to which they are explained by case characteristics. Table 4 reports regressions of the form

$$1[\text{Dismissed}_{iztjk}] = 1[\text{Minority Filer}_i]\beta_0 + X_i'\omega + \gamma_z + \alpha_t + \delta_j + \kappa_k + \varepsilon_{iztjk} \tag{1}$$

where $1[\text{Dismissed}_{iztjk}]$ indicates dismissal for filer i living in ZIP code z, filing in year t, facing judge j and trustee k. Recall that dismissal corresponds to a filer being denied bankruptcy protection and debt relief. Our most saturated specification includes fixed effects for filer ZIP code (γ_z), filing year (α_t), judge (δ_j), and trustee (κ_k) and a vector of case-specific controls (X_i). These controls (available in the FJC-merged sample) include indicator variables for whether filing was conducted without an attorney (pro se), if the individual has filed a bankruptcy case in the previous 8 years, if the filing has non-exempt assets that can be distributed to creditors, if the individual is a homeowner, and if the filing was a joint filing with a spouse or domestic partner. The included continuous control variables are the log of total assets, the leverage ratio (total debt-to-assets, winsorized at the 1% level), the share of total debt that is secured, and the log of monthly income. The coefficient of interest β_0 multiplies an indicator $1[\text{Minority Filer}_i]$ that the filer race is Black, His-

[26] In line with these upfront costs being a meaningful barrier to Chapter 7 (but not 13), Gross et al. (2014) find that receiving tax rebates caused an increase in Chapter 7 bankruptcy cases but not Chapter 13.

panic, Asian, or Other. Throughout, we cluster standard errors at the federal judicial district level, which is the bankruptcy court district in which the case was adjudicated (there are 94 districts), motivated by the fact that trustees and judges are randomly assigned to cases within a district.

Panel A of Table 4 focuses on Chapter 13 filers. Unconditionally, minority filers are 12.7 pp more likely to be dismissed relative to other filers. This estimate falls to 4.8 pp in Column (2) when including fixed effects for filer ZIP code, filing year, trustee, and judge. Restricting to the FJC-merged sample in Column (3) results in a similar estimate of 5.5 pp. Finally, including all of the fixed effects and the set of case controls available from FJC in Column (4), the White-minority gap in dismissal rates is 3.6 pp, which is 28% of the unconditional racial disparity and nearly 10% of the mean dismissal rate of 59 percent.

Panel B of Table 4 provides a useful contrast by measuring racial disparities in dismissal rates for Chapter 7 filers. Unconditionally, we estimate that Chapter 7 minority filers are 2.3 pp more likely to be dismissed than White filers, but this estimate falls to 0.3 pp when the full set of fixed effects and controls are included. Relative to the average Chapter 7 dismissal probability of around 2.7%, minority filers are about 11% more likely to be dismissed, even when including all controls in Column (4). Roughly half of the attenuation of the minority-White dismissal gap in Column (3) is driven by the necessary restriction of the Column (3) sample to the subsample for which FJC controls are available, with the remainder being explained by the FJC controls themselves in Column (4). The effect on the disparity coefficient of sequentially including the fixed effects and FJC controls is shown for both chapters in Appendix Figure A1.[27]

Taken together, Table 4 shows that minority filers are significantly more likely to be dismissed from both Chapter 7 and Chapter 13 bankruptcy, but the absolute size of the effect is an order of magnitude larger in Chapter 13. Similarly, the portion of the racial gap that is unexplained by control variables is much larger in Chapter 13, where overall dismissal rates are higher and trustees have significantly more discretion in case outcomes. In the sections that follow, we more finely test how racial biases may be driving these outcomes.

5 Decision Model and Econometric Framework

This section presents the framework that guides our empirical analysis of racial bias. While we ground our exposition in the context of consumer bankruptcy, the framework developed here can be applied to study bias in other settings. Notably, our approach can be used in settings where bias is otherwise difficult to study with outcome tests (e.g., the tests formulated in Becker, 1957; Arnold et al., 2018; Hull, 2021) due to, for example, complexity or lack of observability of the outcomes over which the decision-maker (DM) optimizes.

We begin by developing a model of the bankruptcy dismissal decision. The decision can be influenced by three sources of bias: accurate statistical discrimination, inaccurate statistical dis-

[27] Appendix Table A6 presents an abbreviated version of Table 4 that restricts to the subsample where trustee race is known. Disparities, both before and after adding controls and fixed effects, are similar across both tables, suggesting there is not significant selection related to racial disparities in the subsample for which trustee race is known.

crimination, and taste-based discrimination.[28] Our main theoretical results illustrate how *differences* in racial disparities between filers facing DMs of different races (homophily) can be used to (1) test for the presence of racial bias and (2) partially identify the share of observed disparities attributable to racial bias.

5.1 Decision Model

A bankruptcy case is characterized by a random set

$$\{I, R_I, F, R_F, X, D, Y_1, Y_0\}$$

where I indexes an individual decision-maker (DM) who has race $R_I \in \{m, w\}$. In the context of bankruptcy, this could be a judge or a trustee. The other party in the case is a filer, indexed by F with race $R_F \in \{m, w\}$ and non-race characteristic $X \in \mathbb{R}$. We simplify this setting by having only two races: minority (m) and White (w) and by having only a scalar non-race characteristic. Our results are not sensitive to these choices and can be extended to accommodate a larger, finite number of racial identities as well as vectors of non-race characteristics.

The DM selects a binary decision $D \in \{0, 1\}$; in our context $D = 1$ denotes dismissing the bankruptcy case. The DM's decision influences the "outcome" of the case $Y_D = Y_0 + (Y_1 - Y_0)D$, where $\{Y_0, Y_1\}$ are potential outcomes. The realized outcome $Y_D \in \mathbb{R}^k$ is a $k \times 1$ vector containing k "sub-outcomes," each of which may be binary, discrete, or continuous. In the context of bankruptcy, sub-outcomes could include whether the filer receives debt relief, commits fraud in the bankruptcy process, or makes the required bankruptcy payment. It could also include financial compensation received by the DM.

We use lower case letters (i, r_i, f, r_f, x, d) to refer to specific parties and their characteristics/decision. We refer to DMs with she/her pronouns and filers with he/him pronouns.

5.1.1 The Decision-Maker's Problem

The DM's utility depends on the outcome of the case. She chooses whether to dismiss in order to maximize her expected utility. Formally, she solves

$$\max_{d \in \{0,1\}} \; E_i[u(Y_d; i, r_f, x) | r_f, x].$$

Her utility function $u(\cdot)$ is parameterized by (i, r_f, x). This flexibly allows utility functions $u(\cdot)$ to vary with the DM's identity i. This allows, for example, DMs to have different preferences over preventing bankruptcy fraud. It also permits utility to vary with the filer's race r_f and non-race characteristic x for a given outcome and DM. For example, this would allow for a DM to prefer when low-income or White filers receive debt relief (relative to high-income or Black filers).

The expectations operator E_i denotes an expectation calculated using DM i's beliefs about the likelihood that various possible outcomes Y_d are realized. Ex ante, Y_d is unknown to the DM. We

[28] We use the terms "bias" and "discrimination" interchangeably.

do not require that the DM has correct beliefs (i.e., her beliefs do not have to coincide with the true, objective probabilities). We assume that she observes the filer's race and non-race characteristic and may condition her expectation on these variables. For example, she may therefore (correctly or incorrectly) believe that the likelihood of the filer completing all plan payments is predicted by the filer's race and employment status. We denote the utility gain to the DM (i.e., her payoff) from dismissing by

$$\Delta(i, r_f, x) \equiv u(Y_1; i, r_f, x) - u(Y_0; i, r_f, x).$$

With this notation, we can write the DM's optimal decision as

$$D(i, r_f, x) = \mathbf{1}\{E_i[\Delta(i, r_f, x)|r_f, x] \geq 0\}.$$

The DM dismisses the case when her expected payoff is non-negative.

5.1.2 The Sources of Bias and their Influence on Decisions

We next highlight how different forms of bias can influence decisions. Distinguishing types of bias is important because the nature of discrimination affects the efficacy of different policy tools that could be used to reduce bias. We begin by decomposing the DM's payoff into three components. The first component corresponds to prediction error:

$$\mu(i, r_f, x) \equiv E_i[\Delta(i, r_f, x)|r_f, x] - E[\Delta(i, r_f, x)|r_f, x].$$

Above, μ equals the difference in the DM's expected payoff of dismissing under her subjective beliefs versus the the true/objective conditional distribution of (Y_1, Y_0). This difference holds constant the conditioning variables and the arguments of the DM's utility function.

Inaccurate statistical discrimination can occur when the size and likelihood of prediction errors varies with filer race (i.e., $\mu(i, m, x) \neq \mu(i, w, x)$). Stereotyping (e.g., as in Bordalo et al., 2016; Bohren et al., 2023), where DMs hold incorrect priors, can be a source of differentially biased beliefs. In bankruptcy, for example, a trustee could over-estimate the likelihood that Black filers commit fraud if they have a stereotype that Black filers are more dishonest. Another possible source of inaccurate statistical discrimination is differences in ability across DMs in extracting predictive information from filers. For example, if there is more rapport between same-race trustee-filer pairs, trustees may obtain more information from filers when they have the same race. See Fisman et al. (2017) and Frame et al. (2025) for evidence of differential screening ability across vs. within groups.[29] If a White and minority trustee have the same expected Y_d for a particular case, but different levels of *uncertainty*, nonlinearities in their utility function $u(\cdot)$ can cause them to make different predictions about their expected utility gain from dismissing. Across cases, such screening-driven differences in certainty can show up as higher prediction error over their own

[29] Our framework flexibly nests such differences in screening by allowing prediction error $\mu(i, r_f, x)$ to be a function of both the filer's race r_f and the DM's identity i.

utility when facing a different-race filer.

The second component corresponds to *taste-based discrimination*:

$$\beta(i, r_f, x) \equiv E[\Delta(i, m, x)|r_f, x] - E[\Delta(i, w, x)|r_f, x].$$

Here, β captures how the DM's expected payoff changes when evaluating otherwise identical minority versus White filers. Both of the above expectations integrate over the same, objective conditional distributions; this entails conditioning on the filer's actual race r_f and non-race characteristic x. Both expressions also have the same x parameterizing the utility function. A nonzero β therefore arises when changing only the filer's race (i.e., holding constant their potential outcomes and probabilities of those outcomes) affects the DM's payoff), for example: if a DM dislikes missed payments more when the filer is White. Our taste-based discrimination component (β) is closely related to the "taste for discrimination parameter" of Canay et al. (2023).[30]

The third component relates to *accurate statistical discrimination*. To define this component, we must first select a reference group. Without loss of generality, we let White filers be the reference group (the subsequent results we derive do not depend on this choice). The last component is the expected payoff to the DM if she (1) has accurate/objective expectations, (2) uses the conditional distribution implied by the filer's actual race, and (3) her utility function is parameterized by the reference group (here, $r_f = w$):

$$E[\Delta(i, w, x)|r_f, x].$$

Accurate statistical discrimination can influence cases when $E[\Delta(i, w, x)|m, x] \neq E[\Delta(i, w, x)|w, x]$, which means that the filer's race is correlated with unobserved factors that affect the outcomes Y that the DM's utility depends on. Because the utility function is parameterized by the reference group ($r_f = w$), the different payoffs are not due to the influence of filer race on the DM's preferences (i.e., taste-based bias). Additionally, because objective beliefs are used, the payoff also does *not* reflect inaccurate statistical bias. In bankruptcy, accurate statistical discrimination could arise if, for example, the propensity to commit fraud is correlated with race.

We can decompose a DM's expected payoff from discriminating into these three components:

$$E_i[\Delta(i, r_f, x)|r_f, x] = \underbrace{E[\Delta(i, w, x)|r_f, x]}_{\substack{\text{decision under accurate statistical} \\ \text{discrimination only}}} + \underbrace{\mu(i, r_f, x)}_{\text{prediction error}} + \underbrace{\mathbf{1}[r_f = m]\beta(i, m, x)}_{\substack{\text{taste-based} \\ \text{discrimination}}}.$$

A positive accurate statistical discrimination term (first component) implies that the filer's race and non-race characteristic (accurately) predict that the DM would prefer to dismiss when utility is parameterized by a White filer. A positive μ means that the DM's prediction errors lead her to overestimate her utility gain from dismissing, increasing her preference for dismissal. Inaccurate statistical discrimination arises when $\mu(i, m, x) \neq \mu(i, w, x)$. A positive β (taste-based discrimina-

[30] Using the notation of Canay et al. (2023), our $\beta(\cdot)$ equals their $E[\beta(z, m, v) - \beta(z, w, v)|R = r, V = v]$. In essence, our component is the "effect" of filer race on the DM's payoff while their parameter corresponds to a "level" of bias (i.e., slope versus intercept).

tion) indicates that the DM has a higher expected utility gain when dismissing a minority filer, holding constant the other facts of the bankruptcy case, increasing her preference for dismissing minority filers. Negative μ and β terms would instead reduce the DM's preference for dismissal.

The above decomposition does not a priori rule out taste-based discrimination against White filers. The β term disappears in the equation above when the filer is White ($r_f = w$). However, we can rewrite the above instead using minority filers as the reference group for the accurate statistical discrimination term; this version would instead contain a $\mathbf{1}[r_f = w]\beta(i, w, x)$ term.

We present two definitions of racial bias, each defined at the decision-level.

Definition 1: Total racial bias.

(a) *A dismissal decision exhibits* total racial bias *if* $D(i, m, x) \neq D(i, w, x)$.

(b) *A dismissal decision exhibits* total racial bias against minority filers *if* $D(i, m, x) > D(i, w, x)$.

(c) *A dismissal decision exhibits* total racial bias favoring minority filers *if* $D(i, m, x) < D(i, w, x)$.

The term "total" emphasizes that this definition allows any of the three forms of bias to influence the dismissal decision. Our definitions of bias are similar to those of Hull (2021) and Lodermeier (2025) in that whether a DM's biases alter her *decision* when the filer's race changes is central. A DM may still have differing payoffs when dismissing two otherwise identical White and minority debtors, but that need not alter her decision. Such a case, under our definition, would not be *exhibiting* total bias. Our definition of total bias is also similar to the "local bias" of Canay et al. (2023) in that it allows for a given DM to be biased in some cases and not in others, or biased against minority or White filers depending on a non-race characteristic.

Our second definition of bias pertains to the influence of taste-based and inaccurate statistical-discrimination. First, we decompose the DM's decision into two components:

$$D(i, r_f, x) = \widetilde{D}(i, r_f, x) + \widetilde{\beta\mu}(i, r_f, x)$$

where

$$\widetilde{D}(i, r_f, x) \equiv \mathbf{1}\{E[\Delta(i, w, x)|r_f, x] \geq 0\}$$
$$\widetilde{\beta\mu}(i, r_f, x) \equiv D(i, r_f, x) - \widetilde{D}(i, r_f, x).$$

The $\widetilde{D}(\cdot)$ term is the decision that a DM would make if only influenced by accurate statistical discrimination with a White filer reference group. The $\widetilde{\beta\mu}$ term captures the net influence of both taste-based and inaccurate statistical discrimination. When $\widetilde{\beta\mu} = 1$, this indicates that the case was dismissed but would *not* have been dismissed in the absence of taste-based and inaccurate statistical discrimination. When $\widetilde{\beta\mu} = 0$, taste-based and inaccurate statistical discrimination on net did not alter the dismissal decision. Lastly, when $\widetilde{\beta\mu} = -1$, taste-based and inaccurate statistical discrimination resulted in a case avoiding dismissal that otherwise would have been dismissed.

Using this notation, our second definition of racial bias follows.

Definition 2: $\beta\mu$-racial bias.

(a) *A dismissal decision exhibits* $\beta\mu$-racial bias *if* $\widetilde{\beta\mu}(i,m,x) \neq \widetilde{\beta\mu}(i,w,x)$.

(b) *A dismissal decision exhibits* $\beta\mu$-racial bias against minority filers *if* $\widetilde{\beta\mu}(i,m,x) > \widetilde{\beta\mu}(i,w,x)$.

(c) *A dismissal decision exhibits* $\beta\mu$-racial bias favoring minority filers *if* $\widetilde{\beta\mu}(i,m,x) < \widetilde{\beta\mu}(i,w,x)$.

This second type of racial bias reflects the combined influence of taste-based and inaccurate statistical discrimination alone, separate from the influence of accurate statistical discrimination.

Our definitions of bias are related to but distinct from definitions of "racial bias" and "statistical discrimination" in Arnold et al. (2022). Our $\beta\mu$-racial bias is equivalent to their "racial bias" except that our definition includes inaccurate statistical discrimination arising from differences in screening ability. Arnold et al. (2022) instead classify such differences as "statistical discrimination," along with accurate statistical discrimination ($\widetilde{D}(\cdot)$, in our notation). Our definitions are motivated by the policy significance of these different forms of bias, which we discuss below.

Policy Significance of Different Forms of Racial Bias. It is useful to distinguish between total racial bias and $\beta\mu$-racial bias because their welfare implications differ. If the social welfare function does not allow for racial animus in preferences, then taste-based discrimination is inefficient. Inaccurate statistical discrimination is similarly inefficient—by definition, DMs would make different choices if they had accurate beliefs. Hence, eliminating $\beta\mu$-racial bias increases social welfare. Accurate statistical discrimination is different because it entails trade-offs. Suppose, for example, that elderly borrowers are more likely to default on loans. Lenders wishing to maximize profits may deny their applications at a higher rate. Eliminating differences in denial rates across age improves equality across borrowers, but this comes at the cost of lower profits to the lender. Such a trade-off may be socially desirable on net but requires weighing the benefits against the costs.

The efficacy of policies aimed at reducing disparities can also vary with the source of bias. If discrimination arises from inaccurate beliefs, improving the quality of information available to DMs—through better data or prediction tools or implicit bias training—can reduce bias.[31] If discrimination stems from taste-based preferences, interventions like implicit bias training, blind review processes, or discrimination monitoring may be better suited to reduce bias. When disparities result from accurate statistical discrimination, policies that target the root causes of group-based differences, rather than altering decision-making rules, may be more effective.

5.1.3 Estimands Quantifying the Influence of Bias

We present two estimands that quantify the influence of racial bias on bankruptcy dismissal decisions. We first define the effect of total racial bias on a minority filer's outcomes:

$$\delta \equiv E[D(i,m,x) - D(i,w,x) | r_f = m].$$

[31] We caution that, in practice, bias can arise in algorithms trained on decisions influenced by bias (Arnold et al., 2021; Fuster et al., 2022; Arnold et al., 2024) or when data quality varies across groups (Blattner and Nelson, 2020).

