Eligibility Screening and Means Testing in Consumer Bankruptcy

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Abstract
In the U.S. consumer bankruptcy system, the most important decision a debtor makes is whether to file under Chapter 7 or Chapter 13. This paper investigates the role of eligibility screening by courts in this decision. Building on the legal literature, we develop a structural model with two realistic features: (i) multiple legal tests determining eligibility for bankruptcy, and (ii) geographic heterogeneity in the implementation of these tests. In policy analyses, we find that heterogeneous eligibility screening is a key determinant of the longstanding geographic variation in chapter choice and altered the impact of a major bankruptcy reform.

Keywords: Consumer Bankruptcy, Chapter Choice, Eligibility Screening, Regional Disparities
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1 Introduction

In the U.S. consumer bankruptcy system, the most important decision a debtor makes is whether to file under Chapter 7 or Chapter 13. In Chapter 7, debtors obtain a quick discharge of most unsecured debts while paying nothing to unsecured creditors in nearly all cases.[1] In contrast, in Chapter 13 debtors enter a multi-year repayment plan where they repay more and obtain less debt relief.[2] Thus, chapter choice largely resolves the central issue in bankruptcy – how to balance debt relief and creditor repayment – and, as a result, bankruptcy policy changes and proposals regularly strive to influence chapter choice decisions.[3]

Despite the centrality of chapter choice, it has been difficult to uncover what policies or laws influence it. For example, there is persistent and extreme variation in chapter choice across U.S. states, but the underlying causes of this variation remain largely unclear. The geographic patterns have little correlation with prominent laws (asset exemption or wage garnishment restrictions), credit market characteristics, or economic conditions (Keys *et al.*, 2020).[4] As a further example, consider the most recent major bankruptcy reform, the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), which is "built upon a controversial 'means test'" that aimed to alter chapter choice by shifting high-income debtors from Chapter 7 to Chapter 13 (or out of bankruptcy altogether) (Lawless *et al.*, 2008). Although some quantitative models predict large effects, the available empirical evidence finds no evidence that the means test deterred high-income filings.[5] Thus, there remain significant gaps in our understanding of what can explain or influence bankruptcy chapter choice.

[1] While Chapter 7 debtors must repay creditors with nonexempt assets, 94-96% of Chapter 7 cases are no-asset cases in which the debtors hold no nonexempt assets (Jiménez, 2009; Pattison, 2020).

[2] The recovery rate on unsecured debt in Chapter 13 is 13%, compared to 0.5% in Chapter 7. These statistics are for the years 2010-2014. The debt discharge rate in Chapter 13 is 43%, compared to 96% in Chapter 7. To produce these statistics, we combine data from US Trustee Final Reports, which detail actual payments to general unsecured creditors, with data from the Federal Judicial Center's Integrated Database on discharges and outstanding unsecured debts. See Morrison and Uettwiller (2017) for estimates from other samples of recoveries in Chapter 13.

[3] The 1984 Bankruptcy Act and the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act both enacted barriers to Chapter 7. Recent policy proposals, such as Senator Warren's proposed bankruptcy reform, seek to reverse these features of the 2005 Reform or even eliminate Chapter 13 as an option (Warren, n.d.).

[4] Using a "movers" design, Keys *et al.* (2020) shows that bankruptcy variation is largely driven by place-based factors (as opposed to individual characteristics), but these place-based factors (fixed effect estimates) are not strongly correlated with legal factors, credit markets characteristics, or economic conditions.

[5] Gross *et al.* (2021) summarizes their results and the empirical literature as "Overall, we find no evidence to suggest the means test had a large effect on the income composition of bankruptcy filers. This is consistent with anecdotal reports from bankruptcy attorneys (Littwin, 2016) and other evaluations of the reform and the income of bankruptcy filers (Ashcraft *et al.*, 2007; Lawless *et al.*, 2008; Albanesi and Nosal, 2018; Fisher, 2019a)."

