Racial Disparities and Bias in Consumer Bankruptcy *

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Abstract

We document substantial racial disparities in consumer bankruptcy outcomes and investigate the role of racial bias in contributing to these disparities. Using data on the near universe of US bankruptcy cases and self-reported and manually-identified measures of race, we show that minority filers are unconditionally 12.7 and 2.3 percentage points more likely to have their bankruptcy cases dismissed without debt relief in Chapters 13 and 7, respectively. We uncover strong evidence of racial homophily: in Chapter 13, where trustees have more discretion, minority filers are 2.3 percentage points more likely to be dismissed when randomly assigned to a White bankruptcy trustee than to a minority trustee. Black and Hispanic Chapter 13 filers are the most negatively affected by homophily. To interpret our findings, we develop a general decision model and new identification results relating homophily to bias. Our homophily approach is particularly useful in settings where traditional outcome tests for bias are not feasible because the decision-maker's objective is not well defined or decision-relevant outcomes or risk factors are unobserved. Applying this framework to our homophily estimate implies that at least 15% of the unconditional Chapter 13 dismissal gap and 53% of the conditional dismissal gap for minority filers is due to either taste-based or inaccurate statistical racial discrimination.

Keywords: consumer bankruptcy, racial disparities, racial bias, homophily, implicit bias
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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 race (for filers). 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* between bankruptcy filers and legal decision-makers can both signal the presence of racial bias and can quantify the share of observed disparities due to racial bias.[2] As we discuss below, our framework for detecting and measuring bias 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).[3] Compared to White filers, minority Chapter 13 and 7 filers are, respectively, 12.7 percentage points (pp) and 2.3 pp unconditionally more likely to have their cases dismissed. 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, these non-zero estimates indicate 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

[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] We use the term homophily to refer to differences in the treatment of filers when the filer and the legal decision-maker are of the same versus different minority status.

[3] As we discuss below, dismissal has negative causal effects on several important financial and real outcomes.

these two forms of bias.

To empirically illustrate the underlying 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 homophily 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. Further, we show that homophily is larger for less experienced trustees, when caseloads are high, and in counties where White residents have more implicit bias. 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.

We begin by assembling 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 self-reported 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]

We then document racial disparities in dismissal rates. Unconditionally, minority Chapter 13 filers are 12.7 pp (22%) more likely to have their case dismissed without debt relief. Disparities are largest for Black (13.4 pp) and Hispanic (11.7 pp) filers. In Chapter 7, the unconditional disparity is 2.3 pp (85%) for minority filers, and is again largest for Black and Hispanic filers (2.6 and 2.3 pp, respectively). After controlling for observable case characteristics, such as ZIP code, income, and filing pro se (without an attorney), the disparities for minorities decrease to 3.6 pp (6%) for Chapter 13 and 0.3 pp (11%) for Chapter 7.

To assess the role of bias among legal decision-makers (trustees and judges) we examine homophily—the extent to which racial disparities in dismissal change with the race of the decision-maker (DM). To guide the interpretation of our empirical homophily estimates, we develop a general decision model and econometric results relating homophily to bias. We then formalize conditions that are necessary and sufficient for homophily to identify the relative difference in racial bias across DMs of different races, yielding a test for the presence of bias. We present additional conditions that allow us to obtain a sharp lower bound for the share of the overall disparity attributable to bias.

Our homophily framework is well-suited to detect bias in consumer bankruptcy dismissal decisions. Unlike bail decisions, for example, where judges have a clear objective to minimize pre-trial misconduct, the dismissal decision entails optimizing over multiple competing objectives, some of which are difficult to measure. For example, statutory duties of a trustee include,

[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).

among others, collecting money, verifying evidence, identifying domestic support obligations, ensuring filers follow their filed repayment plans, and opposing the discharge of the debt if abuse is presumed (11 USC § 1302). Which of these many duties should be the primary objective of the court is not determined by statute.[5] As part of carrying out these duties, 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, and determining whether filer hardship is "beyond their control." Because these outcomes are difficult to observe and can feature trade-offs, it is difficult to apply an outcome test for bias in bankruptcy.

A key advantage of our homophily approach is that it does not require that the researcher observes (or even knows) the outcomes over which potentially biased DMs optimize. Rather, the necessary data are the race of the DMs and their decisions. This means that our homophily test may be used in situations where a Becker-style outcome test (e.g., Becker, 1957, 1993; Arnold et al., 2018) is infeasible due to a lack of outcome data, DM objectives being abstract or complex, or DMs not having full information. The generality of our framework makes it readily usable to study bias in other contexts, such as lending, real estate transactions, jury convictions, or hiring.

Our homophily estimand corresponds to the difference in disparities across White and minority DMs. Under an assumption that we term "parallel disparities," we show that the homophily estimand identifies the relative difference in bias between White and minority DMs. In the bankruptcy context, parallel disparities requires that the differences in dismissal rates between minority and White filers assigned to White trustees would be the same as the differences 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 homophily 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, homophily instead reflects only taste-based and inaccurate statistical discrimination. If this assumption holds, the homophily 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

[5] Consistent with this diversity, anecdotal conversations with trustees and judges did not produce an informal consensus of court objectives.

would be if filers could manipulate their assignment to trustees. 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 homophily estimate is unchanged after including these interactions, suggesting that such heterogeneity is not confounding the homophily 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. Our main finding is that when minority Chapter 13 filers are randomly assigned to a White trustee, their likelihood of dismissal rises 2.3 pp. The effect of facing a White trustee is largest for Black (3.1 pp) and Hispanic (2.4 pp) filers. Under our framework's assumptions, the non-zero homophily we find for Chapter 13 indicates that bias among 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 homophily 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 homophily effect in Chapter 7, consistent with our discussion below of the more limited scope for trustee bias to impact Chapter 7 cases.

Our principal focus is to examine homophily between the bankruptcy filer and trustee. Our focus on trustees is motivated by the fact that 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 econometric framework. We again 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.

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

[6] Social psychology research on implicit bias in the US suggests this assumption may be 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). In line with this assumption, we also later 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.

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 homophily 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 mostly 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 to allow the filer time 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 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.[7] However, in a mediation analysis, we show that these larger payments do not explain dismissal homophily, leading us to conclude that trustee discretion in responding to nonpayment is a key reason for dismissal homophily.

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.[8] This is made possible by linking bankruptcy cases to self-reported filer race. 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), including finding evidence of attorneys steering Black filers to Chapter 13 (Braucher et al., 2012).[9] A key difference in our paper is that we focus on documenting and explaining *within*-chapter 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

[7] 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.

[8] 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).

[9] 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.

quantifying racial bias. Our homophily approach may be used to complement a Becker-style outcome test (e.g., Becker, 1957, 1993; Knowles et al., 2001; Arnold et al., 2018; Canay et al., 2023; Hull, 2021) or in situations when such a test is infeasible due to unobserved or abstract DM objectives—see Section 5.3 for further discussion. Homophily between agents and DMs has been widely-studied in many contexts, such as policing (Anwar and Fang, 2006; Ba et al., 2021), jury convictions (Anwar et al., 2012; Alesina and La Ferrara, 2014), and mortgage lending (Frame et al., 2023). However, there is limited prior econometric and theoretical work guiding the interpretation of homophily. Notable exceptions are Anwar and Fang (2006) and Alesina and La Ferrara (2014), which propose tests for bias related to homophily. 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 and *quantifying* the influence of taste-based and inaccurate statistical bias. We compare our frameworks in detail in Section 5.3.

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 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 homophily 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.[10] 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 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 and higher mortality rates (Dobbie and Song, 2015; Dobbie et al., 2017). Hamdi et al. (2024) find that the children of bankruptcy filers whose debts 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 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.[11] 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

Below we describe the bankruptcy process, highlighting the role played by trustees and judges and the relevant differences between Chapter 7 and Chapter 13. 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.[12] 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 meet-

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

[11] 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.

[12] 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.

ing 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.[13]

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.[14] 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 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.

Differences Between Chapters 7 and 13. Under Chapter 7, debtors receive forgiveness of all of their debts after forfeiting all non-exempt assets.[15] 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.[16] 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.[17] 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. Trustee 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

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

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

[15] 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.

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

[17] 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.

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 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 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 as compensation (28 USC § 586), giving them a financial incentive to increase payouts to creditors.

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 may 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.[18]

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 bias estimates of racial disparities (Greenwald et al., 2024). Instead, we use self-reported and manually-identified measures of race. To obtain these data for filers, we use the filer's name and residential address to merge

[18] 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.

bankruptcy data with self-reported race from L2.[19] L2 procures this information from sources such as voter and product registration records and surveys. In some cases, L2 may impute race using a proprietary algorithm. To mitigate possible measurement error from imputed race, we later 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 self-reported race via L2. Instead, we manually infer their race from publicly available images.[20] To the extent that this approach may occasionally misclassify the race of a trustee or judge, we note that any such measurement error should bias our results away from finding homophily, making our estimates, if anything, conservative.[21]

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.[22] 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 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) and is the modal outcome for Chapter 13 cases (61% of cases). As discussed above, among other differences, Chapter 13 cases involve payment plans and can be dismissed when debtors fail to make the corresponding payments.

Table 2 describes other characteristics of bankruptcy filers. 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.

[19] 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).

[20] 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.

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

[22] 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, not the original chapter they filed under.

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 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) found evidence of attorney steering of Black filers toward Chapter 13 in an audit study. The experimenters presented attorneys with bankruptcy schedules and randomly varied the names and churches of the filers to signal the race of the filer. Attorneys were 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.[23] 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 the Chapter 13 disparity because Black filers 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

[23] 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.