This estimand describes how much higher the dismissal rate is for minority filers due to total racial bias. Intuitively, a positive value means minority filers on average experience more dismissals than they otherwise would if the only characteristic of theirs that changed were their race.

Our second estimand focuses on the extent to which $\beta\mu$-racial bias (i.e., operating through either taste-based and inaccurate statistical discrimination) impacts minority filer dismissals:

$$\delta^{\beta\mu} \equiv E[\widetilde{\beta\mu}(i, m, x) - \widetilde{\beta\mu}(i, w, x)|r_f = m].$$

Recall that $\widetilde{\beta\mu}$ describes how taste-based and inaccurate statistical discrimination alters dismissal decisions. The estimand above therefore describes the excess dismissal rate due to $\beta\mu$-racial bias.

5.2 Identification: Detecting and Quantifying Bias with Differences in Disparities

Differences in disparities is a widely-studied phenomenon in a variety of settings and is often interpreted to be informative about bias.[32] The econometric framework we introduce below illustrates assumptions that make it possible to draw such conclusions from observational data.

We assume that the researcher observes the race of the filer and DM, and the DM's decision: $\{R_F, R_I, D\}$. We do *not* require that the researcher observes the outcome vector over which the DM optimizes (Y_D), the filer's non-race characteristic (X), nor how DM preferences $u(\cdot)$ vary with their identity I. Furthermore, our framework allows for settings in which the researcher does not know *what* outcomes the DM cares about (i.e., the components of the outcome vector Y_D). In this sense, our framework applies to settings where DMs make abstract or complex decisions. For simplicity, we abstract away from non-race characteristics observable to both the DM and researcher, as the framework below can be readily modified to condition on additional observables.

Identification Challenges. We highlight two identification challenges that make it difficult to learn about bias from disparities. The first is that average differences in dismissal rates do not generally identify the average total racial bias experienced by minority filers (δ):

$$E[D|r_f = m] - E[D|r_f = w] = \underbrace{E[D(i, m, x) - D(i, w, x)|r_f = m]}_{=\delta} \tag{2}$$

$$+ \underbrace{E[D(i, w, x)|r_f = m] - E[D(i, w, x)|r_f = w]}_{=\text{ selection bias}}. \tag{3}$$

The selection bias term can be non-zero if non-race filer characteristics x, observed by the DM but not observed by the researcher, are correlated with filer race and influence the DM's decision. For example, if minority filers face greater risk of job loss, DMs that value avoiding filers failing to make plan payments may be more likely to dismiss minority filers not (directly) because of their race but because of employment risk.

[32] See, for example, police stops and searches (Anwar and Fang, 2006; Antonovics and Knight, 2009), jury convictions (Anwar et al., 2012), and retail lending (Fisman et al., 2017; Frame et al., 2025).

The second identification challenge is separating $\beta\mu$-racial bias from total racial bias. Total racial bias is the sum of accurate statistical racial discrimination and $\beta\mu$-racial bias:

$$\delta = E[\widetilde{D}(i,m,x) - \widetilde{D}(i,w,x)|r_f = m] + \delta^{\beta\mu}.$$

Even with an estimate of δ, we cannot identify $\delta^{\beta\mu}$ without either estimates of accurate statistical discrimination or the assumption that it equals zero. Estimating accurate statistical discrimination directly would be especially difficult as it describes the *hypothetical* decisions that DMs would make in the absence of taste-based and inaccurate statistical discrimination.

5.2.1 Homophily, Differences-in-Disparities, and Identification

Homophily can help researchers learn about either total racial bias (δ) or $\beta\mu$-racial bias ($\delta^{\beta\mu}$). We now detail conditions that enable homophily, estimated via a differences-in-disparities ("diff-in-disp") estimator, to test for bias. We start by making minimal assumptions that make our test possible. We then show how stronger assumptions can help researchers quantify the impact of racial bias. By gradually adding assumptions, we aim to present a menu of assumptions that researchers could use to determine what conclusions they can draw from differences-in-disparities. We also suggest two tests that can help falsify these assumptions.

The Differences-in-Disparities Estimand. Let τ denote the diff-in-disp estimand:

$$\tau \equiv \left\{E[D|r_f = m, r_i = w] - E[D|r_f = w, r_i = w]\right\} - \left\{E[D|r_f = m, r_i = m] - E[D|r_f = w, r_i = m]\right\}.$$

This estimand measures the differences in racial disparities among cases assigned to White versus minority DMs. To minimize notation, going forward we write the conditional expectation $E[D|r_i, r_j] = E_{r_i r_j}[D]$. That is, $E_{mw}[D]$ denotes the average dismissal rate conditional on having a minority filer and White DM. Under this notation, the diff-in-disp estimand is

$$\tau = \left\{E_{mw}[D] - E_{ww}[D]\right\} - \left\{E_{mm}[D] - E_{wm}[D]\right\}.$$

Identifying Total Racial Bias under Parallel Disparities. Our first results highlight a necessary and sufficient condition for the diff-in-disp estimand to identify the average *difference* in racial bias (towards minority filers) among White versus minority DMs. Let:

$$\delta_M \equiv E_{mm}[D(i,m,x) - D(i,w,x)]$$
$$\delta_W \equiv E_{mw}[D(i,m,x) - D(i,w,x)],$$

which correspond to average total bias experienced among minority filers assigned to minority and White DMs, respectively. The key assumption for our first identification result is that bankruptcy dismissal decisions exhibit "parallel disparities," defined below.

Assumption 1: Parallel Disparities.

$$E_{mw}[D(w)] - E_{ww}[D(w)] = E_{mm}[D(w)] - E_{wm}[D(w)]. \tag{4}$$

The left-hand side is the *counterfactual* dismissal disparity between minority and White filers who are assigned to a White DM, if minority filers were (counterfactually) White.[33] That is, it removes the influence of all three sources of racial bias on the disparity. The right-hand-side is the counterfactual disparity (if minority filers were instead White) for filers assigned to minority trustees. In words, the parallel disparities assumption says that the difference in minority and White filer outcomes due to non-race characteristics (which may be correlated with race) would be the same among filers assigned to either White or minority DMs if (counterfactually) minority filers were White. The assumption is so named because it resembles the "parallel trends" assumption from difference-in-differences estimation. Parallel trends requires that counterfactual time trends are on average equal across treatment and control groups. Parallel disparities requires that counterfactual *racial disparities* are on average equal across unbiased White and unbiased minority DMs.

Parallel disparities is a weaker assumption than random assignment of DMs to cases, although it is satisfied by random assignment. Unlike random assignment, parallel disparities allows for filer race and non-race characteristics to be correlated with DM race. It also allows for DM strictness (i.e., baseline propensity to dismiss) to vary with DM race. However, it would need to be the case that these correlations result only in level differences in outcomes and not differences in *disparities* across minority and White filers, similar to how difference-in-differences allows for fixed differences across treatment and control groups. Of course, it is sometimes difficult to be certain that such correlations do not also result in differential disparities. As such, researchers would likely prefer to have the stronger assumption of random DM assignment met.

There are two main scenarios that could violate parallel disparities. The first arises if a non-race characteristic x is differently correlated with filer race across filers facing minority versus White DMs. We would most likely worry about this scenario if filers could choose their DMs or vice versa. For example, suppose low-income White filers prefer (and could choose) to work with White DMs, while income doesn't change minority filer preferences. If DMs are generally more lenient toward lower-income filers, parallel disparities could fail. To test for such violations, balance tests can verify observable filer race and non-race characteristics do not predict DM race.

The second scenario occurs if minority and White DM decisions respond differently to non-race characteristics that are correlated with race. For example, if minority DMs are more lenient with low-income filers, and this characteristic is correlated with filer race, parallel disparities could fail to hold. This violation would lead to the homophily coefficient estimating a combination of racial bias and bias towards other characteristics that are correlated with race. To test for this kind of violation, we recommend researchers interact non-race characteristics with DM race to test for evidence of systematic differences in decision-making (an "interactions test").

[33] To minimize notation, we suppress the dependence of the dismissal decision on DM identity i and the filer's non-race characteristic x.

We next formalize our first identification result below, which shows that the diff-in-disp estimator identifies the *average difference* in total racial bias across White and minority DMs under parallel disparities.

Proposition 1: Identification of Difference in Average Total Racial Bias. *If parallel disparities (Assumption 1) holds, the diff-in-disp estimand identifies the average difference in total racial bias between minority and White DMs. That is,*

$$\tau = \delta_W - \delta_M.$$

Proof. Rewriting the diff-in-disp estimand in terms of potential outcomes,

$$\tau = \{E_{mw}[D(m)] - E_{ww}[D(w)]\} - \{E_{mm}[D(m)] - E_{wm}[D(w)]\}.$$

Adding and subtracting additional potential outcome terms $E_{mw}[D(w)]$ and $E_{mm}[D(w)]$, respectively, from the two terms in brackets, we have

$$\begin{aligned}\tau = &\underbrace{E_{mw}[D(m) - D(w)]}_{=\delta_W} + E_{mw}[D(w)] - E_{ww}[D(w)] \\ &- \underbrace{E_{mm}[D(m) - D(w)]}_{=\delta_M} + E_{mm}[D(w)] - E_{wm}[D(w)].\end{aligned}$$

Applying the parallel disparities assumption from (4) to rewrite the diff-in-disp estimand,

$$\tau = \delta_W - \delta_M.$$

□

Intuitively, under parallel disparities, diff-in-disp overcomes the initial selection problem by differencing out the impact of non-race characteristics on decisions. This leaves the average difference in total racial bias between White and minority DMs.

We next introduce a second assumption, "parallel accurate statistical discrimination" that enables the diff-in-disp estimator to isolate $\beta\mu$-racial bias.

Assumption 2: Parallel Accurate Statistical Discrimination (PASD).

$$E_{mw}[\widetilde{D}(m) - \widetilde{D}(w)] = E_{mm}[\widetilde{D}(m) - \widetilde{D}(w)].$$

Under the PASD assumption, the average effect of the filer's race on the dismissal decision—absent prediction error and taste-based discrimination—is the same for minority and White decision-makers. That is, if both groups rely purely on accurate statistical discrimination, then the filer's race would have a similar effect on dismissal decisions across DM race. Recall the definition $\widetilde{D}(i, r_f, x) = \mathbf{1}\{E[\Delta(i, w, x) \mid r_f, x] \geq 0\}$, which highlights that varying the filer's race only changes

the (true) conditional distribution used by the DM to predict the likelihood of various outcomes in the PASD assumption.

Possible violations of this assumption are similar in nature to those that we would worry about regarding parallel disparities. For example, suppose that low-income status is correlated with filer race and that minority low-income filers are more likely to have a minority DM (but not low-income White filers). PASD could fail to hold in this case if low-income status and race (correctly) jointly predict different case outcomes Y_D. Random assignment of DMs (independent of filer characteristics) would similarly alleviate this concern. Hence, the balance test suggested for attempting to falsify parallel disparities can also provide evidence against violations of PASD.

The second scenario again relates to differences in DM preferences for outcomes by race. If DMs only make decisions based on accurate statistical discrimination, PASD could fail to hold if minority and White DMs have different preferences over outcomes that are (accurately) predicted by filer race. Hence, it is also possible to test for failure of this assumption with the same interactions test. If the diff-in-disp estimate changes after including these interactions, this would suggest that the estimate is conflating $\beta\mu$-racial bias with these systematic differences in decision-making.

Adding the assumption of PASD implies that the diff-in-disp estimator identifies the average difference in $\beta\mu$-racial bias between minority and White DMs. Proposition 2 formalizes this result (see Appendix A.1 for a proof). Intuitively, if accurate statistical discrimination is similar across White and minority DMs, this force is differenced out by the diff-in-disp estimator.

Proposition 2: Identification of Difference in Average $\beta\mu$-racial Bias. *If parallel disparities (Assumption 1) and parallel accurate statistical discrimination (Assumption 2) hold, the diff-in-disp estimand identifies the average difference in $\beta\mu$-racial bias between minority and White DMs. That is,*

$$\tau = \delta_W^{\beta\mu} - \delta_M^{\beta\mu}.$$

5.2.2 Testing for the Presence of Bias

Under Assumptions 1 and 2, the diff-in-disp estimand can be used to test for the presence of $\beta\mu$-racial bias (or total racial bias under only Assumption 1). The remark below summarizes several implications that affect the properties of such a test.

Remark *Under Assumption 1 (and Assumption 2), the following are true.*

1. *Non-zero homophily, $\tau \neq 0$, implies that at least one case was affected by total ($\beta\mu$-)racial bias.*
2. *Positive homophily, $\tau > 0$, does not imply that there is only total ($\beta\mu$-)racial bias against minority filers, nor does $\tau < 0$ rule out some DMs exhibiting total ($\beta\mu$-)racial bias against minority filers.*
3. *Zero homophily, $\tau = 0$, does not imply that no cases are affected by total ($\beta\mu$-)racial bias, as this scenario could arise if there are DMs with opposing biases that cancel out on average.*

This remark highlights that testing a null hypothesis of $H_0\colon \tau = 0$ (zero homophily) serves as a test for the presence of total bias ($\delta \neq 0$) under parallel disparities (Assumption 1) and for $\beta\mu$-racial bias if we also assume PASD (Assumption 2). The remark also describes features of the test that make it conservative. It can fail to detect bias when it is present (in the knife-edge case where biases exactly cancel out on average). However, when $\tau \neq 0$, this always indicates that bias is present. Testing $\tau = 0$ is therefore an underpowered test for the presence of bias but still has exact size.

Another feature of this test is that it does not indicate *who* is biased. Positive homophily could arise from either anti-minority bias among White DMs or anti-White bias among minority DMs. Since the dismissal decision is the result of an interaction between DMs and filers, homophily can also arise due to bias among White or minority filers which then influences the DM's choice. Additional assumptions are necessary for us to attribute bias to a specific group of DMs.

5.2.3 Quantifying the Impact of Bias

Without further assumptions, the diff-in-disp estimator can be used to test for the presence of bias. We show that with additional assumptions, it is also possible to quantify the influence of bias on decisions. Here, we present a menu of increasingly strong assumptions that result in narrower partially identified sets, quantifying the impact of bias. We continue to assume both parallel disparities (Assumption 1) and PASD (Assumption 2) and focus on quantifying $\beta\mu$-racial bias ($\delta^{\beta\mu}$). Analogous results without Assumption 2 can be derived for total racial bias (δ).

Assumption 3. *On average, White DMs weakly exhibit bias against minority filers/in favor of non-minority filers:* $\delta_W^{\beta\mu} \geq 0$.

Assumption 4. *On average, minority DMs weakly exhibit bias against minority filers/in favor of non-minority filers:* $\delta_M^{\beta\mu} \geq 0$.

Note that for $\tau > 0$, Assumption 4 implies Assumption 3. Let $p = \Pr(r_i = m)$, which corresponds to the proportion of minority DMs. With this notation we can write $\delta^{\beta\mu} = p\delta_M^{\beta\mu} + (1 - p)\delta_W^{\beta\mu}$. Note that neither assumption requires that all DMs of a given race exhibit the same direction of bias. Instead, the assumptions relate to average bias across DM groups. The following proposition summarizes our partial identification results under Assumptions 1-4.

We note that these assumptions are difficult to directly test, and they effectively involve taking a stance on whether bias on average comes from anti-minority White trustees or vice versa. We discuss evidence supporting the plausibility of these assumptions in our empirical analysis. Importantly, neither Assumption 3 nor 4 are necessary for our estimator to still serve as a test for the *presence* of bias.

Below, Proposition 3 formalizes a "menu" of increasingly strict lower bounds on the role of $\beta\mu$-racial bias in influencing dismissals ($\delta^{\beta\mu}$) obtained under increasingly strong assumptions. Assumptions 1 and 2 imply an upper bound of $1 - p\tau$. With Assumption 4, the lower bound on

the impact of $\beta\mu$-racial bias is the proportion of White DMs multiplied by the diff-in-disp estimand: $(1-p)\tau$. One can characterize the relative importance of $\beta\mu$-racial bias by dividing the identified set for $\delta^{\beta\mu}$ by the observed disparity $E[D|r_f = m] - E[D|r_f = w]$, which corresponds to the share of the observed disparity attributable to $\beta\mu$-racial bias. Proposition 3 may aid future research on racial bias by helping researchers determine the appropriate identified set based on which assumptions they believe are appropriate for their setting. See Appendix A.1 for its proof.

Proposition 3: Partial Identification of Average Bias. *Suppose that homophily is positive ($\tau > 0$) and that parallel disparities (Assumption 1) and parallel accurate statistical discrimination (Assumption 2) both hold, then*

1. *With no further assumptions, τ partially identifies $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [(1-p)\tau - 1, 1 - p\tau]$.*
2. *Under Assumption 3 ($\delta_W^{\beta\mu} \geq 0$), τ implies a higher lower bound, partially identifying $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [-p\tau, 1 - p\tau]$.*
3. *Under Assumption 4 ($\delta_M^{\beta\mu} \geq 0$), τ implies a higher lower bound, partially identifying $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [(1-p)\tau, 1 - p\tau]$.*

5.3 Summary of Model Extensions

Our decision model can be extended in a variety of ways that make it more realistic without fundamentally changing our identification results. In Appendix A, we present four extensions that feature: noisy observation of non-race characteristics x by the DM, dynamics and DM learning, additional actions among DMs (such as choosing effort in gathering and processing information), and two-tier decision-making model where a trustee makes a recommendation to the judge. These extensions do not alter our results nor significantly affect their interpretation.

5.4 Comparison with Related Tests for Bias

Here, we contrast our approach with other methods for detecting bias. The outcome test is a popular approach for detecting bias (Becker, 1957, 1993; Canay et al., 2023; Hull, 2021). The idea behind the outcome test is that bias can result in DMs applying different standards across groups, leading to differences across groups in equilibrium outcomes at the margin. For example, higher loan profitability for marginally approved borrowers from discriminated groups can indicate differential ex-ante lending standards.

Applying an outcome test in settings like bankruptcy is difficult for two reasons. The first is that an outcome test requires the researcher observe the outcome over which the DM is optimizing. The objective function of trustees and judges is complex. It depends on multiple, possibly interacting outcomes, many of which are difficult to measure. Trustee objectives include maximizing payouts to creditors (we observe proposed payments as of the end of the case, not actual payments made), minimizing fraud (requires knowledge of filer intentions), avoiding recommending infeasible plans (difficult to assess), allowing reasonable time to cure a missed payment (subjective), and setting necessary expenses to a reasonable level (subjective).