In this paper, we investigate the role of a critical but understudied factor – eligibility screening – in chapter choice decisions. When a debtor files under Chapter 7 or Chapter 13, the case is subsequently screened by the bankruptcy court to determine whether the debtor is eligible for the chosen chapter. Ineligible cases are dismissed (or sometimes converted to the other chapter). Building on the legal literature, we develop a two-stage model of chapter choice that incorporates key features of eligibility screening: (i) multiple legal tests determining eligibility, and (ii) heterogeneity in how different courts implement these tests. This heterogeneity in eligibility screening is emphasized in qualitative legal research (Wells *et al.*, 1991; Braucher, 1993; Sullivan *et al.*, 1994), but this is the first study (to our knowledge) to measure it and examine its impact. We estimate the model using national, case-level data on more than two million consumer bankruptcy filings, allowing us to estimate separate eligibility screening parameters for more than eighty court districts. Our estimates show that eligibility screening is a primary determinant of chapter choice and that there is widespread geographic heterogeneity in how such screening is implemented. We then conduct two policy counterfactuals, showing that heterogeneous eligibility screening generates large geographic differences in the impact of BAPCPA, and explains about one quarter of the persistent historical variation in chapter choice across districts.

To begin, we construct and estimate an innovative, two-stage model of a debtor's chapter choice that incorporates eligibility screening and geographic heterogeneity. Like earlier chapter choice models, in the first stage bankruptcy filers choose between Chapter 7 and Chapter 13 (Domowitz and Sartain, 1999; Zhu, 2011; Lawless and Littwin, 2017). However, we also incorporate a second stage where the case is screened according to the eligibility rules of the filer's chosen chapter. Our second-stage screening model incorporates BAPCPA's well-known means test, but also the lesser known totality test which turns out to play an important role. The screening model also allows for heterogeneity across court districts in the implementation of these eligibility rules, reflecting the variation in "local legal culture" emphasized by legal scholars (Wells *et al.*, 1991; Braucher, 1993; Sullivan *et al.*, 1994; Lawless and Littwin, 2017). We assume debtors and their attorneys are informed about local screening practices and forward-looking. As a result, they account for the probability of dismissal when making their first-stage chapter choice decisions.

To estimate the model, we use data on all consumer bankruptcy filings from fiscal years 2011-2015. The large sample size allows us to estimate district- and chapter-specific models to fully characterize how each of 83 court districts implements eligibility screening and, in turn, how these differences affect initial chapter choice decisions.[6] We find that the totality test and the means test both play an economically and statistically significant role in chapter choice. Moreover, there is substantial heterogeneity across districts in how these tests are implemented. Some districts have lenient eligibility screening that allows most debtors to file Chapter 7, while others strictly screen debtors and regularly deem them ineligible.

We then use the model estimates to examine two policy counterfactuals. The first focuses on the impact of BAPCPA's flagship feature: the means test. The existing literature has generally found little effect of the means test on filings, but because it was a uniform change in federal law the lack of cross-sectional variation creates an identification challenge.[7] Using our model, however, we can generate district-specific counterfactual predictions of the impact of the means test. Specifically, heterogeneity in eligibility screening and the characteristics of filers creates variation in the impact of the means test across districts. The model predicts that implementing the means test has little effect in some districts, while in others it reduces the share of bankruptcies under Chapter 7 by more than 20 percentage points. These model-generated predictions closely match observed district-level changes around BAPCPA, thereby providing an out-of-sample test of the model's validity.

In our second policy analysis, we examine the role of eligibility screening in explaining the vast and persistent geographic differences in chapter choice. Across federal court districts, the share of consumer bankruptcies filed under Chapter 7 varies from less than 30% to more than 90%. Legal scholars have long attributed this variation to differences in local legal culture and many have called for increased uniformity across districts (Braucher, 1993; Sullivan *et al.*, 1994; Westbrook, 1998; Lawless and Littwin, 2017; American Bankruptcy Institute, 2019). We examine the effect of uniformity in one aspect of local legal culture: eligibility screening. We find that if all districts applied a uniform "average" eligibility screening procedure, then the total geographic variation in chapter choice would be reduced by about one quarter.

Our study makes three primary contributions. First, our analysis indicates that the heteroge-

[6]Of the 94 federal court districts in the United States, our sample uses the 83 that are not U.S. territories, which have small sample sizes, and also drops districts within North Carolina and Alabama, which are not administered by the U.S. Trustee Program that oversees eligibility screening.