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 self-reported filer race is Black, Hispanic, 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.[24]

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 a variety of 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; Bohren et al., 2022) 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 discrimination, and taste-based discrimination.[25] Our main theoretical results illustrate how *differences* in racial disparities among 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 this choice and can be extended to accommodate a larger, finite number of racial identities as well as vectors of non-race characteristics. Additionally, without loss of generality, we could alternatively interpret X as a noisily-measured signal of a non-race characteristic (but for simplicity, below we do not explicitly model measurement error in X).

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 $Y_D = Y_0 + (Y_1 - Y_0)D$.

[24] Appendix Table A2 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.

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

We allow this outcome to be a vector containing multiple "sub-outcomes," that is, Y_D is a $k \times 1$ vector with $k \geq 1$. In the context of bankruptcy, sub-outcomes could include whether the filer receives debt relief, whether the filer committed fraud in the bankruptcy process, whether the filer makes the required bankruptcy payments, or the compensation received by the DM. We use lower case letters (i, r_i, f, r_f, x) to refer to specific parties and their characteristics. 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 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 do not explicitly model other non-race characteristics that are unobserved by the DM and influence outcomes. Rather, we capture this in a simplified way by allowing the case outcome Y_d to be uncertain.

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 in hand, 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. Our definition of prediction error mirrors that of Canay, Mogstad and Mountjoy (2023), defined in the context of our generalized decision problem.

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 differential ability among DMs in extracting predictive information from filers (i.e., "screening" ability).[26] 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. This could lead to higher prediction error 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. The two expectations both use the same, objective conditional distributions; this entails conditioning on the filer's actual race r_f. Both terms also have same non-race characteristic x parameterizing the utility function. A nonzero β therefore arises when there exists some outcomes Y_d where the DM's payoff varies with the race of the filer, for example, if a DM dislikes missed payments more when the filer is White.

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

[26] We do not explicitly model belief formation. However, our framework 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.

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, DMs dislike bankruptcy fraud and the propensity to commit fraud is correlated with race.

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

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

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, decreasing her preference for dismissal. A positive β (taste-based discrimination) 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. Whether a DM's biases *alter* her decision when the filer's race changes is central in this definition. Note that a DM may still have differing payoffs when dismissing two otherwise identical White and minority debtors, but that need not alter their decision. Such a case, under our definition, would not be *exhibiting* total bias. This notion of total bias is similar to the "local bias" of Canay, Mogstad and Mountjoy (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 definitions of bias are also similar to that of Hull (2021) and Lodermeier (2025) in that they relate to the *decision* made by the DM (as opposed to the outcomes over which the DM optimizes).

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

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

The $\widetilde{D}$ 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.

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. Inaccurate statistical discrimination is inefficient—by definition, DMs would make different choices if they had accurate beliefs. And if the social welfare function does not allow for racial animus in preferences, then taste-based discrimination is similarly inefficient. In this sense, eliminating $\beta\mu$-racial bias is a "free lunch" in that it can only increase social welfare. Accurate statistical discrimination is different because it entails trade-offs. Consider an example from another setting: if 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.

It is also useful to differentiate between types of bias because the effectiveness of policies aimed at reducing them can vary with the bias source. 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.[27] If discrimination stems from taste-based preferences, interventions like implicit bias training or blind review processes, 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:

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

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 the $\widetilde{\beta\mu}$ term 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 Homophily

How can homophily help researchers detect and quantify bias? Homophily is a widely-studied phenomenon in a variety of settings and is often interpreted to be informative about bias.[28] The econometric framework we introduce below illustrates assumptions that make it possible to draw such conclusions from observational data.

In what follows, we assume that the researcher observes the filer's and the DM's races and the dismissal decisions $\{R_F, R_I, D\}$. Notably, 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

[27] 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).

[28] See, for example, police stops and searches (Anwar and Fang, 2006), jury convictions (Anwar et al., 2012), and mortgage lending (Frame et al., 2023).

to both the DM and researcher, as the framework below can be readily modified to condition on additional observables.

Identification Challenges. We highlight two distinct identification challenges. The first is that simply comparing differences in dismissal rates across filer outcomes does not 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.

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 and Identifying Assumptions

Fortunately, homophily can help researchers learn about either total racial bias (δ) or $\beta\mu$-racial bias ($\delta^{\beta\mu}$). We start by making minimal assumptions and then show how stronger assumptions can help researchers obtain sharper conclusions about the presence and size 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 homophily estimates. We also suggest two tests that can help falsify these assumptions.

The Homophily Estimand. Let τ denote the homophily estimand:

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

The homophily estimand describes 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 homophily estimand is

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

Identifying Total Racial Bias under Parallel Disparities. Our first results highlight a necessary and sufficient condition for the homophily 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.

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

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.[29] 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 (though 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 results only in level differences in outcomes and not differences

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

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 are not also resulting 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").

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

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

Proof. Rewriting the homophily 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 homophily estimand,

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

□

Intuitively, under parallel disparities, homophily overcomes the initial selection problem by differencing out the impact of non-race characteristics on decisions. With only the parallel disparities assumption, the homophily estimand could reflect either accurate statistical, inaccurate statistical, or taste-based discrimination. We next introduce a second assumption, "parallel accurate statistical discrimination" that further sharpens the interpretation of the homophily estimand.

Assumption 2: Parallel Accurate Statistical Discrimination (PASD).

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

Assumption 2 (PASD) states that, on average, the effect of changing minority filers' race on the dismissal decision that would arise in the absence of prediction error and taste-based discrimination is the same across minority and White DMs. In other words, if minority and White DMs make decisions based purely on accurate statistical discrimination, the effect of the filer's race on dismissal would be similar across both groups of DMs. Recalling the definition of $\widetilde{D}(i, r_f, x) = \mathbf{1}\{E[\Delta(i, w, x)|r_f, x]\}$ 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. As such, it is also possible to test for failure of this assumption with the same interactions test. If DMs react differently to non-race characteristics, this suggests that there are systematic differences in how White and minority DMs make decisions, which would complicate separating differences in decisions driven by race versus non-race factors. Additionally, if the homophily estimate changes after including these interactions, this would suggest that the homophily estimate is conflating $\beta\mu$-racial bias with these systematic differences in decision-making.

The additional assumption of PASD implies that the homophily estimand identifies the average difference in $\beta\mu$-racial discrimination between minority and White DMs. Proposition 2 formalizes this result.

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 homophily 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 homophily 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

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

□

5.2.2 Testing for the Presence of Bias

Under Assumptions 1 and 2, the homophily 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 1 *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 $H_0 : \tau = 0$ (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 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 important feature of this test is that it does not indicate *who* is biased. If positive homophily is found, this could be due to either anti-minority bias among White DMs or anti-White bias among minority DMs. Additional assumptions are necessary in order for us to attribute bias to a specific group of DMs.

5.2.3 Quantifying the Impact of Bias

Without further assumptions, the homophily estimate can be used to partially identify average racial bias. However, the identified set for average racial bias can be further narrowed under additional assumptions, potentially yielding tight and informative lower bounds on the impact of racial bias on decisions. Below, 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.

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 $\delta^{\beta\mu} \in [(1-p)\tau, 1 - p\tau]$.*

Proposition 3 shows how increasingly strong assumptions allow researchers to obtain stricter lower bounds on the role of $\beta\mu$-racial bias in influencing dismissals ($\delta^{\beta\mu}$). 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 homophily estimand: $(1-p)\tau$. Another way to characterize the relative importance of $\beta\mu$-racial bias is to divide the identified set for $\delta^{\beta\mu}$ by the observed disparity $E[D|r_f = m] - E[D|r_f = w]$, which characterizes the share of the observed disparity due 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. It also provides a menu of implications for the various sets of assumptions.

5.3 Comparison with Related Tests for Bias

Here, we contrast our approach with other well-known methods for detecting and quantifying bias. One approach that has received significant attention in recent years is known as the outcome test (Becker, 1957, 1993; Canay et al., 2023; Hull, 2021). The key idea behind the outcome test is that bias can result in DMs applying different standards across groups, leading to differences in equilibrium outcomes across groups on the margin. For example, higher ex-post loan profitability for marginally approved borrowers from discriminated groups indicates differential ex-ante lending standards.[30]

Implementing an outcome test requires that the researcher observes the outcome over which the DM is optimizing. They must have a known objective function and the outcome must be measurable. A related concern with outcome tests, known as the inframarginality problem, is that even group-identity-blind decision-making can result in differences in marginal outcomes across groups if DMs do not have full information or ignore some information (Simoiu et al., 2017). These requirements generally make an outcome test infeasible in settings like bankruptcy. Unlike bail (Arnold et al., 2018) and lending (Dobbie et al., 2021) decisions, the objective function of trustees (and judges) is complex (i.e., a function of many, possibly interacting outcomes) and potentially abstract (i.e., difficult to measure). For example, trustees may aim to maximize payouts to creditors (theoretically measurable), minimize fraud (abstract—it depends on assessments of filer intentions), avoid approving infeasible plans (abstract), allow reasonable time to cure a missed payment (abstract), and setting necessary expenses to a reasonable level (abstract). These challenges motivate our focus on homophily as a means to learn about bias.

The homophily approach has both advantages and disadvantages in comparison to the outcome test. The primary advantage is that homophily does not require that the researcher observes (or knows) the DM's objective function. Many economic and legal decisions of interest have complex or abstract objectives. Homophily can be used either as a complement to an outcome test or in place of an outcome test when it is not feasible due to complexity or data limitations. A second strength is that our framework suggests two tests that can be used to falsify assumptions that impact whether the homophily estimand detects $\beta\mu$-racial bias. 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 framework 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

[30] To overcome the empirical challenge of identifying people at the margin, Arnold et al. (2018) exploit the LATE property of IV (and random assignment of DMs of differing leniency) to estimate differences in outcomes (pre-trial misconduct) for marginal Black and White defendants.