A second reason that an outcome test is not appropriate for testing for bias in bankruptcy is that the outcomes that trustees and judges value can feature trade-offs that vary by filer race. This can lead to differences in marginal outcomes for filers of different races *even in the absence of bias*, essentially by causing the DM to apply a different threshold rule to filers of different races. See Canay et al. (2023) for a detailed analysis of such scenarios. For example, suppose that trustees value preventing fraud and also maximizing payments to creditors. These goals are in tension. The trustee could immediately dismiss 100% of cases and ensure there is no fraud, but this comes at the cost of no payments to creditors. If the trustee never dismisses cases, payments are maximized but some fraud will likely occur. An optimizing trustee will tend to dismiss some fraction of cases. She may follow a threshold decision rule, dismissing cases when the likelihood of fraud outweighs the value of higher creditor payments. However, if these trade-offs vary by filer race (i.e., expected payments and the probability of fraud covary differently across groups) then an optimizing but unbiased trustee may apply different thresholds to minority and White filers. This could result in payments received from marginal minority and White filers differing. In this scenario, an outcome test could incorrectly suggest that the trustee is biased. Ultimately, both the difficulty in observing DM objectives in bankruptcy and the presence of trade-offs motivates our diff-in-disp approach.

Relative to the outcome test, a disadvantage of our framework is that it also requires measuring DM characteristics like race, which can also be difficult. Additionally, while outcome tests can point identify the size of bias, homophily generally partially identifies its size. However, an informative lower bound can be obtained (as in our application).

Our approach is related to those of Anwar and Fang (2006) and Alesina and La Ferrara (2014), which both propose rank order tests for bias. The logic of their tests is similar in spirit to ours: they compare how outcomes for defendants vary with the race of police officer (DMs) and victims, respectively. Our decision model has several important generalizations relative to theirs. First, we allow DMs to value multiple outcomes and for DMs to differ in their preferences over outcomes. This allows the model to apply to complex decisions, for DM-specific trade-offs across outcomes, and clarifies the assumptions needed to identify bias in the presence of heterogeneous DM preferences. Second, our model allows for inaccurate statistical discrimination to arise through biased beliefs, clarifying the relationship of homophily to this form of bias. Third, our framework presents a necessary and sufficient condition for homophily to identify $\beta\mu$-racial bias, netting out the influence of accurate statistical discrimination.

Our framework has several econometric innovations relative to Anwar and Fang (2006). First, our test for the presence of bias generally has more asymptotic power. Both tests may fail to reject when bias is present. However, while our test will correctly reject the null of no bias in all cases when the Anwar and Fang (2006) test rejects, our test will also correctly reject in cases where the Anwar and Fang (2006) test fails to reject (asymptotically).[34] Our framework also differs from

[34]In our notation, Anwar and Fang (2006) rejects when $E_{mw}[D] - E_{mm}[D]$ and $E_{ww}[D] - E_{wm}[D]$ have opposite signs. That is, when minority filers are more likely to be dismissed when facing White DMs and White filers are less likely to be dismissed when facing White DMs. However, suppose *all* filers are more likely to be dismissed by White DMs,

Anwar and Fang (2006) and Alesina and La Ferrara (2014) in that we show how our estimate can be used to not only test for bias but to also *quantify* its influence. Lastly, our framework also clarifies threats to identification and proposes falsification tests.

Behavioral Adaptation by the Examinee in Response to the Examiner. A universal challenge for detecting bias arises when the examiner and examinee interact with each other. The interpretation of outcome tests, rank order tests, and our diff-in-disp approach can be affected by behavioral adaptations on the part of the examinee during (or in response to) interactions with the examiner. For example, if minority filers have prejudice towards White trustees and are standoffish when interacting with them, the White trustee may interpret this behavior as a signal about the filer's honesty. Our framework nests this possibility if we allow the non-race characteristic x to be a behavior chosen by the filer. If minority and White filers differentially adapt behavior in response to the trustee's race *and* this behavior accurately predicts case outcomes Y, parallel disparities could be violated. However, if such behavior is not predictive of Y, then any impact on dismissal decisions of filer behavioral adaptation would instead be a form of inaccurate statistical discrimination.[35] Similarly, an outcome or rank order test can also conflate bias with unobserved behavioral adaptation.[36]

Our framework clarifies this important but rarely discussed interpretation challenge. Motivated by this, we later provide evidence in line with dismissal disparities arising from trustee bias by examining how racial disparities in dismissal rates covary with regional measures of implicit and explicit bias by Whites but not by Blacks, inconsistent with *examinee*-driven homophily (see Section 7.3). We also show that *trustee* heterogeneity (low caseload and more experience) is associated with lower homophily, further consistent with *examiner*-driven bias (see Section 7.2). We recommend future researchers using a diff-in-disp estimator conduct similar tests to shed light on which party is most plausibly the source of bias. Settings that are plausibly immune to this limitation are audit studies (e.g., Bertrand and Mullainathan, 2004; Braucher et al., 2012) or settings like that of Low and Pistaferri (2024) where applicants under review do not directly interact with their reviewer. Despite this limitation, it is nonetheless important to study bias in settings featuring interaction, as interaction can make traits like race more salient and may therefore be especially

making both of the differences positive. Anwar and Fang (2006) would fail to reject bias. However, if minority filers experience a *larger* increase in dismissal rates when moving from minority to White DMs (compared to White filers), our diff-in-disp estimand would still be positive and hence reject the null of no bias.

[35]This statement follows if we assume either that (1) behavior x does not affect DM decisions purely through DM preferences or that (2) such effects constitute a form of bias. An argument in favor of the latter interpretation is the following. Continuing with our example, suppose that trustees may prefer when standoffish filers are dismissed. This is not a legitimate reason to dismiss a bankruptcy case if it is not predictive of statutory criteria like ability to make payments. Arguably, such behavior is a form of de facto discrimination, in that it results in non-justifiable disparities.

[36]For example, suppose Black and White defendants react differently to judges with different leniency. This could occur if lenient judges tend to speak with more empathy to defendants during arraignment. If Black defendants are more responsive to this empathy, perhaps due to greater skepticism of fairness in the legal system, Black defendants facing lenient judges may become more likely to comply with conditions of release. This could result in lower rates of pretrial misconduct among marginally released Black defendants if judges do not take into account the effect of their leniency on defendant behavior. Similarly to our discussion above, one could nonetheless consider this a de facto form of bias.

prone to bias. Moreover, as in our case, many policy implications of homophily hold regardless of the source of the bias.

6 Homophily Analysis: The Role of Bias in Disparities

This section applies our framework to estimate racial homophily in consumer bankruptcy outcomes. We focus primarily on homophily between filers and bankruptcy trustees because of the central role of trustees in interacting with and evaluating filers. However, we report homophily estimates for judges as well.

We begin by estimating filter-trustee homophily for dismissal using specifications of the form

$$\begin{aligned} 1[\text{Dismissed}_{iztjk}] = 1[\text{Minority Filer}_i]\beta_0 + (1[\text{Minority Filer}_i] \times 1[\text{White Trustee}_k])\,\tau \\ + X_i'\omega + \gamma_z + \alpha_t + \delta_j + \mu_k + \varepsilon_{iztjk} \end{aligned} \tag{5}$$

which augments Equation (1) to include an interaction of the minority filer indicator with an indicator for having a White trustee. Judge and trustee fixed effects control for any fixed propensity to dismiss by DMs.[37] These fixed effects also absorb the race of the judge and trustee, eliminating the need to directly control for their race. As outlined in Section 5, we are interested in τ, which corresponds to the diff-in-disp estimand introduced in Section 5.2.1. Recall that the diff-in-disp estimand captures how the difference in minority and non-minority filers' dismissal rates changes when cases are assigned to a White trustee. Meanwhile, β_0 describes differences in dismissal rates between minority and non-minority filers who are assigned to minority trustees.

Random assignment of trustees is a key feature of bankruptcy that makes our assumption of parallel disparities plausible. In Chapter 7, trustees are assigned via a blind rotation system. However, Morrison et al. (2019) find evidence in three US cities that attorneys may help filers manipulate assignment to Chapter 7 trustees through strategically timing filing. We address this potential concern in two ways. First, we verify in Section 6.4 that filer race and non-race characteristics do not predict the trustee's race, consistent with random assignment. Second, our regressions include trustee fixed effects, which account for any fixed heterogeneity in overall trustee leniency.

In Chapter 13, trustee assignment is quasi-random. Trustees serve a designated region within their bankruptcy district. As a result, trustee assignment is determined by the filer's residential address. Manipulation of trustee assignment in Chapter 13 is therefore unlikely. However, regional variation in diversity could cause filer and trustee race to correlate. For this reason, it is also important that we include geographic fixed effects; our preferred specification uses ZIP code fixed effects. Within a ZIP code, variation in trustee race comes from time variation in who is serving as that region's trustee. For identification, we assume that the trustee's race is uncorrelated with other factors that *differentially* affect the merits of bankruptcy cases for minority and White Chapter 13 filers. For example, we assume Philadelphia is not more likely to have a Black Chapter 13 trustee in years when Black filers in Philadelphia are more likely to have case characteristics

[37] See Chang and Schoar (2013), Dobbie and Song (2015), and Bernstein et al. (2019) for evidence of fixed judge leniency tendencies. We are unaware of similar prior evidence for trustees.

that tend to lead to a higher dismissal rate. In support of this assumption, we also verify in Section 6.4 that observable filer race and non-race characteristics do not predict trustee race in Chapter 13.

Table 5 reports the results of estimating Equation (5) separately for Chapters 13 and 7 in Columns (1)-(2) and (3)-(4), respectively. We use the FJC-merged sample, which has the most conservative disparity estimates, in order to control for case characteristics. Beginning with the minority filer indicator in Column (1), the estimate of β_0 indicates that, when facing a minority trustee, minority Chapter 13 filers are 1.5 pp more likely to be dismissed than White filers. Column (3) reports a smaller difference for Chapter 7 of 0.4 pp. Turning to the diff-in-disp estimate $\hat{\tau}$, we find that switching to facing a White trustee significantly increases the racial disparity in dismissal rates for Chapter 13 but not Chapter 7. We estimate that having a White trustee increases the probability of dismissal by 2.3 pp for for minority Chapter 13 filers (significant at the 0.1% level) such that the conditional-on-observables dismissal rate is 2.5 times higher for minority filers paired with White instead of minority trustees. For Chapter 7, we obtain a precise null estimate of -0.1 pp (statistically and economically insignificant).

We also examine homophily separately for filers of different races in Columns (2) and (4). For Chapter 13, we find that the increase in dismissal rates from facing a White trustee is largest for Black filers (3.1 pp) and for Hispanic filers (2.4 pp). We estimate a null effect for filers identifying as "Other" and obtain a negative diff-in-disp estimate of -3.7 pp for Asian filers.[38] For Chapter 7, we continue to find no evidence of homophily, obtaining precise null estimates in Column (4).

6.1 Relating Homophily to Bias

Applying our framework from Section 5, the non-zero diff-in-disp estimates for Chapter 13 indicate that trustee bias influences dismissals. This follows for total bias, which may include accurate statistical discrimination, under parallel disparities (Assumption 1). If we further assume parallel accurate statistical discrimination (Assumption 2), our estimates imply that taste-based or inaccurate statistical bias ($\beta\mu$) racial bias are contributing to racial disparities in Chapter 13 dismissal rates. In Section 6.4 we provide empirical tests that support these identifying assumptions. For Chapter 7, the lack of homophily implies that we fail to reject the null hypothesis of no racial bias for Chapter 7. As we discuss in more detail in Section 6.3, this is plausibly because trustees have less scope for discretion in Chapter 7 cases compared to 13.

Quantifying the Influence of Bias. Without further assumptions, we cannot sharply quantify the influence of anti-minority bias among White trustees versus anti-White bias among minority trustees.Section 5.2.1 introduces a menu of assumptions that make it possible to use the diff-in-disp estimate to partially identify the share of the overall disparity attributable to bias among

[38] Although we caveat that Asian Chapter 13 filers have a much smaller sample size (11,418 versus 388,206 for Black filers), we note that negative homophily could potentially arise from two sources. One could be if minority trustees are more biased against Asian filers than White trustees. Another could be the influence of the "model minority stereotype," which may lead trustees to expect greater financial prudence or ability to repay among Asian filers. If such a belief is more pronounced or influential among White trustees, this stereotype could lead to lower dismissal rates for Asian filers compared to White filers.

White trustees. Drawing on this framework, we consider the implications of Assumption 4, which states that on average minority decision-makers are either neutral or biased against minority filers. Note that this assumption does not require that this property of bias applies to all trustees, only on average. Regarding the plausibility of this assumption, a common finding in the social psychology literature on implicit bias is that, on average, racial minorities are either neutral or slightly biased in favor of White people relative to Black people.[39] Further adding to the plausibility of this assumption, we later show that Chapter 13 dismissal disparities vary with regional measures of bias among White residents but not Black residents.

Under Assumptions 1–2 and 4, the dismissal disparity due to $\beta\mu$-racial bias is partially identified as $[(1-p)\tau, 1-p\tau]$, where τ is the diff-in-disp estimate and p is the fraction of minority trustees. Plugging in the estimates for Chapter 13 ($\tau = 2.3$ pp and $p = 15.8\%$), we obtain lower and upper bounds of 1.9 and 99.6 pp for the disparity due to anti-minority bias. The large upper bound indicates that it is possible that all of the observed disparity in Chapter 13 dismissal rates is due to anti-minority bias among White trustees. The lower bound of 1.9 pp implies that at least 15% of the unconditional 12.7 pp dismissal disparity for minorities—and 53% of the conditional 3.6 pp dismissal gap from Column (4) of Table 4—is due to anti-minority bias among White trustees. For Black and Hispanic filers, whose diff-in-disp estimates are, respectively, 3.1 pp and 2.4 pp, we find a larger role for bias. At least 20% of Black filers' unconditional 13.4 pp dismissal disparity and 47% of their conditional dismissal disparity is attributable to White trustees' $\beta\mu$-racial bias. For Hispanic filers, at least 17% of their unconditional 11.7 pp disparity, and potentially all of their conditional dismissal disparity, is due to bias.

6.2 Bankruptcy Judges

To gauge the role of judges' racial bias in shaping bankruptcy dismissals, we also examine homophily between filers and judges. Bankruptcy judges (in both Chapters) are also randomly assigned to cases. We re-estimate Equation (5), replacing 1[White Trustee$_k$] with 1[White Judge$_j$]. Table 6 reports these results. Starting with Chapter 13, we find that assignment to a White judge increases minority filers' dismissal rates by 1.6 pp. Similar to our findings for trustees, we also see the effects are largest for Black and Hispanic filers (1.9 and 2.1 pp, respectively). Effects are small and not statistically different from zero for Asian and Other filers. Turning to Chapter 7, we find no differences in disparities on average for minority filers. However, we do find statistically significant homophily on the order of 0.3 pp for Black filers facing White judges. While smaller in absolute terms, this is estimate is economically meaningful in relative terms: it corresponds to 17% of the average dismissal rate in Chapter 7 (1.74%). All other Chapter 7 homophily estimates are smaller and statistically indistinguishable from zero.

Overall, we see a lower level of homophily among judges compared to trustees. Larger homophily among trustees is plausibly due to two factors. First, trustees generally interact much more with filers. In both Chapters 7 and 13, the filer will meet at least once with the trustee or her

[39] See, for example, Nosek et al. (2002), Livingston (2002), and Sabin et al. (2009). More recently, Chan (2024) finds evidence that White and Black patients both exhibit willingness to pay for White physicians over minority physicians.

staff, face-to-face, for the 341(a) Meeting of Creditors. In most Chapter 7 cases, the filer will never appear before the judge, although the judge will observe the filer's name and could thus form beliefs about the filer's race. In Chapter 13, the filer typically only appears before the judge for a plan confirmation hearing. Once the filer is on the Chapter 13 payment plan, the trustee monitors the filer's completion of the payments. The filer will typically not interact with the judge again unless the trustee files a motion in court, such as requesting a plan modification or a dismissal.

A second reason homophily may be more significant for trustees than judges is that trustees can have more influence than judges over dismissal. In conversations with bankruptcy judges, trustees, and attorneys, both Chapters were described as "trustee-driven" process. The trustee and judge have distinct statutory responsibilities. The trustee's role is more investigative. The trustee is responsible for identifying possible misreporting and challenging the proposed Chapter 13 plan. It is also the trustee that directly monitors compliance with the plan. The judge is responsible for assessing whether the Bankruptcy Code is being correctly applied, including assessing whether the proposed plan meets the legal standards outlined in the Bankruptcy Code. If a filer fails to make the required payments, the judge typically only learns of this if the trustee files a motion. Moreover, the trustee has discretion about how to respond to nonpayment. Choices include allowing the filer time to cure the late payments, how quickly to file a motion in court if nonpayment persists, and whether to seek a modified plan, conversion, hardship discharge, or a dismissal. For example, in a small sample of hand-collected proceedings, we find some trustees filing for dismissal after one month of missed payments and some trustees waiting over a year after the first missed payment to file for dismissal. Given the key role of the trustee in administering bankruptcy cases, our remaining empirical analyses focus on trustees.

6.3 Differences between Chapters 13 and 7

Because homophily arises in Chapter 13 and not Chapter 7, comparing the features of these chapters can illuminate what allows racial bias to distort dismissal rates in Chapter 13. Several differences between Chapters 7 and 13 may account for the lack of homophily in Chapter 7. First, the scope for bias may be more limited in Chapter 7 because Chapter 7 is a a more regimented process. Limited discretion may not allow biased beliefs or taste to influence Chapter 7 outcomes, whereas Chapter 13 trustees exercise significant discretion at multiple points, as discussed above. Additionally, dismissal is a much rarer outcome in Chapter 7, with a 2% dismissal rate compared to 55% in Chapter 13 in our analysis sample.

Second, trustees and their offices face different marginal costs of pursuing and obtaining a dismissal depending on the Chapter. To file a motion, Chapter 7 trustees typically hire an attorney on an hourly basis to take this action. In contrast, Chapter 13 trustees typically have salaried staff attorneys that help file motions. The higher marginal cost of dismissal could deter Chapter 7 trustees from seeking dismissal motivated by taste-based discrimination, as they would have to "pay" to pursue this preference.

6.4 Identification and Robustness

Balance Test. As discussed in Section 5.2.1, we can test for failure of parallel disparities and PASD, which allow us to use the diff-in-disp estimates to test for the presence of $\beta\mu$-racial bias. These assumptions could fail if filers are not randomly matched to trustees within the district where they file. Such violations could cause homophily to reflect differences in the population of filers facing the trustees, rather than differences in trustee bias. Our first test of these assumptions is a balance test. The balance test regresses 1[White Trustee$_k$] on the filer's race and non-race case characteristics X_i (e.g., filing pro se, filing jointly, etc.). The regression uses year, ZIP code, and judge fixed effects, and we cluster standard errors by district. Figure 2 plots results. All estimates are small and statistically insignificant, consistent with random assignment of filers to trustees.