[7]One exception is Cornwell and Xu (2014), which finds some evidence of an impact of the means test by exploiting cross-sectional variation in the number of debtors potentially affected by the means test due to differences in within-state income distributions.

neous implementation of eligibility screening is a core determinant of access to relief in bankruptcy. In many districts, access to Chapter 7 bankruptcy is fairly tightly screened by the totality test and means test. This screening may reduce the possibility of moral hazard and help explain why few households file for bankruptcy despite the financial benefits (White, 1998).[8] Second, our analysis allows us to identify the causal effect of the means test under BAPCPA on chapter choice by exploiting new cross-district variation in eligibility identified by the model. Although national studies have found little to no impact (Lawless *et al.*, 2008; Fisher, 2019b; Albanesi and Nosal, 2022; Gross *et al.*, 2021), we find the impact to be highly heterogeneous, with little effect in some districts and large effects in others. Third, we find that heterogeneity in eligibility screening explains about one quarter of the widespread geographic variation in chapter choice, providing some guidance to policymakers aiming to increase uniformity (American Bankruptcy Institute, 2019).

This study adds to three literatures pertaining to bankruptcy in the United States. The first includes a broad set of papers examining the determinants of bankruptcy, chapter choice, and dismissals. Eraslan *et al.* (2017) develop a structural model of plan-length decisions within Chapter 13 and incorporate the possibility of dismissal. The authors then estimate the model using cases from Delaware and use it to examine changes in plan length requirements enacted as a part of BAPCPA. Our paper, in contrast, focuses on chapter choice, uses a national sample that allows for detailed geographic heterogeneity in screening, and examines the BAPCPA's restrictions on access to Chapter 7. Several other papers estimate discrete choice models of bankruptcy and chapter choice, focusing on the role of laws and financial characteristics of debtors in the decision-making process (Domowitz and Sartain, 1999; Gross and Souleles, 2015; Zhu, 2011) as well as the heterogeneous impact of state laws on debtors (Miller, 2019). Other papers study specific determinants of chapter choice or filing decisions, such as asset exemptions (Pattison and Hynes, 2020), liquidity constraints (Gross *et al.*, 2014; Foohey *et al.*, 2016), traffic debt (Foohey *et al.*, 2020; Morrison *et al.*, 2020), payday loans (Skiba and Tobacman, 2019), attorney incentives (Lefgren *et al.*, 2010; McIntyre *et al.*, 2015), and the filer's race (Dickerson, 2012; Braucher *et al.*, 2012a,b), often relying on policy variation or other quasi-experimental approaches. Lastly, some papers use variation in dismissal rates across trustees to examine racial bias (Argyle *et al.*, 2023) and variation

[8]There are likely multiple explanations, including those offered in White (1998) – a lack of non-bankruptcy debt collection and the option value of bankruptcy – and the potentially high nonpecuniary costs and credit market penalties which rationalize filing rates in quantitative models (e.g. Athreya (2002)).

in dismissal rates across judges to identify the impact of Chapter 13 (Dobbie and Song, 2015; Dobbie *et al.*, 2017). Our model builds on this literature by incorporating realistic features of dismissals and geographic heterogeneity into a structural model of chapter choice.

Second, we contribute to the set of papers examining the policy impact of the means test under BAPCPA. Several studies examine the impact of a BAPCPA-style means test using macroeconomic models (Athreya, 2006; Li and Sarte, 2006; Chatterjee *et al.*, 2007; Gordon, 2015; Mitman, 2016; Nakajima, 2017; Gordon, 2017), while others assess the treatment effect of the means test under BAPCPA on bankruptcy filings (Cornwell and Xu, 2014; Gross *et al.*, 2021; Albanesi and Nosal, 2022), health insurance coverage (Mahoney, 2015), and mortgage default Li *et al.* (2011) using various causal inference methods. Our results highlight that geographic differences in pre-existing eligibility screens caused the impact of the means test to differ widely across districts, and we validate the model's predictions against the (out-of-sample) observed changes in chapter choice around BAPCPA.

Finally, we contribute to papers examining the factors driving geographic variation in bankruptcy. Keys *et al.* (2020) show that location-specific fixed effects, as opposed to individual-specific factors, explain a significant share of the geographic variation in bankruptcy. However, the chapter choice patterns are not highly correlated with prominent laws. A complementary legal literature on local legal culture emphasizes the role of local bankruptcy practices or traditions (Braucher, 1993; Sullivan *et al.*, 1994; Lawless and Littwin, 2017). Our paper quantifies the importance of one particular aspect of local legal culture – eligibility screening – finding that it explains almost a quarter of the geographic variation in chapter choice.