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 also has several econometric innovations relative to Anwar and Fang (2006). 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).[31] Our framework also differs from Anwar and Fang (2006) and Alesina and La Ferrara (2014) in that we show how homophily can *quantify* bias by partially identifying the net share of dismissals due to bias, rather than only detect the presence of bias. Lastly, our framework also clarifies threats to identification and proposes falsification tests.

5.4 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. We discuss these extensions in detail in Appendix A and summarize them briefly here.

Noisy observation of x. We allow the DM to only observe a noisy signal related to the non-race characteristic x (rather than observing x directly). If DMs of different races tend to receive noisier signals or differ in their beliefs about how the signal predicts x, these can be sources of inaccurate statistical discrimination and would be reflected in the homophily estimate.

Dynamics and DM Learning. If the DM faces a sequence of cases, the DM can learn over time about how filer race and non-race characteristics predict outcomes Y. Learning can lead to a reduction in inaccurate statistical discrimination over the DM's career.

Allowing for Additional DM Actions. We allow the DM to take multiple other actions during a first stage before choosing whether to dismiss in a second stage. A first stage action could include

[31] 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, 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 homophily estimand would still be positive and hence reject the null of no bias.

choosing how much effort to exert to gather and process information. An interesting feature of this extension is that biases can alter behavior in the first stage and subsequently amplify or attenuate bias in the decision. For example, suppose a trustee dislikes it more when minority filers commit fraud (taste-based bias). This could motivate her to exert more effort to collect information on minority filers in stage 1. This additional information could enable her to be relatively more successful in detecting fraud among minorities, which could result in dismissal disparities in stage 2. This would be reflected in our homophily estimand. Overall, the interpretation of the homophily estimand is little-changed. When multiple actions are present, the extent to which biases motivate different behavior and ultimately different decisions would be reflected in homophily.

Two-Tier Decision-Making. We reformulate the dismissal decision as having two "tiers." First, a one party makes a recommendation $R \in \{0,1\}$ (the trustee) and second party can accept or deviate from their recommendation when choosing the decision D. Under our parallel disparities assumption, homophily still identifies the influence of bias from the trustee. One change is that this bias can embody both a direct effect from bias in the trustee's recommendation as well as indirect effects from how the judge reacts to the trustee and their recommendation. For example, a judge may perceive the social costs of engaging in taste-based discrimination as smaller when they perceive White trustees as engaging in discrimination in their recommendations. Alternatively, judges may instead attempt to undo perceived discrimination. What homophily captures is differences in the net effect of trustees' discrimination (net of reactions from judges). This extension highlights how a multi-tier decision-making environment can amplify or attenuate bias among decision-makers.

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 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 the trustee.[32] 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 homophily estimand introduced in Section 5.2.1. Recall that the homophily es-

[32]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.

timand 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 6.2 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 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 that tend to lead to a higher dismissal rate. In support of this assumption, we also verify in Section 6.2 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 homophily estimate (τ), 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 homophily estimate of -3.7 pp for Asian filers.[33] For Chapter 7,

[33] Although we caveat that Asian Chapter 13 filers have a much smaller sample size (11,418 versus 388,206 for Black

we continue to find no evidence of homophily, obtaining precise null estimates in Column (4).

Relating Homophily to Bias. To interpret the implications of our homophily estimates for racial bias, we apply the framework introduced in Section 5. Under parallel disparities (Assumption 1), the homophily estimand identifies the average difference in total racial bias between White and minority trustees. This assumption states that if, counterfactually, minority filers were instead White, the minority-White disparity in dismissals would be the same for filers assigned to either White or minority trustees. The random assignment of filers to trustees makes this plausible, as White and minority trustees do not face systematically different populations of filers.

Recall that total bias includes not only taste-based and inaccurate statistical bias ($\beta\mu$-racial bias) but also accurate statistical discrimination. If parallel accurate statistical discrimination (PASD, Assumption 2) also holds, accurate statistical discrimination is similar among White and minority trustees on average. This could be violated if, for example, preferences varied systematically with trustee race. For instance, if White trustees prefer to dismiss filers with low education levels, and education is correlated with race, then accurate statistical discrimination could differ by trustee race and Assumption 2 would be violated. We provide empirical tests supporting these identifying assumptions in Section 6.2. If both Assumptions 1 and 2 hold, our homophily estimates imply specifically that $\beta\mu$-racial bias among trustees is contributing to disparities in Chapter 13 dismissal rates.

The lack of homophily within Chapter 7 implies that we fail to reject the null hypothesis of no racial bias for Chapter 7. This is expected, since dismissal is much less common in Chapter 7 and trustees have much less influence over the Chapter 7 process. We note, however, that, as discussed in Section 5, our test is under-powered in that it may fail to reject when the null hypothesis is false (i.e., it may fail to detect bias). This is because homophily identifies *relative* bias (i.e., *differences* in bias between decision-makers). Hence, if there is bias but it is similar among White and minority trustees, homophily could equal zero. In contrast, our test does have exact size; rejecting the null hypothesis occurs only if bias is present.

Bounding the Influence of Bias. Without further assumptions, we cannot sharply quantify the influence of anti-minority/pro-White bias among White trustees versus anti-White/pro-minority bias among minority trustees.[34] Section 5.2.1 presents two additional assumptions that make it possible for homophily to partially identify the share of the overall disparity attributable to bias among White trustees. We derive this share under Assumption 4, which states that on average

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.

[34]Note that one cannot meaningfully differentiate between anti-minority and pro-White bias among White decision-makers (and vice versa for minority decision-makers) in settings like consumer bankruptcy. This is because it is not possible to objectively classify bankruptcy dismissal decisions as correct or incorrect. As a result, we cannot say whether minorities are being incorrectly dismissed or if there is failure to dismiss White filers.

minority decision-makers are weakly biased against minority filers/in favor of non-minority filers. Note that this assumption does not require that this property of bias applies to all minority 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.[35]

Under Assumptions 1–2 and 4, the amount of the dismissal disparity due to $\beta\mu$-racial bias is partially identified as $[(1-p)\tau, 1-p\tau]$ where p is the fraction of minority trustees (15.8%) and τ is the homophily estimate. For Chapter 13, our homophily estimate of $\tau = 2.3$ pp implies lower and upper bounds of 1.9 and 99.6 pp for the amount of the disparity due to anti-minority/pro-White bias. While the upper bound is less informative, 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 $\beta\mu$-racial bias among White trustees. For Black and Hispanic filers, whose homophily 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, it's at least 17% of their unconditional 11.7 pp disparity, and we can't reject that bias explains all of the conditional disparity for Hispanic filers. These results provide strong evidence that $\beta\mu$-racial bias is an important determinant of racial disparities in dismissal rates for Chapter 13.

Bankruptcy Judges. To gauge the role of judges' racial bias in shaping bankruptcy dismissals, we also examine homophily between filers and judges. Most similarly to Chapter 7, bankruptcy judges (in both Chapters) are also randomly assigned to cases. We re-estimate Equation (5), but replace $1[\text{White Trustee}_k]$ with $1[\text{White Judge}_j]$. 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 homophily 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: 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, 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

[35] See, for example, Nosek et al. (2002); Livingston (2002); 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.

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. Given the key role of the trustee in administering bankruptcy cases, our remaining empirical analyses focus on trustees.

6.1 Differences between Chapters 13 and 7

Because homophily arises in Chapter 13 and not Chapter 7, comparing the features of these chapters can uncover 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. 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, there is generally a marginal cost to trustees of pursuing dismissal in Chapter 7 but not Chapter 13. To file a motion, Chapter 7 trustees would typically have to hire an attorney on an hourly basis to take this action. In contrast, Chapter 13 trustees typically have salaried staff attorneys that handle dismissals. A 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.

Third, the total compensation of Chapter 13 trustees is more strongly linked to case outcomes and depends on the size and completion of Chapter 13 plan payments. This heightened financial incentive could enable taste-based bias to have more influence over Chapter 13 dismissals. To see this, suppose trustees trade off maximizing their compensation (by setting a high payment plan, for example) against altruistic utility when filers are able to complete their payment plans and exit bankruptcy with a fresh start. A trustee could almost assure successful completion of a repayment plan by setting a low monthly payment, but this harms his or her compensation. If a trustee has taste-based preferences where they derive more utility from White filers avoiding dismissal, they might forego some compensation in those cases while setting higher required payments for minority filers. Meanwhile, in the vast majority of Chapter 7 cases trustee compensation is a simple flat fee, so this dynamic is not at play.

6.2 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 homophily 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 estimation 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 homophily that we estimate is due to White trustees reacting differently to non-race characteristics that are correlated with race, rather than to race itself. If this was the case, the homophily 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 homophily 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. Notably, our estimates of racial homophily remain unchanged. We find that 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 homophily 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 homophily 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 A3, we verify that our homophily 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 homophily estimates and confidence intervals are unchanged.

To further assess the possibility that measurement error in filer race could be biasing our results, we re-estimate our Chapter 13 homophily results on subgroups with less measurement error. Appendix Table A1 reports these results. Columns (1) and (3) reproduce our main homophily estimates from Table 5 for reference. Columns (2) and (5) restrict to observations where *all* L2 matches linked to the filer have non-missing race.[36] 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 may sometimes impute race when a self-reported measure is not available. Our homophily results are robust to focusing on this subset of states.