Interactions Test. Another way that parallel disparities and PASD could be violated in our setting would be if White trustees respond to non-race characteristics differently than minority trustees do. If this were the case, it is possible that part of the differences in disparities that we estimate is due to White trustees reacting differently to non-race characteristics that are correlated with race, rather than to race itself. In this scenario, the diff-in-disp estimate can be re-interpreted as capturing the sum of "direct" discrimination (i.e., based directly on group identity) and systemic discrimination (i.e., due to differential treatment of characteristics correlated with race) in the sense of Bohren et al. (2022).

To test for this scenario, we re-estimate our main diff-in-disp regression and add interactions of 1[White Trustee$_k$] with each case-level control in X_i. We plot the coefficients on these interaction terms separately by chapter in Figure 3 along with 95% confidence intervals. Our estimates of racial homophily remain unchanged: facing a White trustee increases the likelihood of dismissal for minorities by 2.3 pp in Chapter 13, the same point estimate we obtained without the additional interactions. This means that our diff-in-disp estimate is not due to correlations between the filer's race and the non-race characteristics in X_i. We also again obtain a precise null estimate for Chapter 7. Examining the other interactions for Chapter 13, we do find that White trustees appear to react differently to some non-race characteristics as well. In particular, White trustees are somewhat more likely to dismiss Chapter 13 filers that have a prior history of filing for bankruptcy, a larger percent of secured debt, and higher leverage. They are also more likely to dismiss no-asset cases, although these are extremely rare in Chapter 13 (0.3% of cases). For Chapter 7, the other interactions are generally precise null estimates (except pro se cases, which White trustees are less likely to dismiss). While we see evidence that trustees of different races react differently to some non-race characteristics, this does not appear to account for the racial homophily that we estimate, as evidenced by the stability of the racial homophily estimate. Overall, these results suggest that the diff-in-disp estimator is plausibly capturing $\beta\mu$-racial bias among trustees.

Robustness to Race Measurement Error. We obtain the race of bankruptcy filers by matching on name and address to data from L2. This is necessarily a fuzzy match process because of the textual

nature of address data and the fact that the filer may not be in L2 in the year of their bankruptcy case (at which point they may have a different address). Our merge first tries to match on full name and exact address; we then gradually exclude address components and middle names/initials if no matches are found (up to trying to match on first and last name and state). We do not always obtain a unique match for each filer. In such cases, we take the average of each race indicator across all matches and then round to zero or one. In Appendix Figure A2, we verify that our diff-in-disp estimates are virtually unaffected by the exclusion of of cases where filer race is uncertain (due to being matched to people with different races). The figure reports estimates, varying a threshold for filer race certainty (which is the distance from 0.5 for the unrounded average race). When restricting to people who matched to either exactly one person or multiple people who all share the same race, the diff-in-disp estimates and confidence intervals are unchanged.

To further assess the possibility that measurement error in filer race could bias our results, we re-estimate our Chapter 13 diff-in-disp results on subgroups with less measurement error. Appendix Table A7 reports these results. Columns (2) and (5) restrict to observations where *all* L2 matches linked to the filer have non-missing race.[40] This affects only around a 1,000 observations. Our point estimates and standard errors are unchanged to three decimal places. Lastly, Columns (3) and (6) restrict to filers from seven states where voter registration data is the source for race data. These states are primarily in the South (Florida, North Carolina, South Carolina, Georgia, Tennessee, Louisiana, and Alabama). Recall that, outside of these states, L2 imputes race when a self-reported measure is not available. Our diff-in-disp results are similar in these states (if anything, larger). For example, we see that minority Chapter 13 filers are 3.7 pp more likely to be dismissed when assigned a White trustee. The larger estimates could be a sign that measurement error from imputations in other states is, at worst, biasing downwards our estimates of homophily, making our conclusions conservative. However, the larger estimates may also reflect regional heterogeneity in homophily, which may be larger in the voter data states.

Our last test checks for possible sample selection related to the availability of trustee race data. Appendix Table A6 reproduces dismissal disparity estimates from Table 4 for the subset of observations where trustee race is known, i.e., the sample used to estimate homophily. We find quite similar estimates. Table 1 also shows that dismissal rates and chapter choice are similar in our full sample and the subsample where *filer* race is known, again suggesting that our disparity and diff-in-disp estimates are likely nationally representative.

7 Mechanisms

Our diff-in-disp estimates indicate that racial bias contributes to racial disparities in dismissals for Chapter 13. In this section, we investigate what underlying mechanisms could explain where this bias comes from and what kind of biases are present. We first study the role of nonpayment on Chapter 13 plans and show that most of the racial disparity in dismissal appears to be due to dif-

[40] In our main sample, we exclude those matches but still retain the filer if they are linked to at least one person in L2 with race data.

ferences in how trustees react to missed payments during the 5-year payment plan. We next show that both trustee experience and lower caseloads are associated with smaller homophily. These results are consistent with on-the-job learning and relaxing constraints on information processing both reducing inaccurate statistical bias. Lastly, we relate racial disparities to regional measures of implicit bias, which points most strongly to bias originating from White trustees.

7.1 The Role of Missed Plan Payments

The Timing of Dismissal Homophily. To examine the timing of homophily, Figure 4 plots the cumulative diff-in-disp estimate for Chapter 13 filers over the life of the bankruptcy case. For each day since filing, we estimate Equation (5) with a dependent variable equal to one if the case has been dismissed within d days since filing and plot the diff-in-disp coefficient from each of these regressions as a function of d.

Significant dismissal homophily arises around 250 days after filing and continues to rise, eventually plateauing near the coefficient shown in Table 5. This indicates that homophily primarily arises not during the initial assessment of the filer's financial reporting and confirmation of repayment plan, as this generally is completed within three months of the start of the case. Rather, homophily emerges once the filer is on the repayment plan. This suggests that dismissal homophily in Chapter 13 is driven by either differences in filers' ability to complete their Chapter 13 plan or how trustees react to missed payments. For example, a trustee has discretion to allow filers time to cure plan payment delinquencies and request modified plan payments in response to increases or decreases in filer income or expenses.

Homophily by Dismissal Reason. Examining the reason a case was dismissed further supports this mechanism. To test this, we run regressions similar to Equation (5) where the dependent variable is instead an indicator for being dismissed for a particular reason, such as not paying the filing fee, failing to report required information, or missing plan payments.[41] The results, presented in Table 7, show that nearly all of the homophily we detect arises due to missed plan payments (Columns 5-7). Chapter 13 minority filers that are matched with White Trustees are 1.7 pp more likely to have their case dismissed because of a failure to make plan payments. Building on this, Appendix Figure A3 demonstrates that the timing of homophily in dismissal for non-payment is detectable only after about 300 days, when filers are typically well into their repayment period. Column (3) of Table 7 also shows that there is statistically significant differences in disparities for cases that are dismissed due to failure to report information to the court, but the coefficient is relatively small and does not explain much of the overall diff-in-disp. Taken together, analysis of dismissal reasons provides further evidence that nonpayment is central to understanding why minority filers are dismissed at higher rates when they are matched with a White trustee.

Homophily in Required Plan Payments. Given the random assignment of trustees, nonpayment dismissal homophily could arise either because White trustees set higher monthly payments

[41] See Appendix Table A8 for the distribution of dismissal reasons by chapter.

for minority filers or because White trustees are less lenient when a minority filer misses a payment. To investigate this, we test for diff-in-disp in payment amounts.

Under Chapter 13, filers are required to pay all of their disposable income to the trustee each month for up to five years. However, there is significant discretion in determining the disposable income amount. Disposable income is set by forecasting monthly income and then subtracting out the amount of allowed expenses for the individual. This payment amount is set at the time that the plan is confirmed. If a trustee sets a higher income or allows fewer expenses, this results in high required payments over the next five years. Using data from the FJC on forecasted income and expenses, we measure this income-expense gap and test whether this is higher when a minority filer is paired with a White trustee.[42]

In Column (1) of Table 8, we see that, conditional on the full suite of controls, minority filers have an insignificantly lower income-expense gap of $3.52 among Chapter 13 filers. However, this average masks heterogeneity by whether the minority filer is paired with a White or minority trustee. Column (2) shows that the average minority filer assigned to a minority trustee has an income-expense gap that is $19.35/month lower than the reference group; they have an income-expense gap that is $18.77/month higher if they are randomly assigned to a White trustee. The higher income-expense gap implies higher monthly payments, making it harder for filers to avoid any missed or partial payments. In Column (4), we see that this effect is almost entirely attributable to the experience of Black filers, who pay $35.57 more per month when paired with a White trustee. Moreover, the diff-in-disp result for the income-expense gap holds even conditional on income, suggesting that White trustees are especially strict with minority filers in their allowable expenses.

Higher required plan payments are an important outcome in their own right, as they show that the racial identity of the trustee affects the cost of bankruptcy to filers. The size of this cost is non-trivial. For Black filers, the $35.77 higher monthly payments correspond to over $2,000 higher payments over the life of the five-year plan. Chapter 13 trustees have a financial incentive to set high payment levels, as their compensation is proportional to the size of these payments. The rationale for this arrangement is to align the trustee's incentives with one of their legal duties: to maximize payouts to creditors. To investigate how financial incentives may contribute to this homophily, as a placebo, we also estimate diff-in-disp in the *hypothetical* Chapter 13 plan payments for Chapter 7 filers. This is possible as both sets of filers are required to complete the same forms reporting income and expenses. However, in Chapter 7, the trustee receives either a flat fee in the 94.5% of cases with no non-exempt assets, or compensation in proportion to the value of non-exempt assets. Appendix Table A9 shows that no homophily arises for the hypothetical monthly payment (income minus expenses) for Chapter 7, where trustees do not scrutinize forecasted income and necessary expenses as inputs into a payment plan. These patterns can be explained by taste-based bias. If Chapter 13 trustees trade-off maximizing their compensation with setting "rea-

[42]The income and expense data reported by FJC is *after* any updates that might occur as a trustee examines a filer's information, so it will reflect the influence of the trustee on these amounts.

sonably" high expenses, but value the latter less for minorities, the financial incentives in Chapter 13 could contribute to the payment homophily we observe.

Higher plan payments are also important because they could drive the diff-in-disp we observe in dismissal rates if filers are more likely to fall behind when their payment amount is higher. However, in Column (7) of Table 7, we show that controlling for the income-expense gap has almost no effect on the diff-in-disp estimate for dismissal for missed payments. If monthly payments were the mediating factor causing homophily in dismissal, conditioning on monthly payments should reduce the diff-in-disp coefficient.

Given that controlling for monthly payments has no effect on dismissal homophily, racial disparities likely arise from how White trustees react when a minority filer misses a payment, rather than minorities being more likely to miss payments. Here again, trustees have discretion. When a filer misses a payment, it is up to the trustee to either report this to the court (typically with a petition to dismiss the case) or to grant a grace period. After filing the motion, one of three outcomes follows: dismissal, cure of nonpayment, or modification of the payment plan. In hearings that follow dismissal motions, trustees can advocate for dismissal or plan modification.

Although our data do not contain granular information on whether trustees take these actions, we hand-collected this information for a random sample of 240 cases to better understand how trustees react to missed payments. This sample is stratified to contain equal numbers of Black-Black, Black-White, White-Black, and White-White filer-trustee pairs. We observe how many months a filer was behind before the trustee sought dismissal for 168 dismissal motions. On average, trustees waited 2.8 months but the standard deviation in the sample is 2.1 months, indicating significant variation across trustees. Among 269 dismissal motions with observed outcomes, plans are modified 8.9% of the time.

Using similar regressions to our main specifications, including all control variables and fixed effects for district and year, we test for homophily in case outcomes after dismissal. We do not find significant differences in the number of months a trustee waits before filing a dismissal motion when a Black filer is assigned a White trustee. However, Black filers are 16 pp less likely to have their plans modified following non-payment when they are assigned to White trustees; this coefficient is significant at the 10% level, despite the small size of our hand-collected sample. While these are only suggestive results, they further align with our results pointing to discretion in handling missed payments as an important factor in the overall racial disparities we observe.

7.2 Trustee Heterogeneity

To illuminate what types of racial bias may underlie the Chapter 13 diff-in-disp estimates, and what features of bankruptcy enable bias to affect cases, we examine trustee heterogeneity. To do so, we re-estimate Equation 5 within separate trustee subgroups in Table 9 for Chapter 13 cases.

Columns (1) and (2) partition the sample based on a proxy for experience: the number of years that the trustee has worked as a trustee. Among trustees with high (above-median) years of experience, the diff-in-disp estimate for White trustees facing minority filers is 2.1 pp. Low-experience trustees exhibit larger homophily: 2.7 pp. While our confidence intervals do not rule

out that homophily is the same between these groups at the 95% level, the difference in point estimates is relatively large (33% in relative terms). The decline in homophily with trustee experience suggests that inaccurate statistical discrimination is part of what underlies the $\beta\mu$-racial bias we detect. If trustees learn from experience, this can help mitigate the distortion of inaccurate beliefs on their decision-making over time. Indeed, Iverson et al. (2023) shows that there is significant on-the-job learning for bankruptcy judges handling corporate bankruptcy cases, suggesting there is scope for learning for legal decision-makers in bankruptcy. However, it is also possible that taste-based discrimination decreases over time if working as a trustee causes White trustees to interact with more minorities than they otherwise would (i.e., the contact hypothesis, as in Pettigrew and Tropp, 2006). This latter scenario is less plausible given that bankruptcy tends to be a relatively negative interaction between filers and trustees. Hence, this finding is most suggestive of inaccurate statistical discrimination being present.

We next examine how homophily varies with trustees' workload, as proxied by the number of cases they're handling in the current year. We partition trustee-years into those with an above- and below-median caseload in Columns (3) and (4). Trustees with a high caseload (above median) are much more likely to exhibit homophily; our point estimate is a statistically significant 2.7 pp. In contrast, trustees with a low caseload have much lower homophily with a statistically insignificant point estimate of 1.0 pp. While the 95% confidence intervals overlap, the difference in magnitudes is large. Homophily is nearly three times greater for trustees with a high caseload. If trustees are time constrained by a high caseload, they may be constrained in their information processing capacity for each case. As a result, inaccurate statistical bias could have larger influence if trustees are less able to take time to gather and process information that could influence their perceptions of the filer. Consistent with court congestion impacting information processing ability, Iverson (2018) finds that corporate bankruptcy outcomes tend to be more successful when bankruptcy judges have lower caseloads. Regardless of the source of bias, these results also suggest that reducing caseloads may reduce the influence of bias on dismissals.

These heterogeneity patterns also speak to the role of examiner- versus examinee-driven bias in our setting. For differences-in-disparities to be driven by changes in minority filer behavior when paired with a White trustee, such filers would not only need to somehow react to trustee race in a significant enough way to change their case outcomes but also observe and react differentially to trustee workloads and experience levels.

7.3 Association with Implicit and Explicit Bias

We next present evidence consistent with dismissal homophily arising from racial bias, using data on measures of implicit and explicit racial bias. There is substantial scope for racial bias to affect trustee decision-making given that trustees exercise discretion to make quick decisions with competing objectives and incomplete information.

We measure implicit bias using data from Project Implicit's Implicit Association Test (IAT). IAT scores are a measure of subconscious bias. Experimental evaluations of the test have found that its measures of implicit bias are difficult for takers to manipulate (Banse et al., 2001; Egloff

and Schmukle, 2002). We measure explicit bias from surveys administered by Project Implicit in conjunction with the IAT, which ask respondents to directly rate on a scale from 0 to 10 the warmth of their feelings toward specific groups. Following Bursztyn et al. (2024), we focus on "forced" respondents who were required to take the test as either an assignment for work or school. Our Project Implicit sample spans 2010-2020, and we aggregate implicit and explicit bias measures to the county-year level. We similarly aggregate our case data to the county-year-chapter level and calculate the average difference in dismissal rates between Black and White filers.[43]

Figures 5 and 6 display binscatters relating county-level differences in dismissal rates for Black and White filers to county-level implicit and explicit bias (respectively). We find a strong, positive association between anti-Black implicit bias among White residents and the dismissal disparity for Chapter 13, consistent with the diff-in-disp results being at least partially caused by White trustees' being affected by implicit bias as they exercise discretion in handling bankruptcy cases. A one standard deviation higher IAT score (indicating more anti-Black implicit bias) predicts approximately a two percentage point larger racial disparity in Chapter 13 dismissal rates. We find similar results for explicit bias. By contrast, we find nearly a perfectly flat relationship between Chapter 7 dismissal disparities and White residents' average bias (implicit and explicit), mirroring the disappearance of homophily in our Chapter 7 estimates and consistent with the lack of discretion needed to be exercised by trustees in Chapter 7 cases.

In the bottom panels, we instead relate the Chapter 13 Black-White dismissal gap to each county's average *Black* resident's anti-White bias. For both implicit and explicit bias, we find a flat and insignificant relationship, consistent with bias from White trustees influencing the dismissal rate, rather than Black filers or Black trustees. This has two important implications.

First, it lends credibility to Assumption 4, which states that minority trustees are either neutral or biased against minority filers. Recall that this assumption enables us to quantify the share of disparities due to bias. The lack of correlation between the implicit bias of a county's Black residents and the dismissal gap is consistent with neutrality among Black trustees, further supporting our attribution of homophily to White trustee bias.

Second, this result also illuminates whether bias from *filers* affects dismissals. Minority filers may behave differently when assigned a White trustee if they perceive that trustee to be biased against them.[44] If such behavior is present and related to anti-White bias among filers, we would expect areas with higher implicit bias among Black residents to have larger disparities, resulting in a downward sloping relationship in the bottom panel instead of the flat line that we observe.

Overall, the patterns of Figures 5 and 6 are consistent with bias by White trustees—not Black trustees or Black filers—driving our diff-in-disp results.

[43] We focus on Black and White filers (and residents) because IAT data are more limited for other races, these two races comprise the largest shares of filers and trustees in our data, and homophily is largest for Black filers.

[44] See Ruebeck (2024) for recent evidence on perceived discrimination effects in labor markets.

8 Conclusion

In this paper, we provide first-of-its-kind evidence of significant racial disparities in access to the debt relief provided by consumer bankruptcy. Our analysis leverages a new dataset on the near universe of US bankruptcy cases linked to data on self-reported filer race and manually collected race for thousands of trustees and judges. Minority filers are 12.7 pp (22%) more likely to have their Chapter 13 bankruptcy case dismissed without debt relief compared to White filers. The disparity is 2.3 pp (85%) in Chapter 7.