2 Institutional Background

In the U.S., consumers choose to file for bankruptcy under either Chapter 7 or Chapter 13.[9] The chapter choice decision is made by the debtor and debtor's attorney, and the relative benefits of the two chapters depend on the debtors' goals and financial characteristics. After the debtor chooses a chapter, a bankruptcy trustee and judge review the debtor's case to determine whether the debtor is eligible for the chosen chapter. Ineligible cases are dismissed or converted to the other

[9]Debtors can also file under Chapter 11 or Chapter 12, but these account for less than 0.5% of consumer bankruptcy filings.

chapter, which is costly for the debtor and debtor's attorney. This section provides an overview of the institutional features that govern the chapter choice incentives and eligibility screening of debtors.

2.1 Debtor's Chapter Choice Incentives

The benefits and costs of choosing Chapter 7 and Chapter 13 depend on the debtors' goals and characteristics. In Chapter 7, debtors obtain a quick discharge of most unsecured debts. In exchange, they must repay creditors using any nonexempt assets. In Chapter 13, debtors enter a three- to five-year plan during which they repay creditors out of their disposable income but can retain all of their assets. Chapter 13 debtors only obtain a discharge upon completion of the repayment plan. Roughly half of plans fail before completion, mostly due to the debtor missing payments, leaving the debtor without a discharge. Thus, Chapter 7 typically results in significant debt relief and little creditor repayment, while Chapter 13 results in less debt relief and more creditor repayment.

Most debtors would benefit more from Chapter 7, but Chapter 13 can be better in some situations. Nonexempt assets, secured debts, certain nondischargeable debts, and liquidity constraints may cause a debtor to benefit more from Chapter 13. Debtors with significant nonexempt assets may choose Chapter 13 because it allows them to retain nonexempt assets, while Chapter 7 debtors must forfeit them. A combination of state and federal laws determines which assets are exempt. The largest exemptions are for home equity, and the amount protected varies across states from less than \$10,000 to more than \$500,000 (and is unlimited in seven states).[10] Homeowners and debtors with secured or nondischargeable debts (e.g., tax debt or government debt) may also find Chapter 13 more attractive because it provides more options for addressing foreclosure and addressing delinquencies on secured or nondischargeable debts (Porter, 2011; Tabb, 2020; Morrison *et al.*, 2020). Chapter 13 often has lower upfront attorney fees, which may be important to liquidity-constrained debtors (Gross *et al.*, 2014; Foohey *et al.*, 2016). Debtors may also prefer Chapter 13 if they feel an obligation to repay some of their debt (Braucher, 1993; Porter, 2011), even though this does not translate into better credit scores (Jagtiani and Li, 2015).

[10] Another important aspect of home protection is tenancy-by-the-entirety, which provides additional protection for married filers (Traczynski, 2019). The district-specific coefficients on the indicator for joint filings capture the role of these tenancy-by-the-entirety laws.

2.2 Eligibility Screening

After the debtor decides which chapter to file, the bankruptcy trustee and bankruptcy judge review the case to determine if the debtor is eligible for the chosen chapter. The trustees, acting as the "watchdog over the bankruptcy process" (USTP, 2022), conduct much of the eligibility screening and, if they deem a case ineligible, they move to have the judge dismiss the case (Wells *et al.*, 1991). Judges nearly always agree with the trustee's determination; in more than 98.5% of enforcement actions that were decided by judicial review or consent, the trustee's action was granted (USTP, 2015). Cases facing dismissal under one chapter are often given the option to convert to the other chapter.

Because Chapter 7 generally provides more relief, most eligibility screening aims to restrict access to Chapter 7. There are two primary screens used to decide debtors' eligibility for Chapter 7: the means test and the totality test. For this paper, the key features of these tests are that they (i) apply simultaneously to determine debtors' eligibility, (ii) use different criteria, and (iii) have discretionary components that give rise to geographic heterogeneity in how they are applied.