Our last test checks for possible sample selection related to the availability of trustee race data. Appendix Table A2 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 homophily and disparity estimates are likely nationally representative.

7 Mechanisms

Our homophily 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

[36] 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.

Chapter 13 plans and show that most of the racial disparity in dismissal appears to be due to differences 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 homophily dismissal 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 homophily 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.[37] 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 A2 demonstrates that the timing of homophily in dismissal for nonpayment 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 homophily 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 homophily. 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.

[37] See Appendix Table A9 for the distribution of dismissal reasons by chapter.

Homophily in Required Plan Payments. Given the random assignment of trustees, nonpayment dismissal homophily could arise either because White trustees set higher monthly payments for minority filers or because White trustees are less lenient when a minority filer misses a payment. We examine the role of plan payments by testing for homophily in payment amounts.

Under Chapter 13, filers are required to pay all of their disposable income to the trustee each month for a five-year period. 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 the income-expense gap and test whether this is higher when a minority filer is paired with a White trustee.[38]

In Column (1) of Table 8, we see in 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 minority filers 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 homophily 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 homophily 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 A3 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-

[38]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 homophily 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 homophily estimate for dismissal for missed payments. If monthly payments were the mediating factor causing homophily in dismissal, conditioning on monthly payments should reduce the homophily coefficient.

Given that controlling for monthly payments has no effect on dismissal homophily, racial homophily is likely arising from how White trustees react when a minority filer misses a payment rather than making minorities 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 (potentially with a petition to dismiss the case) or to grant a grace period or even request a modification of the repayment plan. Our data do not contain granular information on whether trustees take these actions, making it impossible for us to directly test if White trustees are more lenient when a White filer misses a payment. But, the balance of filer characteristics across trustee race, the timing of homophily, the reason for case dismissal, and the fact that plan payments do not attenuate the homophily coefficient all suggest that this discretion is likely an important factor in the overall racial disparities we observe in bankruptcy dismissals.

7.2 Trustee Heterogeneity

Are certain types of trustees more likely to exhibit racial homophily? To assess what kind of racial bias underlies the homophily estimates and what features of the bankruptcy process enable this bias to affect cases, we test for trustee heterogeneity. To this end, we examine how homophily varies with trustee experience and workload. To do so, we re-estimate homophily (Equation 5) within separate trustee subgroups in Table 9. Columns (1) and (2) partition the sample based on a proxy for the trustee's experience: the number of years that the trustee has worked as a trustee. Among trustees with above-median years of experience (high experience), the average homophily estimate for White trustees facing minority filers is 2.1 pp, compared to our pooled estimate of 2.3 pp. Low-experience trustees have a homophily estimate of 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.

7.3 Association with Implicit Bias

We next provide additional evidence consistent with dismissal homophily arising from racial bias, using data on measures of implicit bias. There is substantial scope for implicit bias to be a likely type of bias to affect trustee decision-making given that trustees exercise their discretion to make quick decisions with competing objectives and only moderate amounts of information. Our findings suggest that the racial bias is originating from anti-minority bias from White trustees rather than (1) anti-White bias among Black trustees nor (2) anti-White bias among Black filers.

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). 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 IAT sample spans 2010-2020, and we aggregate IAT scores 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. We focus on Black and White filers (and residents) because IAT data is 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.

Figure 5 displays binscatters relating county-level differences in dismissal rates for Black and White filers to county-level IAT scores. We find a strong, positive association between anti-Black implicit bias among White residents and the dismissal disparity for Chapter 13, consistent with the homophily 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 2 percentage point larger racial disparity in Chapter 13 dismissal rates. By contrast, in the middle panel of Figure 5, we find nearly a perfectly flat relationship between White residents' implicit bias and Chapter 7 dismissal disparities, 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 panel of Figure 5, we relate the Chapter 13 Black-White dismissal gap to each county's average *Black* resident's anti-White implicit bias. Here, 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 asserts that minority trustees are either neutral or biased against minority filers. Recall that this assumption is what allows us to quantify the share of the disparity due to bias. The lack of any 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 panel also helps us consider whether bias from *filers* could be affecting case outcomes. It is possible that minority filers behave differently when assigned a White trustee if they perceive that trustee to be biased against them.[39] For example, if Black filers anticipate discrimination, this may affect their effort or cooperation with the trustee. If such behavior is present and related to anti-White/pro-minority bias among filers, we would expect areas with higher implicit bias among Black filers 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 Figure 5 are consistent with bias by White trustees—not Black trustees or Black filers—driving dismissal disparities and our homophily results.

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 that formalize necessary and sufficient conditions for homophily to detect and quantify the influence of bias. Intuitively, the difference in disparities across groups of decision-makers is informative about relative differences in bias. Our identification results can be applied to study bias in a variety of 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.

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

We find substantial homophily 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. 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, considering both 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.

References

Albanesi, Stefania and Jaromir Nosal, "Insolvency After the 2005 Bankruptcy Reform," 2018.

Alesina, Alberto and Eliana La Ferrara, "A test of racial bias in capital sentencing," *American Economic Review*, 2014, *104* (11), 3397–3433.

Allcott, Hunt, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow, "The welfare effects of social media," *American Economic Review*, 2020, *110* (3), 629–676.

Anwar, Shamena and Hanming Fang, "An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence," *American Economic Review*, 2006, *96* (1), 127–151.

—, Patrick Bayer, and Randi Hjalmarsson, "The impact of jury race in criminal trials," *The Quarterly Journal of Economics*, 2012, *127* (2), 1017–1055.

—, —, and —, "A jury of her peers: The impact of the first female jurors on criminal convictions," *The Economic Journal*, 2019, *129* (618), 603–650.

—, —, and —, "Politics in the courtroom: Political ideology and jury decision making," *Journal of the European Economic Association*, 2019, *17* (3), 834–875.

Argyle, Bronson, Benjamin Iverson, Taylor D Nadauld, and Christopher Palmer, "Personal bankruptcy and the accumulation of shadow debt," 2021. NBER Working Paper No. 28901.

Arnold, David, Will Dobbie, and Crystal S Yang, "Racial bias in bail decisions," *The Quarterly Journal of Economics*, 2018, *133* (4), 1885–1932.

—, —, and Peter Hull, "Measuring racial discrimination in algorithms," in "AEA Papers and Proceedings," Vol. 111 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 2021, pp. 49–54.

—, —, and —, "Measuring Racial Discrimination in Bail Decisions," *American Economic Review*, September 2022, *112* (9), 2992–3038.

—, Will S Dobbie, and Peter Hull, "Building Non-Discriminatory Algorithms in Selected Data," 2024. NBER Working Paper No. 32403.

Auclert, Adrien, Will S. Dobbie, and Paul Goldsmith-Pinkham, "Macroeconomic Effects of Debt Relief: Consumer Bankruptcy Protections in the Great Recession," 2019.

Ba, Bocar A, Dean Knox, Jonathan Mummolo, and Roman Rivera, "The role of officer race and gender in police-civilian interactions in Chicago," *Science*, 2021, *371* (6530), 696–702.

Banse, Rainer, Jan Seise, and Nikola Zerbes, "Implicit attitudes towards homosexuality: Reliability, validity, and controllability of the IAT," *Zeitschrift f"ur experimentelle Psychologie*, 2001, *48* (2), 145–160.

Baron, E Jason, Joseph J Doyle Jr, Natalia Emanuel, Peter Hull, and Joseph Ryan, "Discrimination in Multiphase Systems: Evidence from Child Protection," *The Quarterly Journal of Economics*, 2024, p. qjae007.

Bayer, Patrick, Fernando Ferreira, and Stephen L Ross, "What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders," *The Review of Financial Studies*, 2018, *31* (1), 175–205.

Becker, Gary S., *The Economics of Discrimination*, University of Chicago Press, 1957.

—, "Nobel Lecture: The Economic Way of Looking at Behavior," *Journal of Political Economy*, 1993, *101* (3), 385–409.

Bernstein, Shai, Emanuele Colonnelli, and Benjamin Iverson, "Asset allocation in bankruptcy," *The Journal of Finance*, 2019, *74* (1), 5–53.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination," *American Economic Review*, 2004, *94* (4), 991–1013.

Billings, Stephen B, Eric Chyn, and Kareem Haggag, "The long-run effects of school racial diversity on political identity," *American Economic Review: Insights*, 2021, *3* (3), 267–284.

— **, Noah Braun, Daniel B Jones, and Ying Shi**, "Disparate racial impacts of Shelby County v. Holder on voter turnout," *Journal of Public Economics*, 2024, *230*, 105047.

Blattner, Laura and Scott Nelson, "How Costly Is Noise? Data and Disparities in the US Mortgage Market," 2020.

Bohren, J. Aislinn, Kareem Haggag, Alex Imas, and Devin G. Pope, "Inaccurate Statistical Discrimination: An Identification Problem," *The Review of Economics and Statistics*, 09 2023, pp. 1–45.

Bohren, J Aislinn, Peter Hull, and Alex Imas, "Systemic discrimination: Theory and measurement," 2022.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Stereotypes," *Quarterly Journal of Economics*, 2016, *131*, 1753–1794.

Braucher, Jean, Dov Cohen, and Robert M Lawless, "Race, attorney influence, and bankruptcy chapter choice," *Journal of Empirical Legal Studies*, 2012, *9* (3), 393–429.

Bursztyn, Leonardo, Thomas Chaney, Tarek A. Hassan, and Aakaash Rao, "The Immigrant Next Door," *American Economic Review*, February 2024, *114* (2), 348–84.

Butler, Alexander W, Erik J Mayer, and James P Weston, "Racial disparities in the auto loan market," *The Review of Financial Studies*, 2023, *36* (1), 1–41.