To study the role of bias, we develop a model and new identification results formalizing necessary and sufficient conditions for racial homophily/concordance to detect and quantify the influence of bias.Our identification results can be applied to study bias in many other settings, including those where an outcome test is infeasible because the decision-maker's objective is unknown, unobservable, or difficult to measure. Our framework also builds on Anwar and Fang (2006) and Alesina and La Ferrara (2014) by clarifying how decision-maker preference heterogeneity affects identification, proposing falsification tests, and formalizing conditions to quantify bias.

We find substantial differences in disparities in consumer bankruptcy decisions in Chapter 13; random assignment to a White trustee increases the likelihood of dismissal by 2.3 pp for minority filers. Through the lens of our framework, our estimate implies that at least 15% of the 12.7 pp disparity is due to taste-based and/or inaccurate statistical discrimination. We provide further evidence that homophily primarily emerges here from differences in how trustees react to filers failing to make required monthly payments. In line with trustee discretion enabling bias to influence outcomes, we find a precise null effect of no racial homophily for Chapter 7, where trustees generally have less discretion and face fewer subjective decisions.

Our findings point to several policies worthy of further investigation. Notably, although our evidence on trustee heterogeneity and regional heterogeneity in implicit and explicit bias is most consistent with White trustees being the source of the bias, most of the policy implications apply regardless of the drive of the bias. Most directly, increased diversity among legal decision-makers could reduce dismissal disparities by improving the odds that minority filers are paired with minority trustees. Policymakers could consider mandated reporting of the demographic composition of trustees, trustee staff attorneys, and judges. Second, our findings suggest that discretion is an important source of bias. Standardizing the bankruptcy process to reduce the scope for subjective assessments by trustees and judges may also help. Implicit bias training could also reduce unconscious bias, and there is promising evidence emerging that training on making high-stakes quick judgments can debias the decision-making process (Dube et al., 2024). Third, the more than ten times higher overall dismissal rate of Chapter 13 cases compared to Chapter 7, and the relative lack of homophily in Chapter 7, raises questions about the desirability of improving access to Chapter 7. Barriers to Chapter 7 include an income-based means test and upfront versus backloaded filing and legal fees. Finally, collecting anonymized data on filer race could facilitate transparency, monitoring, and accountability, similar to the intent of the Home Mortgage Disclosure Act's collection and disclosure of data on protected class membership for mortgage applicants.

Such data would also enable future research to more easily study racial disparities in bankruptcy.

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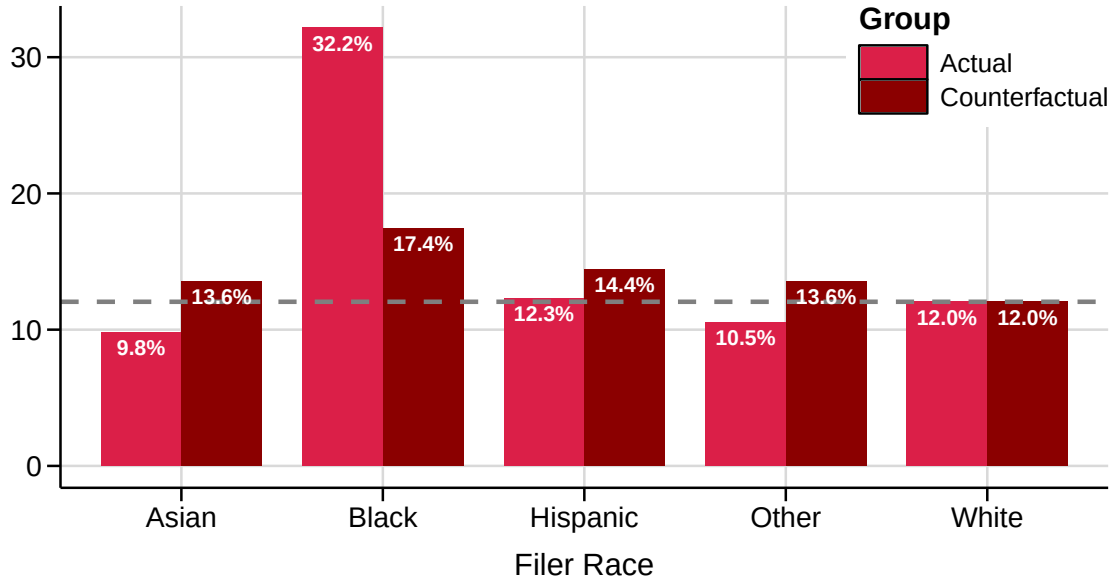
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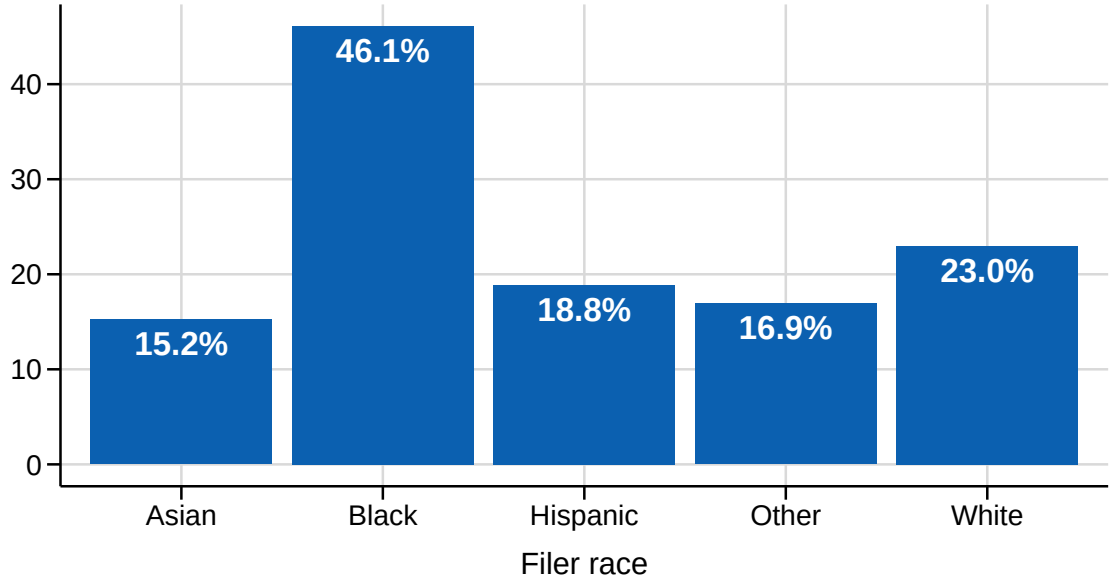
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Figure 1: Bankruptcy Dismissal Rates and Chapter Choice by Petitioner Race

Panel A. Actual and Counterfactual Dismissal Rates by Filer Race

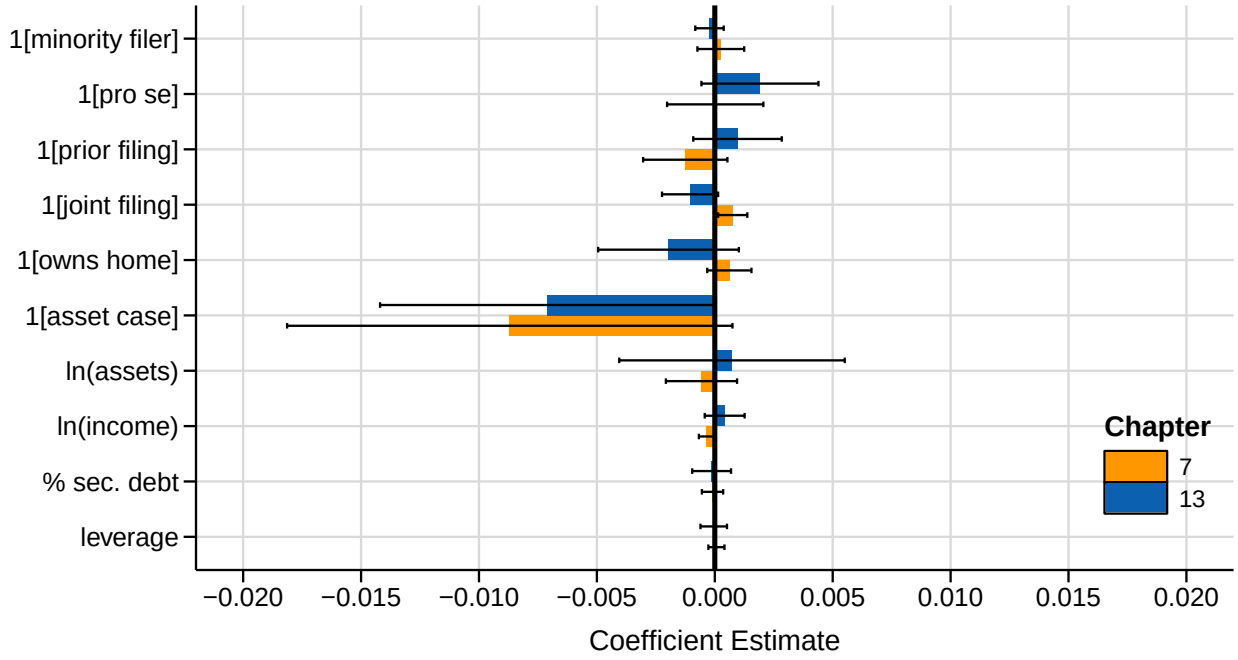


Panel B. Chapter 13 Share of Filings by Filer Race



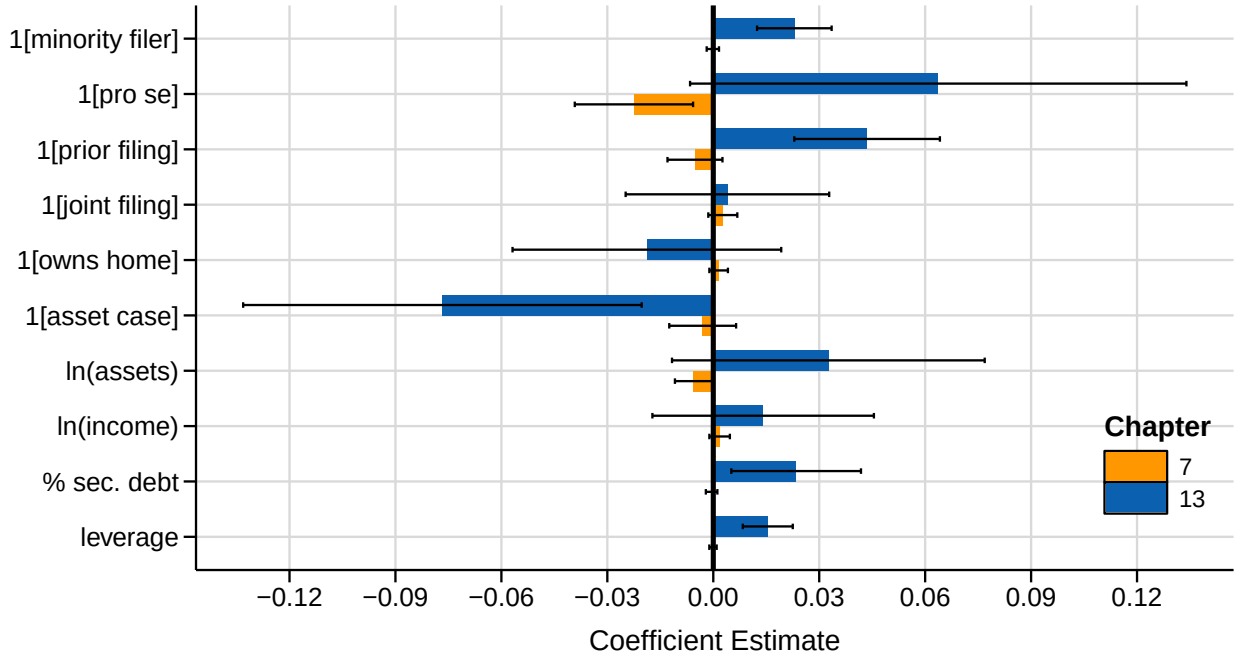
Notes: This figure plots bankruptcy dismissal rates and chapter choice by filer race. Panel A reports dismissal rates for filers under all chapters (7 and 13) by filer race. The light red bars on the left of each pair report the *actual* dismissal rate in our sample. The dark red bars on the right of each pair are *counterfactual* dismissal rates demonstrating the role of chapter choice in accounting for overall disparities. The counterfactual holds constant the dismissal rate within each chapter for all races but instead gives each race the same rate of filing Chapter 13 as White filers. The difference between the light and dark red bars describes the role of chapter choice in explaining overall dismissal rate disparities. Panel B reports the share of cases filed under Chapter 13 by filer race. The sample used in both figures is the subsample with non-missing filer race and FJC controls.

Figure 2: Testing for Balance of Trustee Race by Filer Characteristics



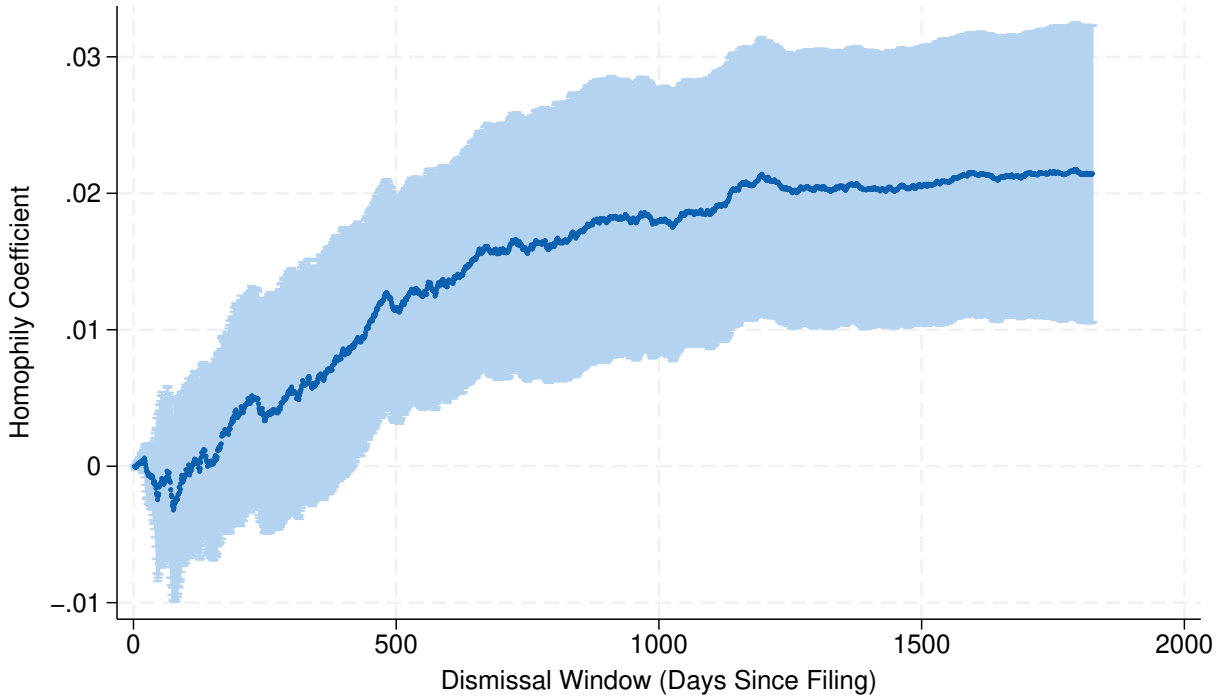
Notes: This figure plots coefficients from a multivariate regression testing for balance of filer characteristics by trustee race. The outcome variable is an indicator for the case's trustee being White. The coefficient for each explanatory variable is plotted along with 95% confidence intervals clustered by court district. Regressions are estimated separately by Chapter; blue bars at the top of each pair denote the Chapter 13 subsample and orange Chapter 7. The regression also includes fixed effects for filing year, ZIP code, and judge, as well as un-interacted FJC controls.

Figure 3: Testing for Interactions between Filer Characteristics and Trustee Race



Notes: This figure plots *interaction* coefficients from a multivariate regression that augments Equation (5) to include interaction variables between the White trustee indicator with each filer characteristic indicated on the y-axis. Error bars denote 95% confidence intervals clustered by court district. Regressions are estimated separately by chapter; blue bars at the top of each pair denote the Chapter 13 subsample and orange Chapter 7. The regression also includes fixed effects for trustee, filing year, ZIP code, and judge.

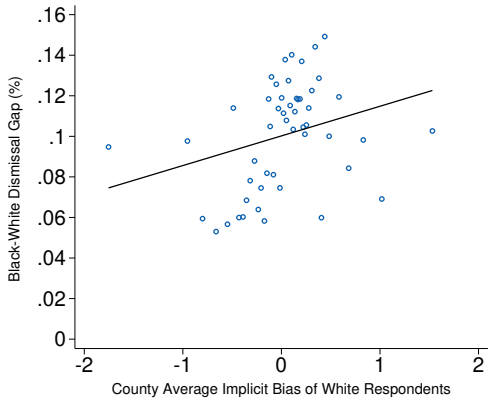
Figure 4: Homophily in the Cumulative Dismissal Rate



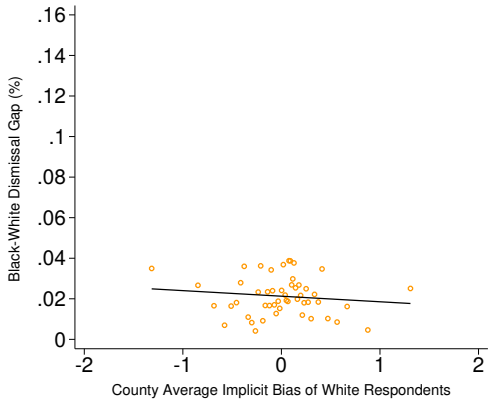
Notes: This figure plots day-by-day regression coefficients, each one from estimating the baseline homophily regression in Equation (5) separately after defining the dependent variable in each regression to indicate whether a case was dismissed with d days of filing for any reason. The x-axis ranges from one day after the case filed to up to 5 years after filing. The regression includes case-level control variables from the FJC sample and fixed effects for trustee, filing year, ZIP code, and judge. The light blue band plots a 95% confidence interval clustered at the district level.