BAPCPA's Means Test

In 2005, the Bankruptcy Abuse Prevention and Consumer Protection Act implemented several major changes to the bankruptcy system, including its flagship feature the *means test*. The means test is a formula-based, two-part test used to assess eligibility for Chapter 7. The test seeks to "ensure that debtors repay creditors the maximum they can afford" (House of Representatives, 2005) by restricting access to Chapter 7 for high-income debtors.[11]

The first part of the means test compares the debtor's recent income to the state's median income for households of the same size. Below-median-income debtors automatically pass the means test. Above-median-income debtors continue to the second part of the test. This second part compares the debtor's income to a set of allowable expense standards. If the debtor's monthly income exceeds the standards by a specified amount, the means test creates "presumption of abuse" that may bar the debtor from filing under Chapter 7.

[11] There are many other provisions of BAPCPA enacted alongside the eligibility screening of the means test, such as the anti-cramdown provision affecting car loans, restrictions on plan length, and changes in how plan payments were calculated (Chakrabarti and Pattison, 2019; Eraslan *et al.*, 2017).

Although the means test is largely formulaic, there is room for discretion and variation across districts. In particular, failing the means test formula only creates a *presumption* of abuse. A debtor can still file under Chapter 7 if they rebut this presumption with special circumstances, such as a recent job loss, illness, or justifiable extra expenses. Trustees exercise discretion when evaluating these mitigating circumstances, frequently siding with debtors (Bartell, 2018). Overall, trustees decline to seek dismissal in more than 60% of cases that fail the formulaic portion of the means test (USTP, 2022). These discretionary decisions of the trustees may lead to substantive differences in how the means test is administered across the 94 federal court districts.

Totality Test

In addition to BAPCPA's means test, debtors may be ineligible for Chapter 7 if their case is deemed an abuse "under the totality of the circumstances." We refer to this as the *totality test*.[12] The first important fact is that the totality test predates BAPCPA and continues to apply in the post-BAPCPA period.[13] As additional evidence, annual reports of the U.S. Trustee Program (USTP) make it clear that "[e]ven if a case is not presumptively abusive under the means test, the Bankruptcy Code permits the USTP to seek dismissal based on the debtor's bad faith or the totality of the circumstances" (USTP, 2020).

There are three key features of the totality test. First, the test applies to *all* Chapter 7 debtors, including those with below-median income or who otherwise pass BAPCPA's means test (Landry III, 2008; Tabb, 2020). Second, although the Bankruptcy Code does not specify exactly what constitutes substantial abuse, courts have consistently used a debtor's ability to pay as the primary consideration in the totality test (Felsenfeld, 1998; Wedoff, 2005; Pottow, 2006).[14] Debtors with an ability to pay risk having their case deemed an abuse of Chapter 7 under the totality test. Ability to pay is typically evaluated through the debtor's monthly disposable income (income less allowed expenses), which is captured in standard bankruptcy forms.

[12] Chapter 7 cases can also be dismissed for "bad faith," but we focus on the totality of the circumstances because dismissals for bad faith alone are extremely rare (Landry III, 2008).

[13] In fact, BAPCPA strengthened the totality test by lowering the bar for dismissal from "substantial abuse" to only "abuse," and by eliminating a presumption in favor of granting relief to the debtor (Landry III, 2014). Post-BAPCPA court rulings, including the three appellate courts, find that the totality test still applies to debtors who pass the means test (Landry III, 2014).

[14] The Senate Report to the 1984 bill clarifies that "if a debtor can meet his debts without difficulty as they come due, use of Chapter 7 would represent a substantial abuse' (S.Rep. No. 65, to Senate Bill 445, 98th Conb., 1st Sess. 43 (1984) as cited in In Re Fitzgerald, 155 B.R. 711 (W.D. Tex. 1993)).