Canay, Ivan A, Magne Mogstad, and Jack Mountjoy, "On the Use of Outcome Tests for Detecting Bias in Decision Making," *The Review of Economic Studies*, 08 2023, *91* (4), 2135–2167.

Chan, Alex, "Discrimination against doctors: A field experiment," 2024.

Chang, Tom and Antoinette Schoar, "Judge Specific Differences in Chapter 11 and Firm Outcomes," 2013. Working Paper.

Chatterjee, Satyajit, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull, "A quantitative theory of unsecured consumer credit with risk of default," *Econometrica*, 2007, *75* (6), 1525–1589.

Cook, Lisa D, Matt Marx, and Emmanuel Yimfor, "Funding black high-growth startups," 2022. NBER Working Paper No. 30682.

Dahl, Gordon B, Joseph Engelberg, Runjing Lu, and William Mullins, "Cross-State Strategic Voting," February 2023. NBER Working Paper No. 30972.

Dávila, Eduardo, "Using elasticities to derive optimal bankruptcy exemptions," *The Review of Economic Studies*, 2020, *87* (2), 870–913.

DeNicola, Louis, "How Much Does it Cost to File Bankruptcy?," https://www.experian.com/blogs/ask-experian/how-much-does-it-cost-to-file-bankruptcy/ 2024. Experian, Accessed: 2025-02-11.

Derenoncourt, Ellora, Chi Hyun Kim, Moritz Kuhn, and Moritz Schularick, "Wealth of two nations: The US racial wealth gap, 1860–2020," *The Quarterly Journal of Economics*, 2024, *139* (2), 693–750.

Diamond, Rebecca and William F Diamond, "Racial differences in the total rate of return on owner-occupied housing," 2024. NBER Working Paper No. 32916.

Dobbie, Will and Jae Song, "Debt relief and debtor outcomes: Measuring the effects of consumer bankruptcy protection," *American Economic Review*, 2015, *105* (3), 1272–1311.

— **, Andres Liberman, Daniel Paravisini, and Vikram Pathania**, "Measuring bias in consumer lending," *The Review of Economic Studies*, 2021, *88* (6), 2799–2832.

— **, Paul Goldsmith-Pinkham, and Crystal S. Yang**, "Consumer Bankruptcy and Financial Health," *Review of Economics and Statistics*, 2017, *99* (5), 853–869.

—, —, **Neale Mahoney, and Jae Song**, "Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports," *Journal of Finance*, 2020.

Dube, Oeindrila, Sandy Jo MacArthur, and Anuj K Shah, "A Cognitive View of Policing*," *The Quarterly Journal of Economics*, 11 2024, p. qjae039.

Egloff, Boris and Stefan C Schmukle, "Predictive validity of an Implicit Association Test for assessing anxiety.," *Journal of personality and social psychology*, 2002, *83* (6), 1441.

Frame, W Scott, Ruidi Huang, Erica Xuewei Jiang, Yeonjoon Lee, Will Shuo Liu, Erik J Mayer, and Adi Sunderam, "The impact of minority representation at mortgage lenders," 2023. NBER Working Paper No. 30125.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walter, "Predictably Unequal? The Effects of Machine Learning on Credit Markets," *The Journal of Finance*, 2022, *77* (1), 5–47.

Ganong, Peter, Damon Jones, Pascal Noel, Fiona Greig, Diana Farrell, and Chris Wheat, "Wealth, race, and consumption smoothing of typical income shocks," 2020. NBER Working Paper No. 27552.

Goldsmith-Pinkham, Paul and Kelly Shue, "The gender gap in housing returns," *The Journal of Finance*, 2023, *78* (2), 1097–1145.

Greenwald, Daniel L., Sabrina T. Howell, Cangyuan Li, and Emmanuel Yimfor, "Regulatory arbitrage or random errors? Implications of race prediction algorithms in fair lending analysis," *Journal of Financial Economics*, 2024, *157*, 103857.

Gross, Tal, Matthew J Notowidigdo, and Jialan Wang, "Liquidity constraints and consumer bankruptcy: Evidence from tax rebates," *Review of Economics and Statistics*, 2014, *96* (3), 431–443.

—, **Matthew J. Notowidigdo, and Jialan Wang**, "The Marginal Propensity to Consume over the Business Cycle," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 351–84.

Hamdi, Naser, Ankit Kalda, and Qianfan Wu, "Intergenerational Effects of Debt Relief: Evidence from Bankruptcy Protection," 2024. SSRN Working Paper No. 4787163.

Herkenhoff, Kyle, Gordon Phillips, and Ethan Cohen-Cole, "How Credit Constraints Impact Job Finding Rates, Sorting, and Aggregate Output," *The Review of Economic Studies*, 11 2023, *91* (5), 2832–2877.

Hull, Peter, "What Marginal Outcome Tests Can Tell Us About Racially Biased Decision-Making," 2021.

Indarte, Sasha, "Moral Hazard versus Liquidity in Household Bankruptcy," *The Journal of Finance*, 2023, *78* (5), 2421–2464.

Iverson, Benjamin, "Get in line: Chapter 11 restructuring in crowded bankruptcy courts," *Management Science*, 2018, *64* (11), 5370–5394.

—, **Joshua Madsen, Wei Wang, and Qiping Xu**, "Financial Costs of Judicial Inexperience: Evidence From Corporate Bankruptcies," *Journal of Financial and Quantitative Analysis*, 2023, *58* (3), 1111–1143.

Kermani, Amir and Francis Wong, "Racial disparities in housing returns," 2021. NBER Working Paper No. 29306.

Keys, Benjamin J., "The Credit Market Consequences of Job Displacement," *The Review of Economics and Statistics*, 2018, *100* (3), 405–415.

Kiel, Paul and Hannah Fresques, "Data Analysis: Bankruptcy and Race in America," Technical Report, Pro Publica 2017.

Knowles, John, Nicola Persico, and Petra Todd, "Racial Bias in Motor Vehicle Searches: Theory and Evidence," *Journal of Political Economy*, 2001, *109* (1), 203–229.

Lefgren, Lars and Frank McIntyre, "Explaining the puzzle of cross-state differences in bankruptcy rates," *The Journal of Law and Economics*, 2009, *52* (2), 367–393.

— , **Frank L McIntyre, and Michelle Miller**, "Chapter 7 or 13: Are client or lawyer interests paramount?," *The BE Journal of Economic Analysis & Policy*, 2010, *10* (1).

Livingston, Robert W, "The role of perceived negativity in the moderation of African Americans' implicit and explicit racial attitudes," *Journal of Experimental Social Psychology*, 2002, *38* (4), 405–413.

Livshits, Igor, James MacGee, and Michele Tertilt, "Consumer bankruptcy: A fresh start," *American Economic Review*, 2007, *97* (1), 402–418.

Lodermeier, Alison, "Racial Discrimination in Eviction Filing," 2025. Working Paper.

Loo, Rory Van, "A tale of two debtors: Bankruptcy disparities by race," *Alb. L. Rev.*, 2009, *72*, 231.

Morrison, Edward R, Belisa Pang, and Antoine Uettwiller, "Race and bankruptcy: Explaining racial disparities in consumer bankruptcy," *The Journal of Law and Economics*, 2020, *63* (2), 269–295.

— , — , **and Jonathon Zytnick**, "Manipulating Random Assignment: Evidence From Consumer Bankruptcies in the Nation's Largest Cities," *Columbia Law and Economics Working Paper*, 2019, (614).

Munnell, Alicia H, Geoffrey MB Tootell, Lynn E Browne, and James McEneaney, "Mortgage lending in Boston: Interpreting HMDA data," *The American Economic Review*, 1996, pp. 25–53.

Musto, David K., "What Happens When Information Leaves a Market? Evidence from Postbankruptcy Consumers," *The Journal of Business*, 2004, *77* (4), 725–748.

Nagel, Faian, "Consumer Bankruptcy Audits," 2024. SSRN Working Paper No. 4991384.

Nosek, Brian A, Mahzarin R Banaji, and Anthony G Greenwald, "Harvesting implicit group attitudes and beliefs from a demonstration web site.," *Group Dynamics: Theory, research, and practice*, 2002, *6* (1), 101.

Pettigrew, Thomas F and Linda R Tropp, "A meta-analytic test of intergroup contact theory.," *Journal of personality and social psychology*, 2006, *90* (5), 751.

Reid, Carolina K, Debbie Bocian, Wei Li, and Roberto G Quercia, "Revisiting the subprime crisis: The dual mortgage market and mortgage defaults by race and ethnicity," *Journal of Urban Affairs*, 2017, *39* (4), 469–487.

Ruebeck, Hannah, "Perceived Discrimination At Work," *SSRN Electronic Journal*, 01 2024.

Sabin, Janice A, Brian A Nosek, Anthony G Greenwald, and Frederick P Rivara, "Physicians' implicit and explicit attitudes about race by MD race, ethnicity, and gender," *Journal of health care for the poor and underserved*, 2009, *20* (3), 896–913.