Figure 5: County Average Implicit Bias versus Black-White Dismissal Disparities

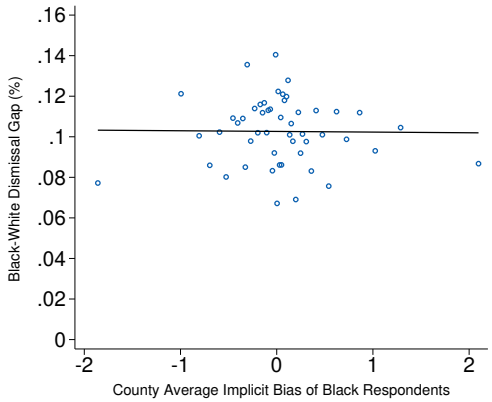
Panel A. Chapter 13, Anti-Black Bias



Panel C. Chapter 7, Anti-Black Bias



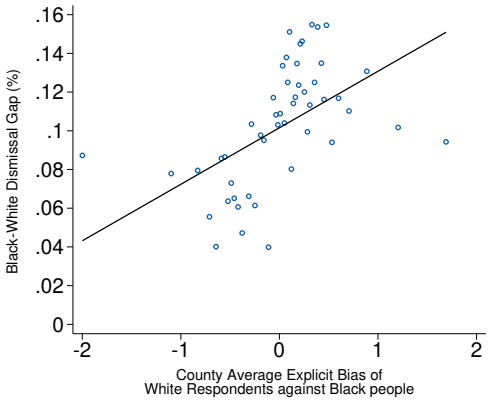
Panel C. Chapter 13, Anti-White Bias



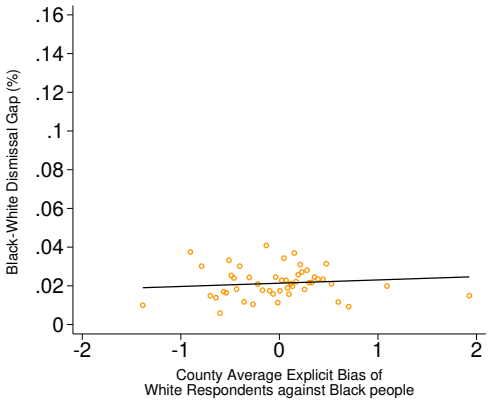
Notes: These figures plot binscatters of the county-year average difference in dismissal rates between Black and White filers against county-year measures of implicit bias from forced respondents to Implicit Bias Tests. See Section 7.3 for a detailed description of this implicit bias measure. In the top and middle panels, higher bias corresponds to larger anti-Black bias among White residents. In the bottom panel, higher bias corresponds to greater anti-White bias among Black residents. We z-score both bias measures so that zero corresponds to the national average amount of bias.

Figure 6: County Average Explicit Bias versus Black-White Dismissal Disparities

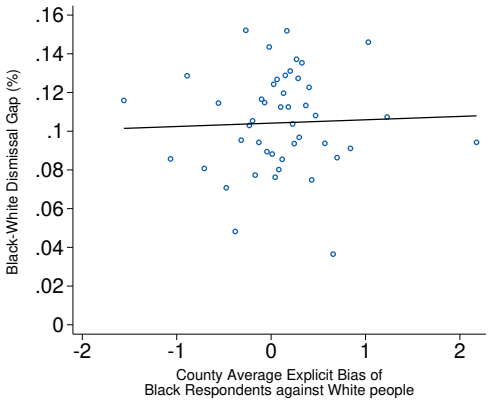
Panel A. Chapter 13, Anti-Black Bias



Panel B. Chapter 7, Anti-Black Bias



Panel B. Chapter 13, Anti-White Bias



Notes: These figures plot binscatters of the county-year average difference in dismissal rates between Black and White filers against county-year measures of explicit bias from forced respondents to Implicit Bias Tests. See Section 7.3 for a detailed description of this implicit bias measure. In the top and middle panels, higher bias corresponds to larger anti-Black bias among White residents. In the bottom panel, higher bias corresponds to greater anti-White bias among Black residents. We z-score both bias measures so that zero corresponds to the national average amount of bias.

Table 1: Chapter Choice and Dismissal Rates by Participant Race

All Chapters			Chapter 13		Chapter 7		
Ch. 7 %	Dism. %	N	Dism. %	N	Dism. %	N	Sample
Panel A. All Races							
73.2	18.3	26,044,416	60.8	6,969,041	2.7	19,075,375	Full
72.4	18.2	15,090,610	58.8	4,159,804	2.7	10,930,806	Known Filer Race
73.9	15.5	6,857,766	54.5	1,791,883	1.7	5,065,883	+ FJC
Panel B. Subsamples by Filer Race							
84.8	9.8	118,436	50.8	18,044	2.5	100,392	Asian
53.9	32.2	1,200,123	66.4	553,095	2.8	647,028	Black
81.2	12.3	1,042,274	54.9	196,450	2.4	845,824	Hispanic
83.1	10.5	138,610	52.5	23,474	2.0	115,136	Other
77.0	12.0	4,358,323	48.0	1,000,820	1.3	3,357,503	White
Panel C. Subsamples by Trustee Race							
79.9	10.2	71,480	41.2	14,369	2.4	57,111	Asian
40.7	42.5	259,283	70.2	153,634	2.1	105,649	Black
66.7	17.9	61,707	49.6	20,534	2.1	41,173	Hispanic
100.0	3.0	302	-	0	3.0	302	Other Trustee
74.3	14.8	3,910,052	52.7	1,004,724	1.7	2,905,328	White
Panel D. Subsamples by Judge Race							
76.3	15.7	86,293	58.4	20,494	2.4	65,799	Asian
67.0	22.5	320,178	64.4	105,609	1.9	214,569	Black
88.5	7.9	75,062	52.6	8,617	2.2	66,445	Hispanic
73.7	15.5	5,141,032	54.0	1,350,091	1.8	3,790,941	White
75.1	14.3	1,235,201	53.4	307,072	1.4	928,129	Unknown

Notes: This table reports dismissal rates and observation counts by sample, chapter choice, filer race, trustee race, and judge race. The first three columns report the Chapter 7 share, dismissal rate, and count across all cases. The other two pairs of columns report dismissal rates and counts separately by chapter. The full sample in Panel A corresponds to our full sample of cases with a known final disposition (i.e., dismissal or discharge). Known filer race corresponds to the subsample where filer race is known (merged in from L2 data). The final row in Panel A limits the subsample further to cases present in the FJC data. Panels B–D break out these statistics for our analysis sample (known filer race and linked to the FJC) by filer race, trustee race, and judge race.

Table 2: Descriptive Statistics on Consumer Bankruptcy Petitioners

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	4.8	5.7	2.4
1[Prior Filing] %	13.6	6.8	33.0
1[Non-Exempt Assets] %	30.1	5.5	99.7
1[Homeowner] %	52.3	46.7	68.1
1[Joint Filing] %	27.7	27.0	29.8
Assets ($000)	142.8	128.1	184.0
	(174.9)	(168.2)	(186.0)
Leverage Ratio	630.3	745.2	305.0
	(1,452)	(1,611)	(764)
Secured Debt %	45.0	39.1	61.7
	(35.6)	(35.0)	(31.9)
Monthly Income ($)	3,851.0	3,548.0	4,706.0
	(2,144.0)	(1,970.0)	(2,373.0)
Monthly Inc. - Exp. ($)	-20.8	-329.6	852.0
	(1,046.0)	(875.1)	(994.0)
Observations	6,857,766	5,065,883	1,791,883

Notes: This table reports means and (standard deviations) of case characteristics for all filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table 3: Racial Composition of Bankruptcy Parties

Chapter	Asian	Black	Hispanic	Other	White
Panel A. Filers					
All	1.73	17.50	15.20	2.02	63.55
Chapter 7	1.98	12.77	16.70	2.27	66.28
Chapter 13	1.01	30.87	10.96	1.31	55.85
Panel B. Trustees					
All	1.66	6.03	1.43	0.01	90.87
Chapter 7	1.84	3.40	1.32	0.01	93.43
Chapter 13	1.20	12.88	1.72	0.00	84.20
Panel C. Judges					
All	1.53	5.69	1.34	0.00	91.44
Chapter 7	1.59	5.19	1.61	0.00	91.62
Chapter 13	1.38	7.11	0.58	0.00	90.93

Notes: This table reports the share of filers (Panel A), trustees (Panel B), and judges (panel C) in each race category, including by Chapter.

Table 4: Racial Disparities in Dismissal Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Chapter 13								
1[Minority Filer]	0.127***	0.048***	0.055***	0.036***				
	(0.013)	(0.005)	(0.006)	(0.004)				
1[Asian Filer]					0.085*	0.008	0.000	0.000
					(0.037)	(0.007)	(0.006)	(0.005)
1[Black Filer]					0.134***	0.062***	0.083***	0.056***
					(0.017)	(0.007)	(0.007)	(0.006)
1[Hispanic Filer]					0.117**	0.030***	0.017**	0.009+
					(0.038)	(0.006)	(0.006)	(0.005)
1[Other Filer]					0.078***	0.016***	0.011**	0.007+
					(0.020)	(0.004)	(0.004)	(0.004)
Observations	4,159,804	4,159,804	1,791,883	1,791,883	4,159,804	4,159,804	1,791,883	1,791,883
R2	0.016	0.175	0.226	0.267	0.017	0.176	0.227	0.268
Panel B. Chapter 7								
1[Minority Filer]	0.023***	0.009***	0.005***	0.003**				
	(0.004)	(0.001)	(0.001)	(0.001)				
1[Asian Filer]					0.020**	0.006*	0.006*	0.006**
					(0.007)	(0.003)	(0.002)	(0.002)
1[Black Filer]					0.026***	0.015***	0.009***	0.004***
					(0.003)	(0.001)	(0.001)	(0.001)
1[Hispanic Filer]					0.023**	0.006*	0.003+	0.003
					(0.007)	(0.002)	(0.002)	(0.002)
1[Other Filer]					0.014***	0.004***	0.003**	0.003***
					(0.003)	(0.001)	(0.001)	(0.001)
Observations	10,930,806	10,930,806	5,065,883	5,065,883	10,930,806	10,930,806	5,065,883	5,065,883
R2	0.004	0.027	0.018	0.052	0.004	0.027	0.018	0.052
Trustee Fixed Effects		✓	✓	✓		✓	✓	✓
Year Fixed Effects		✓	✓	✓		✓	✓	✓
ZIP Fixed Effects		✓	✓	✓		✓	✓	✓
Judge Fixed Effects		✓	✓	✓		✓	✓	✓
Sample	Full	Full	FJC	FJC	Full	Full	FJC	FJC
FJC Controls				✓				✓

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. The explanatory variables are indicators for the race of the filer. Panel A reports estimates for Chapter 13, and Panel B reports for Chapter 7. Columns (1) through (4) estimate the coefficient on a single indicator for whether the filer belongs to a minority race, and Columns (4) through (8) estimate for more granular minority race categories. Columns (1), (2), (5), and (6) use the full sample, and Columns (3), (4), (7), and (8) use only the subsample matched to FJC cases. Columns (1) and (5) contain no fixed effects; the other columns have trustee, year, ZIP code, and judge fixed effects. Columns (4) and (8) also include the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table 5: Filer-Trustee Racial Homophily in Dismissals

	(1)	(2)	(3)	(4)
1[Minority Filer]	0.015**		0.004*	
	(0.005)		(0.002)	
1[Minority Filer] × 1[White Trustee]	0.023***		-0.001	
	(0.006)		(0.001)	
1[Asian Filer]		0.032**		0.009
		(0.009)		(0.006)
1[Asian Filer] × 1[White Trustee]		-0.037***		-0.003
		(0.010)		(0.004)
1[Black Filer]		0.025***		0.003*
		(0.005)		(0.002)
1[Black Filer] × 1[White Trustee]		0.031***		0.000
		(0.007)		(0.001)
1[Hispanic Filer]		-0.009		0.003
		(0.006)		(0.003)
1[Hispanic Filer] × 1[White Trustee]		0.024***		0.000
		(0.006)		(0.001)
1[Other Filer]		0.006		0.005+
		(0.005)		(0.003)
1[Other Filer] × 1[White Trustee]		0.000		-0.001
		(0.006)		(0.002)
Year Fixed Effects	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓
Chapter	13	13	7	7
Observations	1,193,261	1,193,261	3,109,563	3,109,563
R2	0.271	0.271	0.056	0.056

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. The explanatory variables are indicators for the race of the filer and interactions of these with an indicator for if the trustee is White. Columns (1) and (3) regress a single indicator for the filer being of a minority race, while (2) and (4) use more granular filer race categories. Columns (1) and (2) report results for Chapter 13, and Columns (3) and (4) report for Chapter 7. All contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table 6: Filer-Judge Racial Homophily in Dismissals

	(1)	(2)	(3)	(4)
1[Minority Filer]	0.020***		0.003	
	(0.006)		(0.002)	
1[Minority Filer] × 1[White Judge]	0.016**		0.001	
	(0.006)		(0.001)	
1[Asian Filer]		0.004		0.010*
		(0.011)		(0.005)
1[Asian Filer] × 1[White Judge]		-0.003		-0.003
		(0.011)		(0.003)
1[Black Filer]		0.037***		0.001
		(0.006)		(0.001)
1[Black Filer] × 1[White Judge]		0.019**		0.003**
		(0.006)		(0.001)
1[Hispanic Filer]		-0.012		0.003
		(0.010)		(0.004)
1[Hispanic Filer] × 1[White Judge]		0.021*		-0.001
		(0.010)		(0.002)
1[Other Filer]		-0.005		0.005*
		(0.011)		(0.002)
1[Other Filer] × 1[White Judge]		0.012		-0.001
		(0.012)		(0.001)
Year Fixed Effects	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓
Chapter	13	13	7	7
Observations	1,484,811	1,484,811	4,137,754	4,137,754
R2	0.279	0.279	0.055	0.055

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. The explanatory variables are indicators for the race of the filer and interactions of these with an indicator for if the judge is White. Columns (1) and (3) regress a single indicator for the filer being of a minority race, and Columns (2) and (4) use more granular filer race categories. All contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Columns (1) and (2) report results for Chapter 13, and Columns (3) and (4) report for Chapter 7. Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table 7: Racial Homophily by Dismissal Reason (Chapter 13)

	(1) Abuse	(2) Unpaid Filing Fee	(3) Missing Filing Info	(4) Other	(5) Missed Plan Pay.	(6) Missed Plan Pay.	(7) Missed Plan Pay.
1[Minority Filer]	0.000	0.000	-0.001	0.009**	0.007	0.015*	0.017**
	(0.000)	(0.002)	(0.001)	(0.003)	(0.006)	(0.006)	(0.006)
1[Minority Filer] ×	0.000	0.003	0.004***	0.000	0.016*	0.017*	0.016*
1[White Trustee]	(0.000)	(0.003)	(0.001)	(0.004)	(0.007)	(0.007)	(0.007)
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓	✓	✓	✓
Req. Known Reason						✓	✓
Inc-Exp Gap Control							✓
Observations	1,193,261	1,193,261	1,193,261	1,193,261	1,193,261	964,261	964,261
R2	0.022	0.110	0.086	0.122	0.142	0.235	0.240
Dependent Var. Mean	0.0007	0.025	0.020	0.192	0.311	0.311	0.311

Notes: The outcome variable is an indicator for whether the bankruptcy case was dismissed for a specific reason (indicated under the column numbers). The explanatory variables are an indictor for whether the filer belongs to a racial minority and its interaction with an indicator for if the trustee is White. For cases dismissed for missed payments, Columns (6) and (7) restrict the sample to cases with a reason other than "Other," and Column (7) also includes an income-expenditure gap control. All regressions contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table 8: Racial Homophily in Chapter 13 Plan Payments (Income-Expenditure Gap)

	(1)	(2)	(3)	(4)
1[Minority Filer]	-3.520	-19.353+		
	(7.099)	(9.796)		
1[Minority Filer] × 1[White Trustee]		18.774+		
		(11.263)		
1[Asian Filer]			-47.322**	-30.855
			(17.442)	(23.980)
1[Asian Filer] × 1[White Trustee]				-19.440
				(30.225)
1[Black Filer]			20.556*	-8.402
			(8.055)	(9.643)
1[Black Filer] × 1[White Trustee]				35.569**
				(13.372)
1[Hispanic Filer]			-36.873***	-42.182*
			(7.063)	(16.870)
1[Hispanic Filer] × 1[White Trustee]				5.597
				(17.570)
1[Other Filer]			-48.646***	-23.471
			(11.960)	(36.661)
1[Other Filer] × 1[White Trustee]				-29.109
				(38.112)
Year Fixed Effects	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓
Observations	1,193,261	1,193,261	1,193,261	1,193,261
R2	0.335	0.335	0.355	0.335

Notes: The outcome variable is the Chapter 13 monthly plan payment in dollars. The explanatory variables are indicators for the race of the filer and interactions of these with an indicator for if the trustee is White. Columns (1) and (3) describe racial disparities while Columns (2) and (4) include interactions to measure homophily. Columns (1) and (2) use only an indicator for the filer being a minority while Columns (3) and (4) use more granular filer race categories. All regressions contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table 9: Racial Homophily by Trustee Experience and Caseload

	(1)	(2)	(3)	(4)
	Trustee Experience		Current Caseload	
	High	Low	High	Low
1[Minority Filer]	0.010**	0.017***	0.009***	0.029**
	(0.005)	(0.005)	(0.002)	(0.011)
1[Minority Filer] × 1[White Trustee]	0.021***	0.027***	0.027***	0.010
	(0.006)	(0.007)	(0.005)	(0.011)
Year Fixed Effects	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓
Observations	586,549	606,712	603,009	590,252
R2	0.284	0.290	0.263	0.301

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. The explanatory variables are an indictor for whether the filer belongs to a racial minority and the interaction of this term with an indicator for if the trustee is White. Columns (1) and (2) restrict to subgroups where the trustee has a high or low amount of experience (respectively) measured in years. Columns (3) and (4) restrict to subgroups where the trustee has a high or low current caseload (respectively). All regressions contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Racial Disparities and Bias in Consumer Bankruptcy

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Internet Appendix

A Theory Appendix

In this appendix, we present proofs not given in the main text and discuss several potential extensions to the decision model presented in Section 5.