Third, since the Bankruptcy Code does not define what constitutes an ability to pay, the totality test relies largely on court discretion. This has led to geographic heterogeneity in how the test is implemented. Some courts scrutinize all cases exceeding a certain dollar amount of monthly disposable income, with the dollar amount varying from $100, $166, or $200-400 (Wells *et al.*, 1991; Wedoff, 2006). Others focus on the share of unsecured debt that could be repaid out of disposable income over a hypothetical Chapter 13 plan, with different courts finding abuse if the debtor could repay at least 20%, 35%, 50%, 80%, or 100% of his unsecured debt.[15] Some courts consider factors beyond, including whether the cause was a sudden event (job loss, illness), the reasonableness of the debtor's budget, and the debtor's recent spending behavior.[16] Courts place different weights on these other factors, with some viewing ability to pay alone as sufficient to constitute abuse, while others require it to be accompanied by other indications of abuse or bad conduct (Felsenfeld, 1998; Wedoff, 2005). As a result of these differences, the totality test screens Chapter 7 eligibility using ability to pay, but it is not a formulaic and there is, anecdotally, significant variation across courts in how the test is applied.

The totality test and other good faith requirements are also present in Chapter 13, although the implementation differs. In particular, the test under Chapter 13 requires that the debtor's repayment plan must be feasible, i.e., the debtor must have sufficient disposable income to fund a Chapter 13 plan and have a reasonable chance of completing the plan. These tests are enforced by Chapter 13 trustees and judges often through discretionary minimum payment requirements for Chapter 13 plans (Braucher, 1993; Morrison and Uettwiller, 2017; Morrison *et al.*, 2020). While most eligibility screening is focused on limiting access to Chapter 7, the discretionary requirements for Chapter 13 feasibility further contribute to geographic heterogeneity in chapter choice.

[15]See In re Vianese, 192 B.R. 61, 71 (Bankr. N.D.N.Y. 1996) for a case that uses a 19% threshold, and In Re Lipford, 397 B.R. 320 (Bankr. M.D.N.C. 2008) and In re Boule 415 B.R. 1 (Bankr. D. Mass. 2009) for a review of different court practices.

[16]Some courts use a list, known as the Green factors from 934 F.2d 568 (4th Cir. 1991), to determine abuse. In addition to ability to pay, these factors include whether the bankruptcy petition was filed due to sudden illness, calamity, disability, or unemployment; if the debtor incurred cash advances and consumer purchases beyond their ability to repay; if the proposed family budget is excessive or unreasonable; if the debtor's financial statements accurately reflect their true financial condition; and if the petition was filed in good faith (Mitchell, 1997).

Evidence of Screening and Heterogeneity

To motivate our later analysis, we provide some descriptive statistics of the importance of and geographic heterogeneity in eligibility screening on debtors' disposable incomes. First, we show that access to Chapter 7 is screened based on debtors' ability to pay, and that this screening seems to affect chapter choice. Both the means test and the totality test prevent debtors who are able to pay from filing under Chapter 7. Consistent with this, the national average line in Figure 1(a) shows that once the primary measure of ability to pay – monthly disposable income – becomes positive, Chapter 7 cases are much more likely to be dismissed or converted to Chapter 13. The risk of dismissal also affects chapter choice, as Figure 1(b) shows that the share of bankruptcies under Chapter 7 declines precipitously around the same disposable income threshold.[17] These patterns are not solely due to the means test, as the figures remain similar when the sample is restricted to only below-median-income debtors, all of whom automatically pass the means test (Online Appendix Figure A2).

Second, there is significant geographic heterogeneity in eligibility screening across court districts. For both dismissals and chapter choice, Figure 1 also plots the 10^{th} and 90^{th} percentiles of the cross-district averages. There is extreme variation. In Figure 1(a), the share of cases with \$400 in monthly disposable that are dismissed varies from 15% of cases in the 90^{th} percentile district to 1.7% of cases in the 10^{th} percentile district. Similarly, among cases with \$400 in disposable income, the share under Chapter 7 varies from 51% in the 90^{th} percentile district to 4.6% in the 10^{th} percentile district. Our goal is to incorporate eligibility screening and geographic heterogeneity in its implementation within a model of chapter choice.

3 Model and Empirical Strategy

In this section, we introduce the models for eligibility screening and debtor's chapter choice and then discuss estimation and identification. The objectives are to identify the importance of eligibility screening in chapter choice, as well as how eligibility screening varies across districts. In the first stage of the model, the debtor decides whether to file under Chapter 7 or Chapter 13. In

[17] In contrast, Chapter 13 dismissals and conversions rise once disposable income becomes negative (see Online Appendix Figure A1).

the second stage, the court district's trustees and judges (hereafter referred to as "the district") decide whether to permit the filing under the debtor's chosen chapter or deem it ineligible, causing the case to be dismissed or converted to the alternative chapter. The district's decision regarding the filing is what we refer to as *eligibility screening*. Debtors (and/or their attorneys) account for expected eligibility screening when making their chapter choice decision in the first stage. It is important to note that our model and counterfactual analyses focus on the chapter choice decision *conditional on filing for bankruptcy*. We discuss the implications of not modeling the initial decision to file at the end of this section.