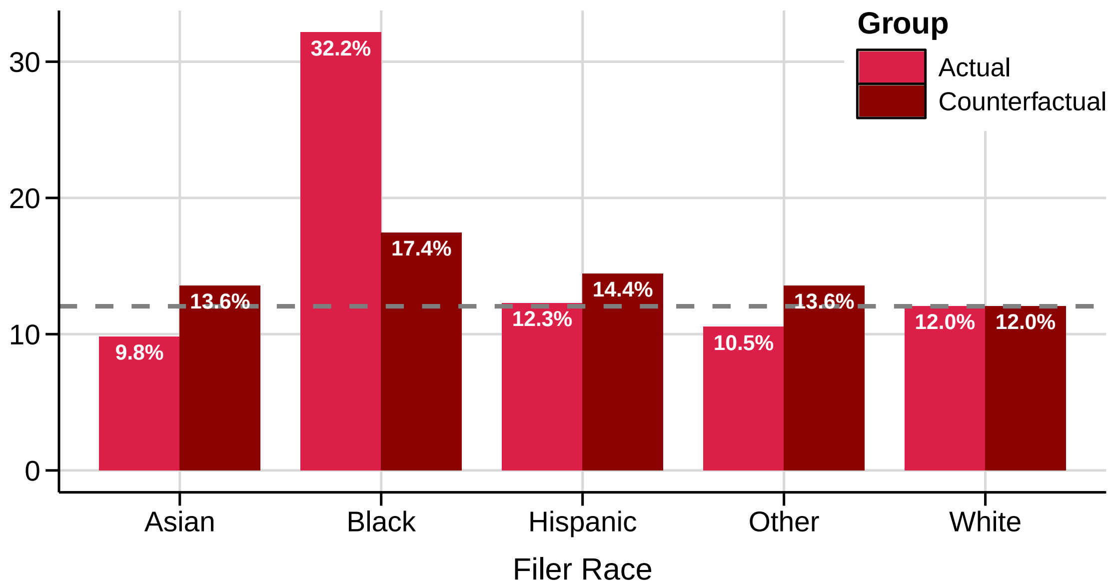
Simoiu, Camelia, Sam Corbett-Davies, and Sharad Goel, "The Problem of Infra-Marginality in Outcome Tests for Discrimination," *The Annals of Applied Statistics*, 2017, *11* (3), 1193–1216.

Spriggs, William, "Is now a teachable moment for economists?," 2020. Federal Reserve Bank of Minneapolis.

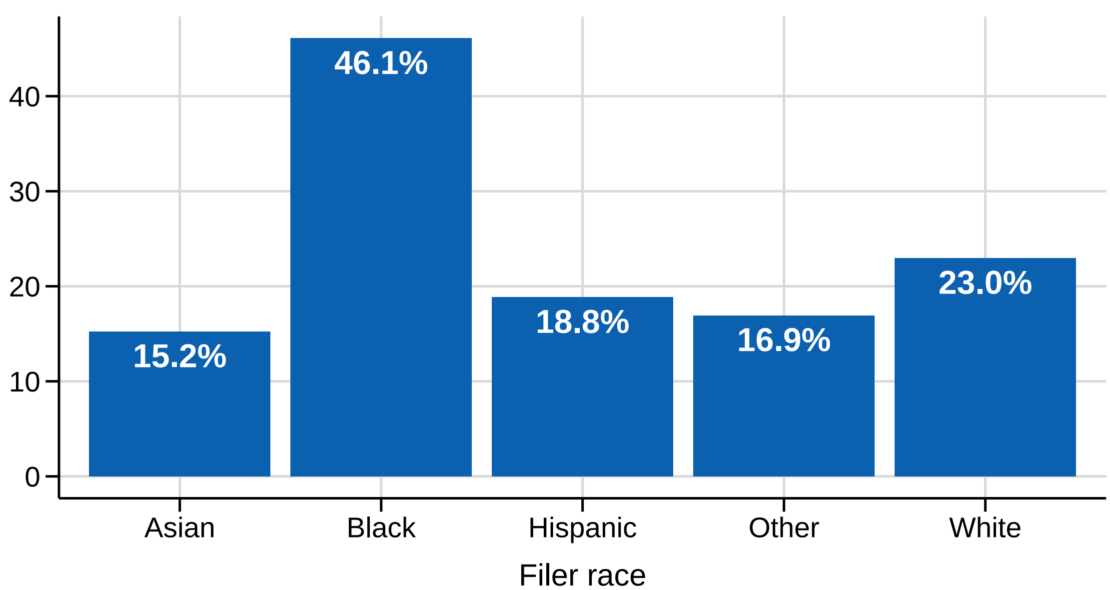
Stavins, Joanna, "Credit card borrowing, delinquency, and personal bankruptcy," *New England Economic Review*, 2000, (Jul), 15–30.

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

Panel A. Actual and Counterfactual Dismissal Rates by Filer Race

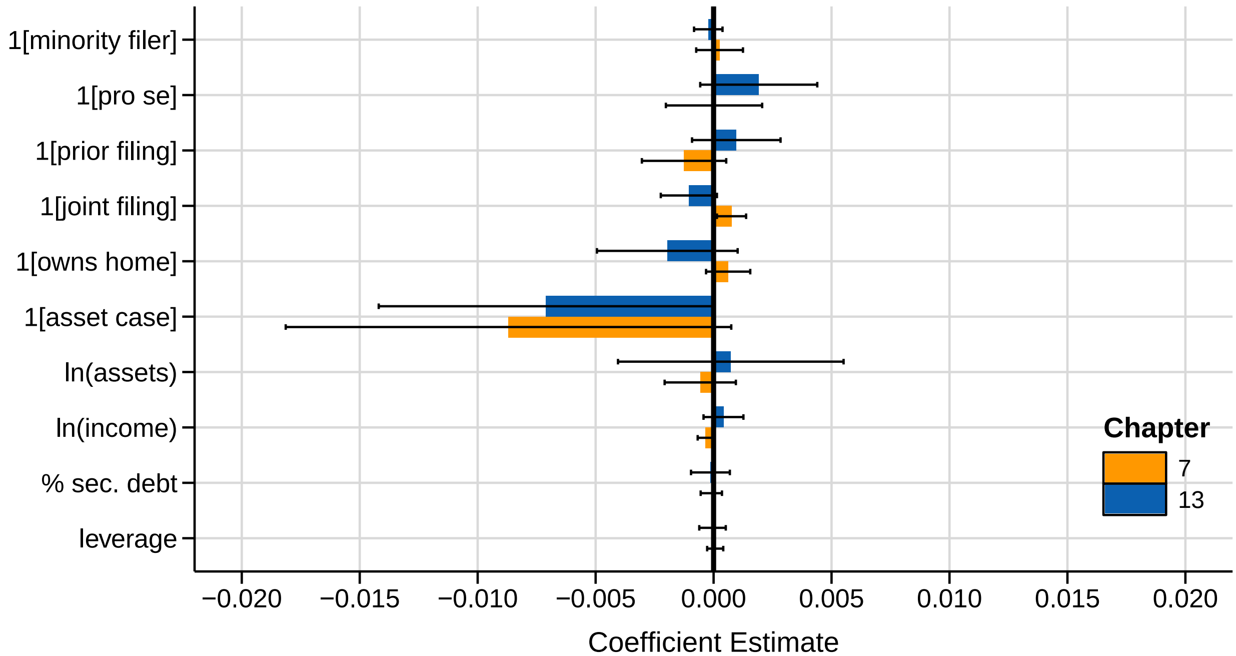


Panel B. Chapter 13 Share of Filings by Filer Race



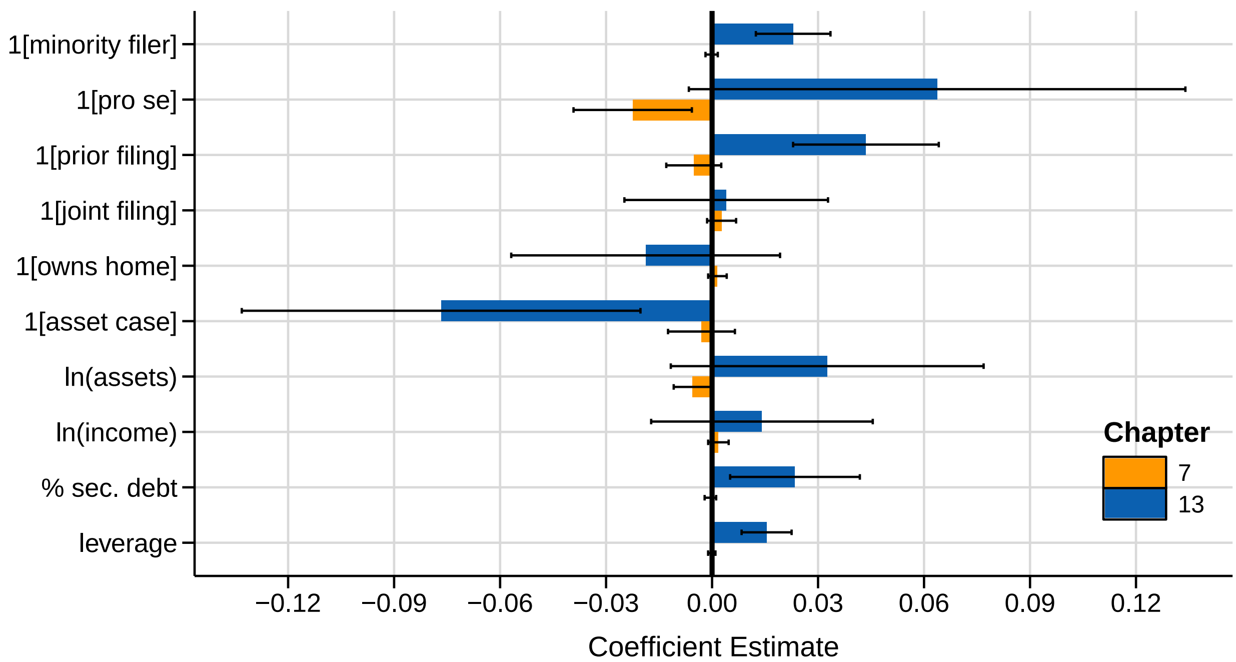
Notes: This figure plots bankruptcy dismissal rates and chapter choice by filer race. Panel A reports dismissal rates for filers under all chapters (7 and 13) by filer race. The light red bars on the left of each pair report the *actual* dismissal rate in our sample. The dark red bars on the right of 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