A.1 Proofs

Proposition 2: Identification of Difference in Average $\beta\mu$-racial Bias. *If parallel disparities (Assumption 1) and parallel accurate statistical discrimination (Assumption 2) hold, the diff-in-disp estimand identifies the average difference in $\beta\mu$-racial bias between minority and White DMs. That is,*

$$\tau = \delta_W^{\beta\mu} - \delta_M^{\beta\mu}.$$

Proof. Using Assumption 1 and Proposition 1, we rewrite the diff-in-disp estimand as

$$\tau = \{E_{mw}[D(m) - D(w)]\} - \{E_{mm}[D(m) - D(w)]\},$$

which corresponds to the average difference in total racial bias across minority and White DMs. Substituting in the decomposition of the decision D, the two terms become

$$E_{mw}[D(m) - D(w)] = E_{mw}[\widetilde{D}(m) + \widetilde{\beta\mu}(m) - \widetilde{D}(w) - \widetilde{\beta\mu}(w)]$$
$$E_{mm}[D(m) - D(w)] = E_{mm}[\widetilde{D}(m) + \widetilde{\beta\mu}(m) - \widetilde{D}(w) - \widetilde{\beta\mu}(w)].$$

Under PASD, the $\widetilde{D}$ terms cancel, leaving

$$\tau = E_{mw}[\widetilde{\beta\mu}(m) - \widetilde{\beta\mu}(w)] - E_{mm}[\widetilde{\beta\mu}(m) - \widetilde{\beta\mu}(w)] = \delta_W^{\beta\mu} - \delta_M^{\beta\mu}.$$

□

Proposition 3: Partial Identification of Average Bias. *Suppose that homophily is positive ($\tau > 0$) and that parallel disparities (Assumption 1) and parallel accurate statistical discrimination (Assumption 2) both hold, then*

1. *With no further assumptions, τ partially identifies $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [(1-p)\tau - 1, 1 - p\tau]$.*
2. *Under Assumption 3 ($\delta_W^{\beta\mu} \geq 0$), τ implies a higher lower bound, partially identifying $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [-p\tau, 1 - p\tau]$.*
3. *Under Assumption 4 ($\delta_M^{\beta\mu} \geq 0$), τ implies a higher lower bound, partially identifying $\delta^{\beta\mu}$ as $\delta^{\beta\mu} \in [(1-p)\tau, 1 - p\tau]$.*

Proof. Given assumptions 1 and 2, $\tau = \delta_W^{\beta\mu} - \delta_M^{\beta\mu}$. We can rewrite the expression for $\beta\mu$-bias $\delta^{\beta\mu} = p\delta_M^{\beta\mu} + (1-p)\delta_W^{\beta\mu}$, substituting $\delta_M^{\beta\mu} = \delta_W^{\beta\mu} - \tau$, to yield

$$\begin{aligned}\delta^{\beta\mu} = p\delta_M^{\beta\mu} + (1-p)\delta_W^{\beta\mu} &= p(\delta_W^{\beta\mu} - \tau) + (1-p)\delta_W^{\beta\mu} \\ &= p\delta_W^{\beta\mu} - p\tau + (1-p)\delta_W^{\beta\mu} \\ &= \delta_W^{\beta\mu} - p\tau. \end{aligned} \tag{6}$$

Alternatively, we can rewrite this expression, substituting $\delta_W^{\beta\mu} = \delta_M^{\beta\mu} + \tau$, to yield

$$\begin{aligned}\delta^{\beta\mu} = \delta_W^{\beta\mu} - p\tau = \delta_M^{\beta\mu} + \tau - p\tau \\ = (1-p)\tau + \delta_M^{\beta\mu}. \end{aligned} \tag{7}$$

By construction, both $\delta_M^{\beta\mu}$ and $\delta_W^{\beta\mu}$ are bounded by $[-1, 1]$. Thus, if $\tau > 0$, then $\delta_W^{\beta\mu} > \delta_M^{\beta\mu}$, and for a given positive τ, expression 6 implies that $\delta^{\beta\mu}$ is maximized by $\delta_W^{\beta\mu} = 1$ and expression 7 implies that it is minimized by $\delta_M^{\beta\mu} = -1$, implying a range of $\delta^{\beta\mu} \in [(1-p)\tau - 1, 1 - p\tau]$.

Under Assumption 3 ($\delta_W^{\beta\mu} \geq 0$), it follows from expression 6 that $\delta^{\beta\mu}$ is minimized when $\delta_W^{\beta\mu} = 0$ such that the range for $\delta^{\beta\mu}$ is now $[-p\tau, 1 - p\tau]$.

Similarly, under Assumption 4 ($\delta_M^{\beta\mu} \geq 0$), it follows from expression 7 that $\delta^{\beta\mu}$ is minimized when $\delta_M^{\beta\mu} = 0$ such that the range for $\delta^{\beta\mu}$ is $[(1-p)\tau, 1 - p\tau]$. □

A.2 Decision Model Extension: Noisy Observation of Non-Race Characteristic

One way to enrich the model is to suppose that, instead of observing the filer's non-race characteristic x, the DM observes a noisy signal s that may be correlated with x. In the context of bankruptcy, x could be the filer's ability to complete a Chapter 13 plan, which is ex-ante uncertain to the DM. In this scenario, the filer's recent income history could be s. Suppose also that the precision of the signal can vary across DMs and filers. This allows, for example, for minority trustees to receive stronger signals about minority filers (and vice versa for White filers and trustees).

Specifically, suppose that the DM observes

$$s = x + \sigma,$$

where σ is a random variable that may be correlated with x, r_f, or i. The DM may have inaccurate beliefs about the distribution of σ (including how it is correlated with other variables). These inaccurate beliefs, as well as the noise introduced by σ, can both be sources of prediction error.

The DM's payoff, $\Delta(i, r_f, x)$, still depends on x, but now x is ex-ante uncertain. When making her decision, her subjective expectation now conditions on s instead of x:

$$D(i, r_f, x) = 1\left\{E_i\left[\Delta(i, r_f, x) | r_f, s\right]\right\}.$$

In presence of this model feature, we generalize the definition of prediction errors to reflect errors

due to both inaccurate beliefs ($E(\cdot)$ vs. $E_i(\cdot)$) and due to the imperfect observation of x (x vs. s):

$$\mu(i, r_f, x, s) = E_i[\Delta(i, r_f, x)|r_f, x] - E[\Delta(i, r_f, x)|r_f, s]$$

The prediction error now depends on both the signal s and the true x. As before, inaccurate statistical discrimination arises when changing only the filer's race changes the prediction error:

$$\mu(i, r_f = m, x, s) \neq \mu(i, r_f = w, x, s).$$

With a signal instead of a perfectly observed x, what changes relative to our baseline model is that there is now an additional channel through which inaccurate statistical discrimination may differ across DMs. Because the signal can flexibly depend on i, r_f, x, it is possible, for example, that White DMs tend to receive noisier signals about x when facing a minority filer. This extension underscores how imperfect information can contribute to or exacerbate inaccurate statistical discrimination.

For this extension, our definitions for taste-based and accurate statistical discrimination remain unchanged; we continue to define those objects with respect to accurate conditional expectations (i.e., conditioning on x).

A.3 Decision Model Extension: Dynamics and DM Learning

The model in the main text is static. One feature of bankruptcy and other settings of interest is that DMs may learn information about a filer over time. For example, trustees in Chapter 13 cases may observe how the filer's income evolves over the five-year repayment plan. To allow for this, we can interpret x as the DM's information set at the time that they are making their decision, without explicitly modeling the evolution of their information set. Trustees could react differently to information that is revealed over the life of the payment plan in ways influenced by bias. For example, biased beliefs among White trustees about minorities' effort to make payments could make them more likely to seek dismissal in response to a minority filer's missed payment.

We can also add a further dynamic interpretation to our model by allowing the vector of outcomes Y to include outcomes related to future cases. For example, the DM could anticipate that her decision to dismiss a filer's case may affect her likelihood of dismissing future cases, detecting fraud in the future, or the predictability of how their future choices relate to distant outcomes. Regarding the latter example, it is in this sense that our model could feature DM learning over time or sophistication in the form of predicting how DM actions affect their future information sets.

Adding these features has little effect on the interpretation of our main theoretical results. Rather, they highlight particular real-world mechanisms that could be behind racial bias.

A.4 Decision Model Extension: Additional DM Actions

In our model, the DM optimizes by choosing one variable: whether to dismiss. In reality, DMs may take a number of actions that may also influence their dismissal decision. For example, a

trustee may choose how much time to invest in reviewing the filer's submitted paperwork.

A natural way to incorporate this feature into our setting is to break the DM's decision into two stages. The second stage consists of the dismissal decision (as modeled in the main text). The first stage entails the DM choosing a vector of actions $a \in \mathcal{A}(i, f)$, where their choice set $\mathcal{A}(i, f)$ may depend on the identity of the DM (i) and the filer (f) that they face (and, hence, the filer's race and non-race characteristics). The stage 1 actions could affect both the vector of outcomes Y (e.g., exerting more effort could increase total time spent on the case) and the DM's information set (e.g., the DM may be able to exert effort to improve precision in predicting the relationship between r_f, x, and Y). A sophisticated DM could choose their stage 1 actions while considering how these choices will affect their stage 2 dismissal decision.

The main impact of the multi-stage extension would be to allow for interesting interactions between statistical and taste-based discrimination. For example, suppose the DM's sense of fairness is one component of the outcome Y that they care about. Taste for discrimination could manifest as a DM only valuing fairness in cases with White filers. This could lead the DM to invest less effort in stage 1 to improve the accuracy of their subjective expectation $E_i(\cdot)$ when facing a minority filer. In this sense, taste-based bias can result in inaccurate statistical discrimination.

A.5 Decision Model Extension: Two-Tier Decision-Making

We next augment our baseline decision model to instead feature "two-tier" decision-making. By this, we mean the decision is made over two stages where, at each stage, a different party exerts influence over the decision. Specifically, we suppose that party one ("trustees") make a recommendation R to another party ("judges"), who ultimately decides.

In this setting, we now write the dismissal decision as a function of the trustee's recommendation R and a random variable e:

$$D(i, r_f, x, R, e) = R(i, r_f, x) + e(i, r_f, x, R).$$

From the perspective of the trustee, it is as if her decision is subject to "noise" e. We allow the judge's influence e to be flexibly correlated with $\{i, r_f, x, R\}$, writing e as a (possibly stochastic) function of these objects.

Trustee's Optimal Recommendation. The trustee's optimal recommendation has the same formula

$$R(i, r_f, x) = \mathbf{1}\{E_i[\Delta(i, r_f, x)|r_f, x] \geq 0\}.$$

Under this extension, the trustee may also have uncertainty about how the judge will react to their recommendation. She may also have biased beliefs about the likely reaction. The trustee may be strategic in that she takes into account how her recommendation R may affect e.

Note that we can also allow the outcome vector Y to include outcomes such as the judge disagreeing with the trustee ($R \neq D$), which the trustee may dislike. Among other things, this formulation would allow trustee discrimination to emerge because of anticipation of judge's desire

to discriminate. Regarding homophily, discrimination from this motivation would be differenced out if it's equally likely to happen for White and minority trustees. Hence, if trustees were all unbiased, other than this channel, we would find zero homophily as long as judges are randomly assigned to cases. Non-zero homophily therefore rejects this being the only source of trustee bias.

Bias Definitions and Parameters of Interest. We can decompose the recommendation R into inaccurate statistical, taste-based, and accurate statistical bias just as we did with the decision D in the main text. We can also define average total and $\beta\mu$-racial bias, respectively, in the trustee's recommendation similar to before:

$$\rho \equiv E[R(i,m,x) - R(i,w,x)|r_f = m]$$
$$\rho^{\beta\mu} \equiv E[\widetilde{\beta\mu}(i,m,x) - \widetilde{\beta\mu}(i,w,x)|r_f = m].$$

If one has data on recommendations, our main text's framework could immediately be applied to learn about these parameters. In our data, however, we observe only the final decision D, which is influenced not only by the recommendation R but the judge's influence e.

Changes to the Interpretation of the diff-in-disp estimand. Despite not being able to observe recommendations, we show here that homophily in dismissals is still informative about trustee bias. To see this, first recall that our diff-in-disp estimand is

$$\tau \equiv \{E_{mw}[D(m)] - E_{ww}[D(w)]\} - \{E_{mm}[D(m)] - E_{wm}[D(w)]\}.$$

If we continue to assume parallel disparities, as formulated in the text, that is,

$$E_{mw}[D(w)] - E_{ww}[D(w)] = E_{mm}[D(w)] - E_{wm}[D(w)],$$

then we retain the result

$$\tau = \delta_W - \delta_M.$$

Under parallel disparities, we still identify how changing the race of the trustee affects racial disparities in dismissal rates. We next show how this relates to the bias in the trustee's recommendation. To do so, we rewrite the estimand as follows:

$$\begin{aligned}
\tau = \delta_W - \delta_M &= \{E_{mw}[D(m) - D(w)]\} - \{E_{mm}[D(m) - D(w)]\} \\
&= \{E_{mw}[R(m) + e(m,R(m)) - R(w) - e(w,R(w))]\} - \{E_{mm}[R(m) + e(m,R(m)) - R(w) - e(w,R(w))]\} \\
&= \underbrace{\rho_W - \rho_M}_{\text{diff. in rec. bias}} + \underbrace{\{E_{mw}[e(m,R(m)) - e(w,R(w))] - E_{mm}[e(m,R(m)) - e(w,R(w))]\}}_{\text{diff. in indirect effects}}.
\end{aligned}$$

Above, we have partitioned the estimand into the difference in average total bias in trustees' recommendations across White and minority trustees ($\rho_W - \rho_M$), where ρ_W and ρ_M are defined anal-

ogously to δ_W and δ_M for R (instead of D). We call the second term the "difference in the indirect effects." These indirect effects capture the influence of additional sources of bias. Fundamentally, it captures whether judges differ in their likelihood of exhibiting or reacting to bias as a function of the trustee's race. For example, if White judges are more likely to exhibit bias against a minority filer when the filer is paired with a White trustee, this could appear as $E_{mw}\left[e(m, R(m))\right] > E_{mm}\left[e(m, R(m))\right]$ and $E_{mw}\left[e(w, R(w))\right] = E_{mm}\left[e(w, R(w))\right]$. Another example is if judges on average attempt to undo bias if they suspect it. If White trustees' recommendations exhibit more racial bias than minority trustees', a judge may react to their recommendations differently (e.g., $E_{mw}[e(m, R(m)) - e(w, R(w))] < E_{mm}[e(m, R(m)) - e(w, R(w))]$).

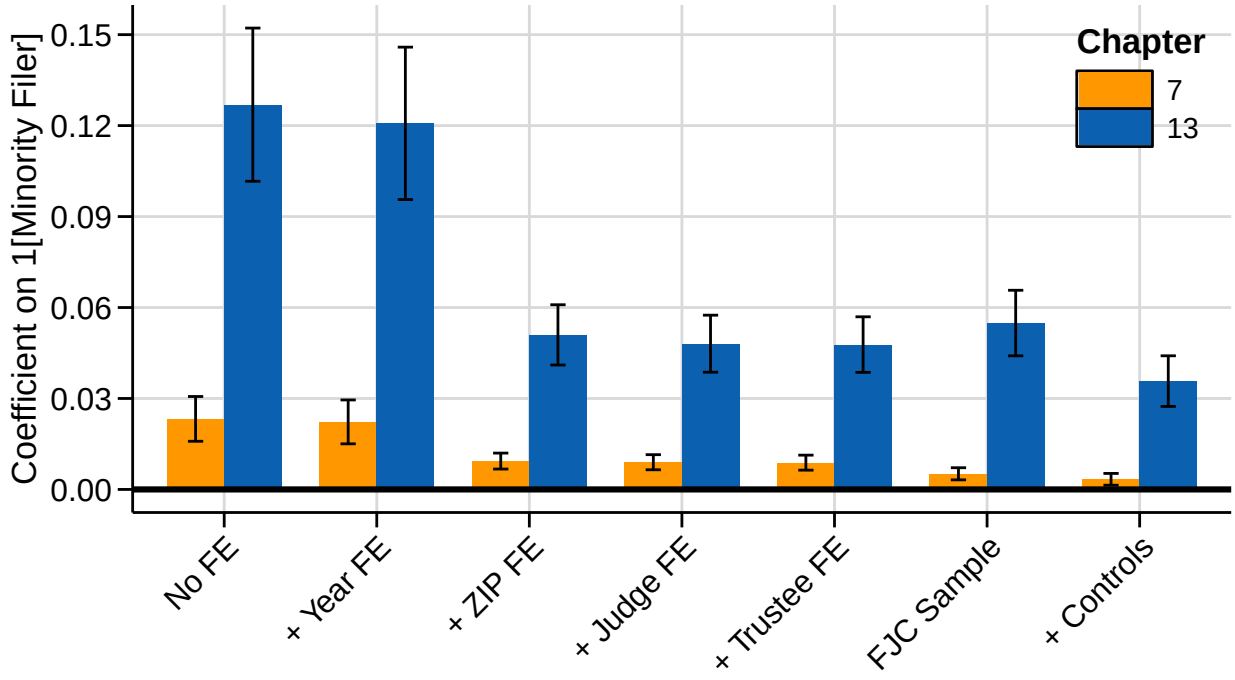
Note also that if we assume parallel accurate statistical discrimination (redefined with respect to recommendation R instead of decision D), then

$$\rho_W - \rho_M = \rho_W^{\beta\mu} - \rho_M^{\beta\mu}.$$

To summarize, in the two-tier extension, the diff-in-disp estimand still describes average differences in the influence of trustee bias. It captures both direct effects from bias in the trustee's recommendation as well as indirect effects through how judges react to the trustee's recommendation (or to the trustee themselves). In this sense, it captures differences in discrimination net of the influence of judges, which may either amplify or attenuate bias in the trustee's recommendation.