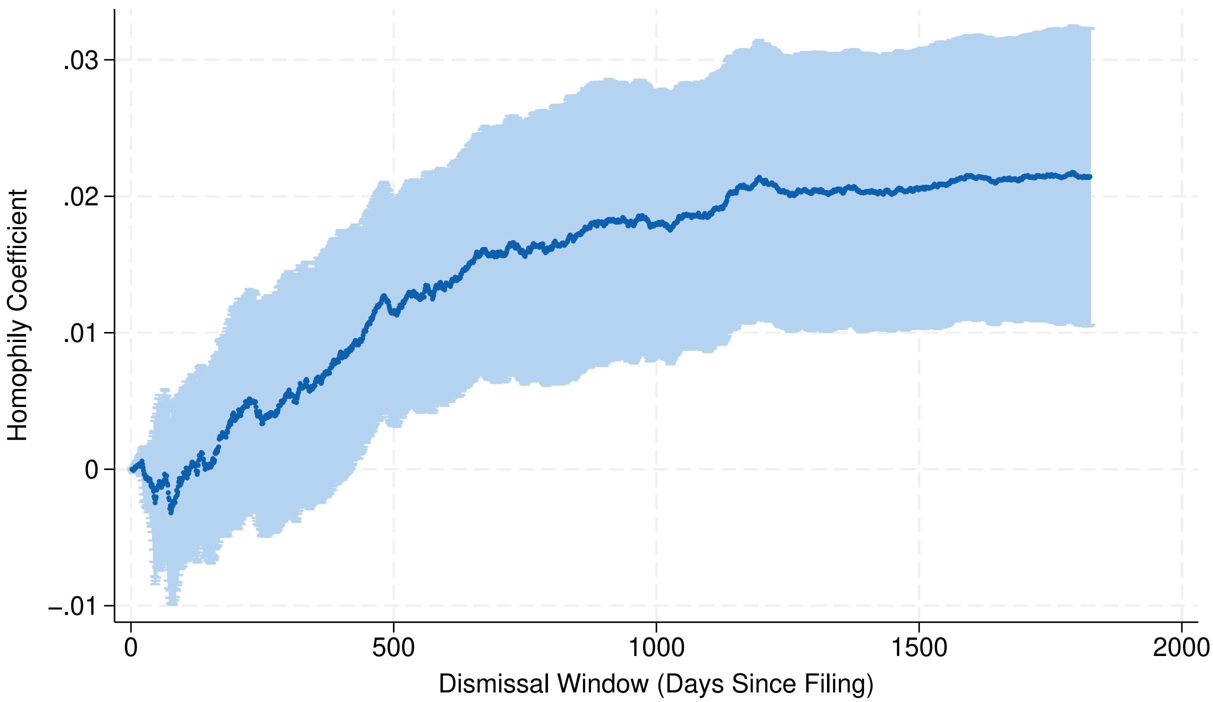
Notes: This figure plots coefficients from a multivariate regression testing for balance of filer characteristics by trustee race. The outcome variable is an indicator for the case's trustee being White. The coefficient for each explanatory variable is plotted along with 95% confidence intervals clustered 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.

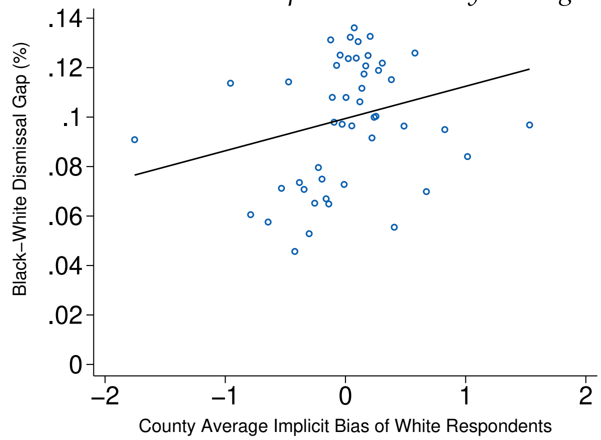
Figure 4: Homophily in the Cumulative Dismissal Rate



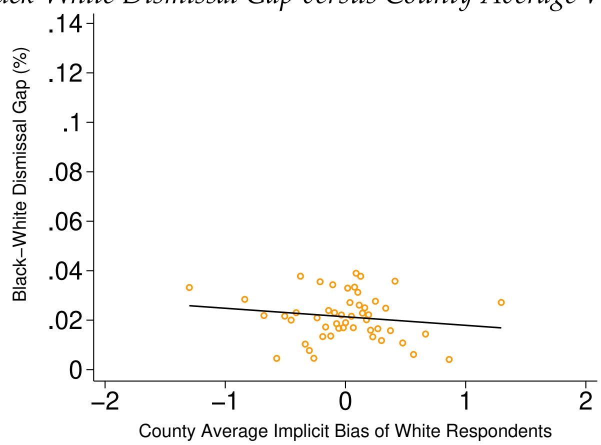
Notes: This figure plots day-by-day regression coefficients, each one from estimating the baseline homophily regression in Equation (5) separately after defining the dependent variable in each regression to indicate whether a case was dismissed with *d* days of filing for any reason. The x-axis ranges 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

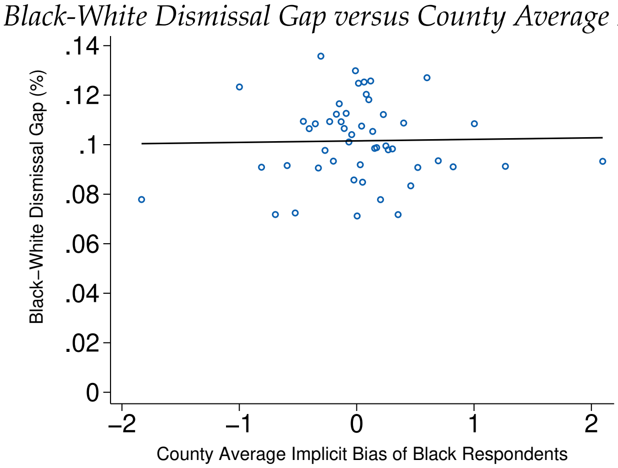
Panel A. Ch. 13 Black-White Dismissal Gap versus County Average White Implicit Bias



Panel B. Ch. 7 Black-White Dismissal Gap versus County Average White Implicit Bias



Panel C. Ch. 13 Black-White Dismissal Gap versus County Average Black Implicit 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 implicit bias corresponds to larger anti-Black implicit bias among White residents. In the bottom panel, higher implicit bias corresponds to greater anti-White implicit bias among Black residents. We z-score both implicit bias measures so that zero corresponds to the national average amount of implicit 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] × 1[White Trustee]	0.000	0.003	0.004***	0.000	0.016*	0.017*	0.016*
	(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

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

Bronson Argyle, Sasha Indarte, Benjamin Iverson, Christopher Palmer

Online Appendix

A Theory Appendix

In this appendix, we present and discuss several potential extensions to the decision model presented in Section 5.

A.1 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):

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

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.2 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.3 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.4 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 Homophily 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 homophily 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 analogously 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 $E_{mw}[e(m, R(m))] > E_{mm}[e(m, R(m))]$ and $E_{mw}[e(w, R(w))] = E_{mm}[e(w, R(w))]$. 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.,

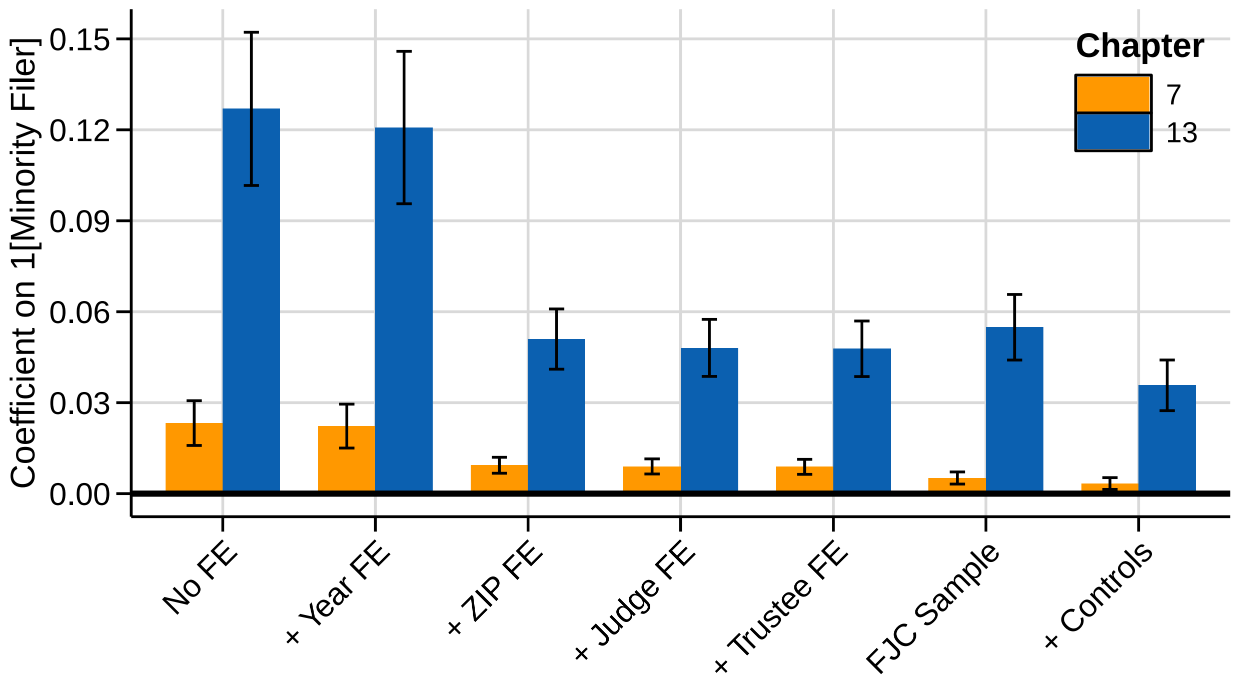
$E_{mw}[e(m, R(m)) - e(w, R(w))] < E_{mm}[e(m, R(m)) - e(w, R(w))]$).

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

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

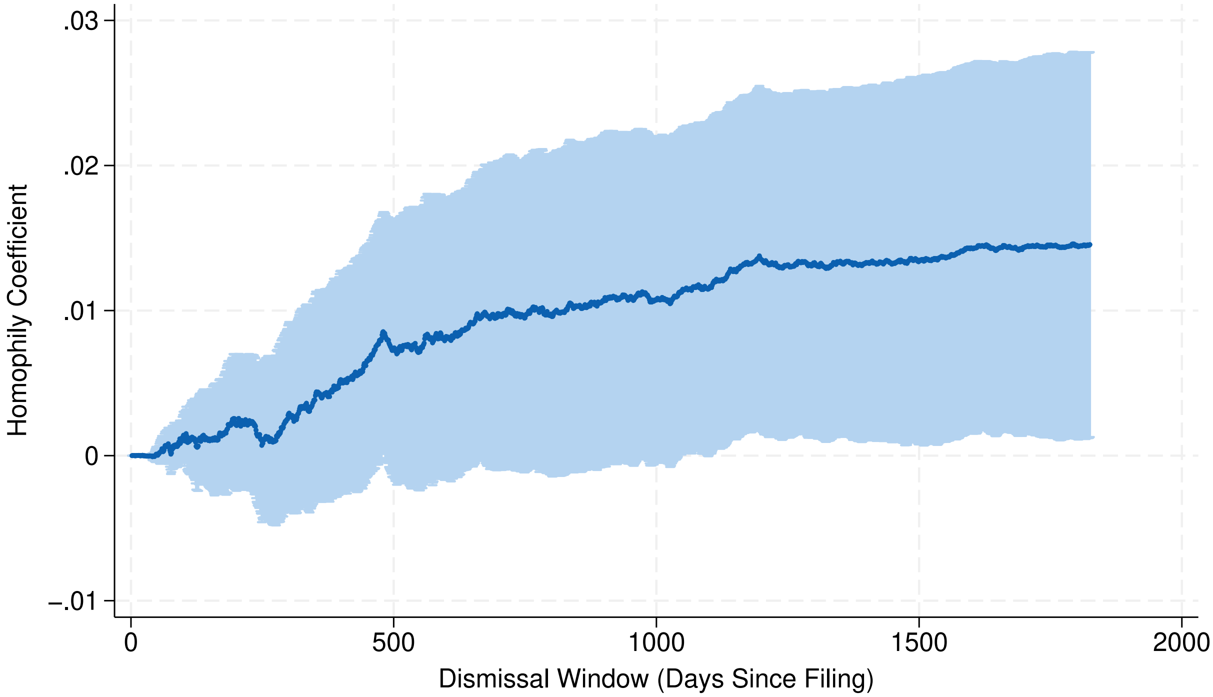
To summarize, in the two-tier extension, the homophily estimand still describes average differences in the influence of trustee bias. It captures both direct effects from bias in the trustee's recommendation as well as indirect effects through how judges react to the trustee's recommendation (or to the 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.

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.

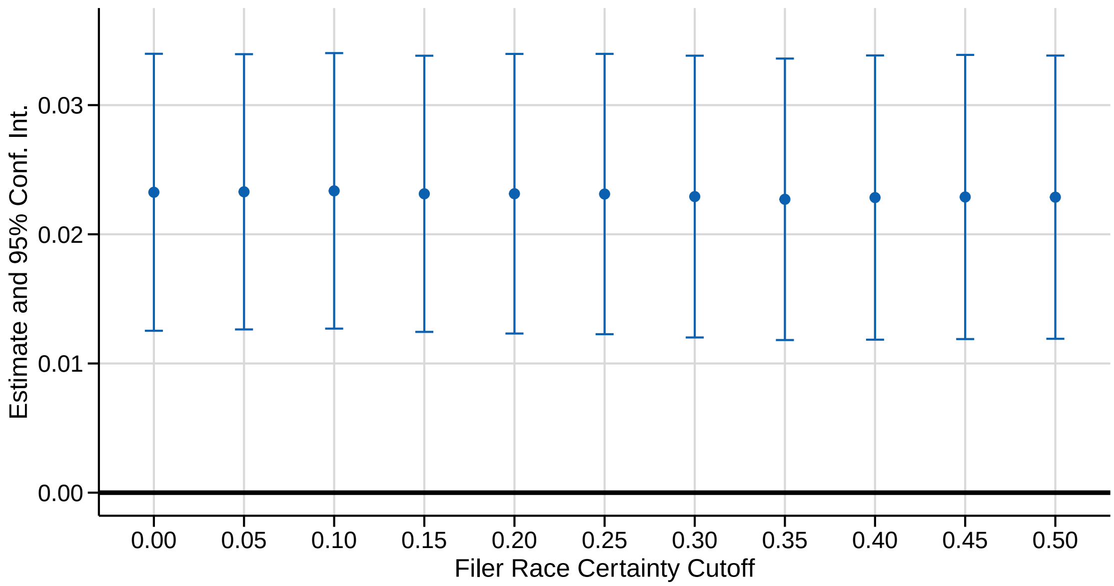
Figure A2: Homophily in the Cumulative Dismissal for Non-Payment Rate



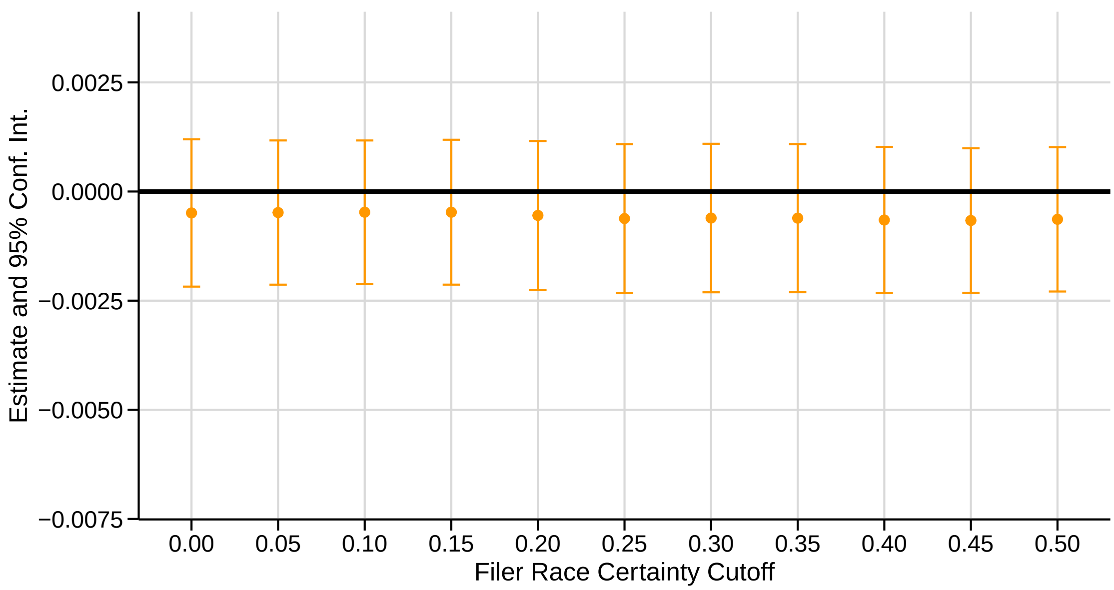
Notes: This figure plots day-by-day regression coefficients, each one from estimating the baseline homophily regression in Equation (5) separately after defining the dependent variable in each regression to indicate whether a case was dismissed with *d* days of filing for nonpayment. The x-axis ranges 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.

Figure A3: Robustness to Filer Race Uncertainty

Panel A. Ch. 13 Homophily Coefficient Estimate



Panel B. Ch. 7 Homophily Coefficient Estimate



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.

Table A1: Robustness of Dismissal Homophily to Highest-Quality Data Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
1[Minority Filer]	0.015**	0.015**	0.021**			
	(0.005)	(0.005)	(0.006)			
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***	-0.099**
				(0.009)	(0.009)	(0.029)
1[Asian Filer] × 1[White Trustee]				-0.037***	-0.037***	0.081*
				(0.010)	(0.010)	(0.031)
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	-0.017
				(0.006)	(0.006)	(0.014)
1[Hispanic Filer] × 1[White Trustee]				0.024***	0.024***	0.033**
				(0.006)	(0.006)	(0.011)
1[Other Filer]				0.006	0.006	-0.018
				(0.005)	(0.005)	(0.026)
1[Other Filer] × 1[White Trustee]				0.000	0.001	0.033
				(0.006)	(0.006)	(0.026)
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	432,887	1,193,261	1,192,375	432,887
R2	0.271	0.271	0.254	0.271	0.271	0.255

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 A2: 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 A3: 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***.

Table A4: 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 A5: 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 A6: 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 A7: 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 A8: 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 A9: 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.