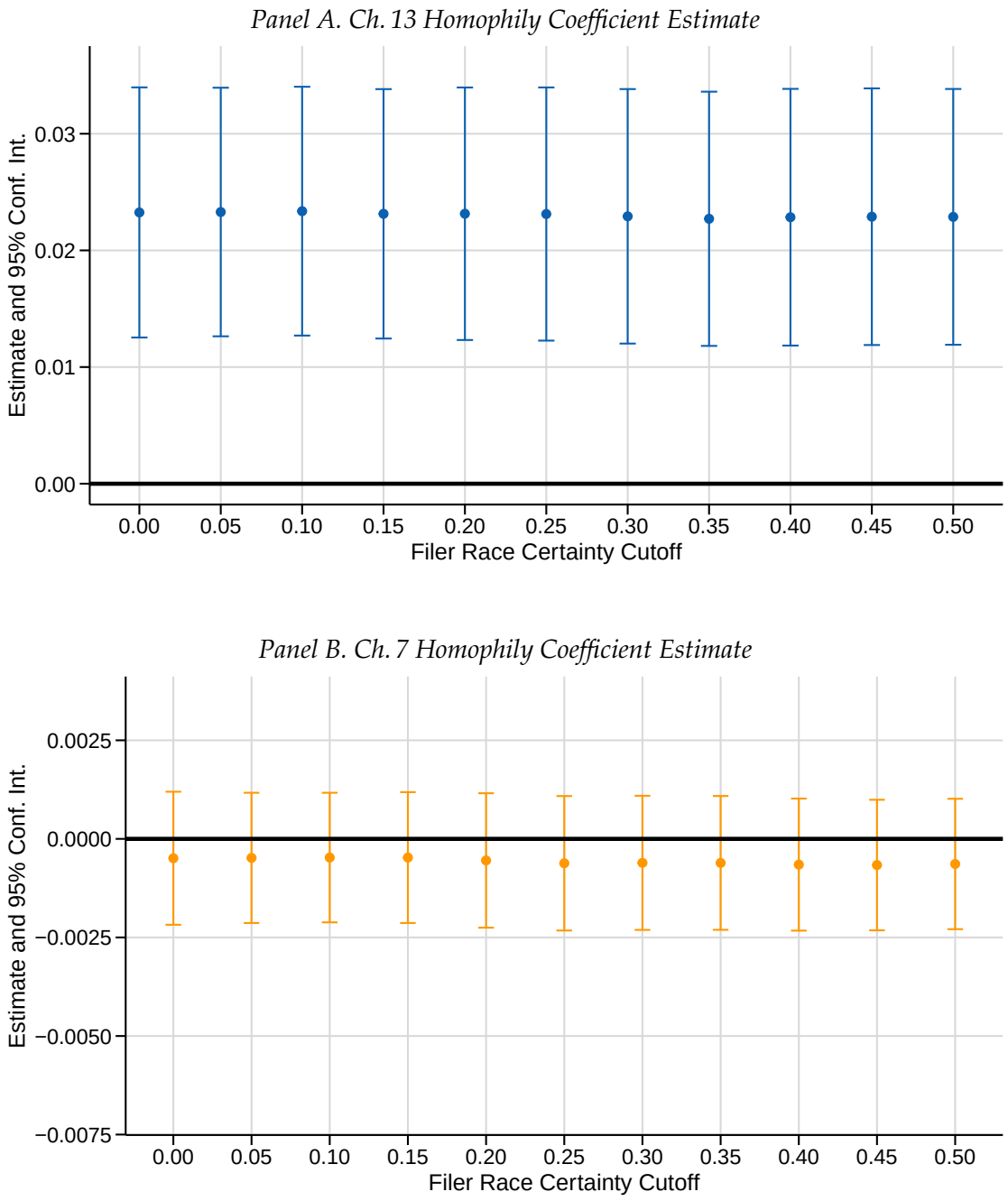
Additional Figures and Tables

Figure A1: Effects of Controls on Disparity Coefficient



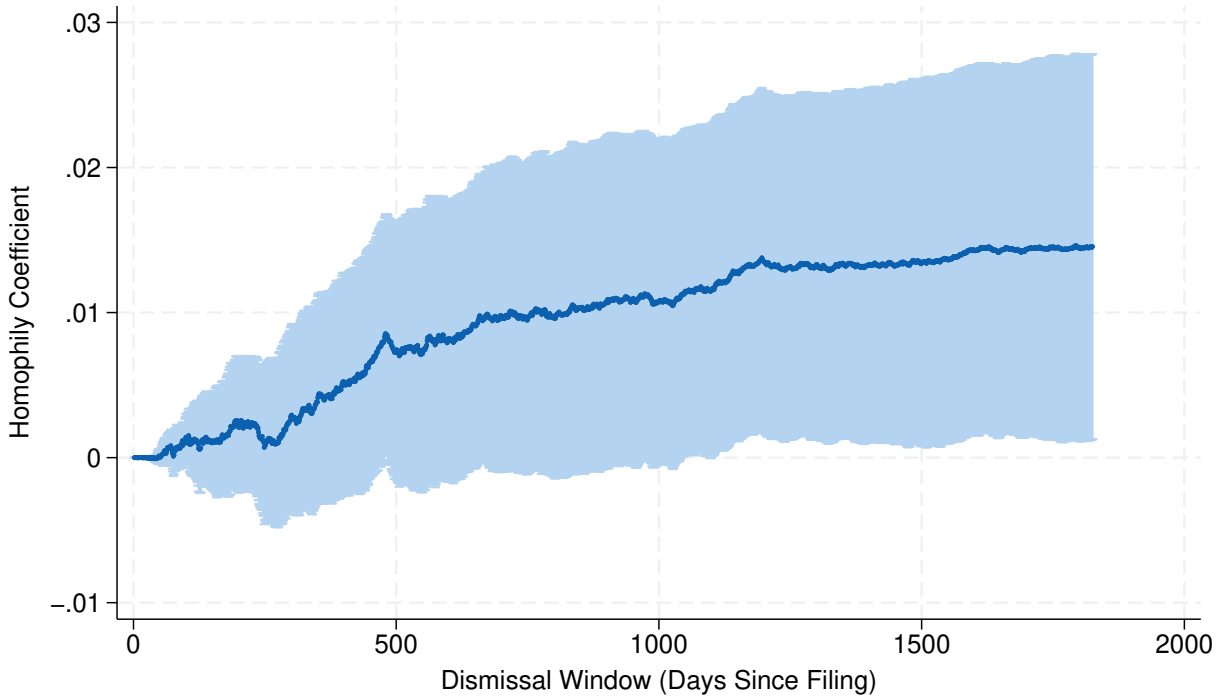
Notes: This figure plots coefficients on the minority filer indicator for regressions similar to Equation (1). Moving from left to right, we cumulatively add to the specification the indicated fixed effects, restrict to the subsample linked to the FJC, and finally add FJC controls variables. Standard errors are clustered by court district.

Figure A2: Robustness to Filer Race Uncertainty



Notes: These figures display homophily point estimates for various subgroups. The top panel reports estimates for Chapter 13 and the bottom panel for Chapter 7. Bars indicate 95% confidence intervals. Because some filers are linked to multiple potential matches in the L2 data, we take the average value of their indicators for each race. Our regressions use rounded values of these averages. We measure filer race certainty as $|P - 0.5|$, where P is the proportion of matches that are White. Certainty is maximized when P equals one or zero (i.e., all or none of the matches are White). We vary our minimum certainty cutoff from 0 (strictest) to 0.5 (most relaxed) along the x-axis. Regressions all have the same form as Equation (5) and 95% confidence intervals are clustered by court district.

Figure A3: Homophily in the Cumulative Dismissal for Non-Payment Rate



Notes: This figure plots day-by-day regression coefficients, each one from estimating the baseline homophily regression in Equation (5) separately after defining the dependent variable in each regression to indicate whether a case was dismissed with d days of filing for nonpayment. The x-axis ranges from one day after the case filed to up to 5 years after filing. The regression includes case-level control variables from the FJC sample and fixed effects for trustee, filing year, ZIP code, and judge. The light blue band plots a 95% confidence interval clustered at the district level.

Table A1: Case Characteristics (Asian Filers)

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	5.9	6.0	5.2
1[Prior Filing] %	8.3	4.8	27.6
1[Non-Exempt Assets] %	19.0	4.6	99.1
1[Homeowner] %	46.8	41.5	76.6
1[Joint Filing] %	25.4	24.5	30.4
Assets ($000)	186.9	163.3	318.0
	(234.2)	(221.3)	(259.0)
Leverage %	1,013.0	1,135.0	335.0
	(2,119.0)	(2,244.0)	(960.0)
Secured Debt %	39.4	34.7	65.5
	(37.3)	(36.0)	(33.1)
Monthly Income ($)	3,762.0	3,430.0	5,607.0
	(2,356.0)	(2,152.0)	(2,582.0)
Monthly Inc. - Exp. ($)	-318.2	-528.2	850.0
	(1,191.0)	(1,064.0)	(1,183.0)
Observations	118,436	100,392	18,044

Notes: This table reports means and (standard deviations) of case characteristics for Asian filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table A2: Case Characteristics (Black Filers)

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	6.2	9.8	1.9
1[Prior Filing] %	25.2	11.7	41.1
1[Non-Exempt Assets] %	47.9	3.4	99.8
1[Homeowner] %	44.8	35.8	55.4
1[Joint Filing] %	11.8	11.1	12.7
Assets ($000)	96.1	79.8	115.0
	(132.2)	(125.2)	(138.0)
Leverage %	628.1	869.7	345.0
	(1,389.0)	(1,712.0)	(781.0)
Secured Debt %	44.9	34.1	57.5
	(35.1)	(33.3)	(32.9)
Monthly Income ($)	3,466.0	3,167.0	3,816.0
	(1,874.0)	(1,690.0)	(2,014.0)
Monthly Inc. - Exp. ($)	221.9	-237.1	759.0
	(931.4)	(739.0)	(842.0)
Observations	1,200,123	647,028	553,095

Notes: This table reports means and (standard deviations) of case characteristics for Black filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table A3: Case Characteristics (Hispanic Filers)

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	8.3	8.9	6.1
1[Prior Filing] %	9.5	5.2	28.1
1[Non-Exempt Assets] %	22.4	4.5	99.4
1[Homeowner] %	50.8	44.1	79.6
1[Joint Filing] %	28.6	27.3	34.3
Assets ($000)	164.3	141.2	264.0
	(199.4)	(187.2)	(219.0)
Leverage %	693.6	790.4	277.0
	(1,585.0)	(1,702.0)	(794.0)
Secured Debt %	45.2	39.4	70.1
	(37.8)	(36.9)	(30.8)
Monthly Income ($)	3,934.0	3,615.0	5,304.0
	(2,191.0)	(2,000.0)	(2,435.0)
Monthly Inc. - Exp. ($)	-131.5	-368.2	888.0
	(1,051.0)	(883.0)	(1,106.0)
Observations	1,042,274	845,824	196,450

Notes: This table reports means and (standard deviations) of case characteristics for Hispanic filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table A4: Case Characteristics (Other-Race Filers)

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	5.2	5.3	4.8
1[Prior Filing] %	9.2	5.2	28.6
1[Non-Exempt Assets] %	20.8	4.8	99.4
1[Homeowner] %	49.9	44.2	78.0
1[Joint Filing] %	26.5	25.3	32.4
Assets ($000)	180.7	156.8	298.0
	(224.2)	(211.4)	(247.0)
Leverage %	919.0	1,039.0	329.0
	(1,951.0)	(2,077.0)	(950.0)
Secured Debt %	41.4	36.3	66.8
	(37.3)	(36.2)	(31.9)
Monthly Income ($)	3,954.0	3,628.0	5,553.0
	(2,382.0)	(2,191.0)	(2,619.0)
Monthly Inc. - Exp. ($)	-270.6	-501.5	862.0
	(1,178.0)	(1,031.0)	(1,197.0)
Observations	138,610	115,136	23,474

Notes: This table reports means and (standard deviations) of case characteristics for Other filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table A5: Case Characteristics (White Filers)

Variable	All Chapters	Chapter 7	Chapter 13
1[Pro Se] %	3.6	4.1	1.9
1[Prior Filing] %	11.7	6.3	29.7
1[Non-Exempt Assets] %	27.6	6.1	99.6
1[Homeowner] %	54.9	49.7	72.4
1[Joint Filing] %	32.0	30.1	38.2
Assets ($000)	148.2	132.1	202.0
	(172.9)	(165.1)	(187.0)
Leverage %	596.1	688.1	288.0
	(1,391.0)	(1,520.0)	(738.0)
Secured Debt %	45.3	40.3	62.2
	(35.1)	(34.7)	(31.1)
Monthly Income ($)	3,936.0	3,606.0	5,044.0
	(2,176.0)	(1,990.0)	(2,396.0)
Monthly Inc. - Exp. ($)	-45.2	-325.9	897.0
	(1,054.0)	(882.7)	(1,036.0)
Observations	4,358,323	3,357,503	1,000,820

Notes: This table reports means and (standard deviations) of case characteristics for White filers for all Chapters, Chapter 7, and Chapter 13 filers. 1[Pro Se] is an indicator for filing *pro se* (i.e. self-representing in court), 1[Prior Filing] indicates of the filer has a previous bankruptcy filing, and 1[Non-Exempt Assets] indicates whether the filer owns assets not protected under Chapter 7 rules. 1[Homeowner] and 1[Joint Filing] indicate if the filer owns their home or is filing joint with another individual, respectively. We report also assets (thousands of dollars), the leverage ratio in percentage terms (e.g., leverage of 600% corresponds to a leverage ratio of 6), the secured share of debt (%), monthly income, and the difference between income and reported expenses (monthly).

Table A6: Dismissal Disparities in Subsample with Known Trustee Race

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1[Minority Filer]	0.129***	0.034***	0.024***	0.003**				
	(0.014)	(0.004)	(0.004)	(0.001)				
1[Asian Filer]					0.081*	0.000	0.022**	0.006*
					(0.033)	(0.005)	(0.008)	(0.002)
1[Black Filer]					0.143***	0.051***	0.026***	0.003***
					(0.017)	(0.006)	(0.004)	(0.001)
1[Hispanic Filer]					0.098***	0.012**	0.024**	0.002
					(0.028)	(0.004)	(0.008)	(0.002)
1[Other Filer]					0.066***	0.007	0.015***	0.004**
					(0.017)	(0.004)	(0.004)	(0.001)
Trustee Fixed Effects		✓		✓		✓		✓
Year Fixed Effects		✓		✓		✓		✓
ZIP Fixed Effects		✓		✓		✓		✓
Judge Fixed Effects		✓		✓		✓		✓
Sample	Full	FJC	Full	FJC	Full	FJC	Full	FJC
FJC Controls		✓		✓		✓		✓
Chapter	13	13	7	7	13	13	7	7
Observations	2,509,065	1,193,261	6,474,364	3,109,563	2,509,065	1,193,261	6,474,364	3,109,563
R2	0.017	0.271	0.005	0.056	0.018	0.271	0.005	0.056

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. This table reproduces regressions from Table 4 but restricts the sample to only observations where trustee race is known. The outcome variable is dismissal and the explanatory variables are indicators for the race of the filer. Chapters 13 and 7 are estimated separately. Columns (1)-(4) regress a single indicator for the filer being of a minority race, while (5)-(8) use more granular filer race categories. Columns (1), (3), (5), and (7) use the full sample and Columns (2), (4), (6), and (8) use the matched FJC sample and the additional FJC controls in Table 2 (except for the income-expense gap), as well as fixed effects for trustee, year, ZIP code, and judge. Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table A7: Robustness of Dismissal Homophily to Highest-Quality Data Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
1[Minority Filer]	0.015**	0.015**	0.022***			
	(0.005)	(0.005)	(0.007)			
1[Minority Filer] × 1[White Trustee]	0.023***	0.023***	0.037***			
	(0.006)	(0.006)	(0.009)			
1[Asian Filer]				0.032**	0.032***	-0.093***
				(0.009)	(0.009)	(0.021)
1[Asian Filer] × 1[White Trustee]				-0.037***	-0.037***	0.073**
				(0.010)	(0.010)	(0.032)
1[Black Filer]				0.025***	0.025***	0.024***
				(0.005)	(0.005)	(0.007)
1[Black Filer] × 1[White Trustee]				0.031***	0.031***	0.043***
				(0.007)	(0.007)	(0.010)
1[Hispanic Filer]				-0.009	-0.009	-0.012
				(0.006)	(0.006)	(0.015)
1[Hispanic Filer] × 1[White Trustee]				0.024***	0.024***	0.028**
				(0.006)	(0.006)	(0.013)
1[Other Filer]				0.006	0.006	-0.030
				(0.005)	(0.005)	(0.021)
1[Other Filer] × 1[White Trustee]				0.000	0.001	0.045**
				(0.006)	(0.006)	(0.021)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓	✓	✓
Req. Complete Race Info		✓			✓	
Voter States Only			✓			✓
Observations	1,193,261	1,192,375	432,648	1,193,261	1,192,375	432,648
R2	0.271	0.271	0.251	0.271	0.271	0.251

Notes: The outcome variable is an indicator for whether the bankruptcy case is dismissed. The outcome variable is dismissal. The explanatory variables are indicators for the race of the filer and interactions of these with an indicator for if the trustee is White. The sample is Chapter 13 cases. Columns (1) and (4) reproduce our baseline homophily estimates. Columns (2) and (5) restrict to the subsample where none of the L2 observations matched to the filer have a missing race variable. Columns (3) and (6) restrict to states where voter registration data is used to measure race. All regressions include fixed effects for trustee, year, ZIP code, and judge, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.

Table A8: Share of Cases Dismissed by Dismissal Reason (%)

Chapter	Missed Payment	Missing File Info	Unpaid Filing Fee	Abuse	Other
All	50.3	5.1	5.2	0.4	38.9
7	0.2	16.8	15.1	4.1	63.9
13	54.8	4.0	4.4	0.1	36.7

Notes: This table reports the share dismissed cases by dismissal reason for all chapters, Chapter 7, and Chapter 13.

Table A9: Racial Homophily in Hypothetical Ch. 13 Plan Payments for Ch. 7 Filers

	(1)	(2)	(3)	(4)
1[Minority Filer]	-5.310	-0.585		
	(9.349)	(12.204)		
1[Minority Filer] × 1[White Trustee]		-4.766		
		(8.470)		
1[Asian Filer]			-29.046*	-16.079
			(14.329)	(28.128)
1[Asian Filer] × 1[White Trustee]				-13.813
				(23.108)
1[Black Filer]			-17.062**	-19.711*
			(5.686)	(9.723)
1[Black Filer] × 1[White Trustee]				2.980
				(7.747)
1[Hispanic Filer]			-15.806	27.092*
			(13.312)	(12.294)
1[Hispanic Filer] × 1[White Trustee]				-12.076
				(8.769)
1[Other Filer]			-57.808***	-39.246***
			(9.844)	(8.298)
1[Other Filer] × 1[White Trustee]				-19.981*
				(7.812)
Year Fixed Effects	✓	✓	✓	✓
ZIP Fixed Effects	✓	✓	✓	✓
Judge Fixed Effects	✓	✓	✓	✓
Trustee Fixed Effects	✓	✓	✓	✓
FJC Controls	✓	✓	✓	✓
Observations	3,109,563	3,109,563	3,109,563	3,109,563
R^2	0.193	0.193	0.193	0.193

Notes: The outcome variable is the hypothetical Chapter 13 monthly plan payment in dollars for Chapter 7 filers. The explanatory variables are indicators for the race of the filer and interactions of these with an indicator for if the trustee is White. Columns (1) and (3) describe racial disparities while Columns (2) and (4) include interactions to measure homophily. Columns (1) and (2) use only an indicator for the filer being a minority while Columns (3) and (4) use more granular filer race categories. All regressions contain year, ZIP code, judge, and trustee fixed effects, and the additional FJC controls in Table 2 (except for the income-expense gap). Standard errors are clustered at the district level. Statistical significance: 0.1+, 0.05*, 0.01**, 0.001***.