3.1 Eligibility Screening

Because debtors (and/or their attorneys) account for the eligibility screening process when making chapter choice decisions, we begin by modeling the second-stage screening process. The model of eligibility screening must be sufficiently flexible to capture district heterogeneity in the implementation of the screening tests that we document in Section 2. However, while such *cross-district* heterogeneity is crucial, there is little *temporal* heterogeneity within districts. The persistence of district decision-making is consistent with the literature on local legal culture; such culture is stable within a district or court, reflecting that district's interpretation of the law (Braucher, 1993; Sullivan *et al.*, 1994; American Bankruptcy Institute, 2019). Thus, our model is static and time-invariant.

For a debtor with eligibility-related characteristics X^E, let the probability (from the debtor's perspective) that the debtor will be deemed eligible for chapter $C \in \{7, 13\}$ in district d be $Q_C(X^E; \beta_d, \gamma_d)$.[18] Because each chapter has distinct eligibility criteria, a debtor could be eligible for both chapters or neither, so it is not the case that $Q_7 + Q_{13}$ must equal one. As in Eraslan *et al.* (2017), the district's decision rule for eligibility is assumed to be non-strategic and stochastic from the perspective of the debtor. The terms (β_d, γ_d) are vectors of parameters governing the eligibility screening in district d, with β_d capturing the totality test and γ_d capturing BAPCPA's means test. The full parameterization of the probability that a debtor with characteristics X^E is

[18] In practice, while debtors are unlikely to know the probability they are eligible for each chapter in district d, the debtor's attorney understands the practices of the district and whether a debtor is likely to raise eligibility concerns.

eligible for Chapter C given the eligibility screening of district d is

$$Q_C\left(X^E;\beta_d,\gamma_d\right)=\frac{\exp\left[q_C\left(X^E;\beta_d,\gamma_d\right)\right]}{1+\exp\left[q_C\left(X^E;\beta_d,\gamma_d\right)\right]} \tag{1}$$

where

$$\begin{aligned}q_C\left(X^E;\beta_d,\gamma_d\right)=\ &\beta_0^{Cd}+\beta_1^{Cd}\texttt{disp\_income}+\beta_2^{Cd}\texttt{pct\_repay5}+\beta_3^{Cd}\texttt{incdropbig}\\&+\beta_4^{Cd}\texttt{expense\_gap}+\beta_5^{Cd}\texttt{prose}+\beta_6^{Cd}\texttt{joint\_file}\\&+\gamma_0^{Cd}\texttt{AMI}+\gamma_1^{Cd}\texttt{AMI}\times\texttt{disp\_income}+\gamma_2^{Cd}\texttt{AMI}\times\texttt{pct\_repay5}+\gamma_3^{Cd}\texttt{AMI}\times\texttt{incdropbig}\\&+\gamma_4^{Cd}\texttt{AMI}\times\texttt{expense\_gap}+\gamma_5^{Cd}\texttt{AMI}\times\texttt{prose}\\&+\gamma_6^{Cd}\texttt{AMI}\times\texttt{joint\_file}+\gamma_7^{Cd}\texttt{amt\_above\_means}\end{aligned}$$

and where $\beta_d=(\beta^{7d},\beta^{13d})$ and $\gamma_d=(\gamma^{7d},\gamma^{13d})$ are the coefficient vectors in the chapter-specific eligibility models for district d.

The variables capture the primary factors used to screen for eligibility under the eligibility rules described in Section 2. For the totality test, captured by the β_d coefficients, the primary factor is the debtor's ability to pay, which in practice is measured by a debtor's disposable income (`disp_income`) or the share of a debt that a debtor could repay in a hypothetical five-year Chapter 13 plan (`pct_repay5`). Our empirical measures of these key variables will be the exact information trustees use when screening eligibility. Secondary factors in the totality test of some districts include whether the bankruptcy was caused by a sudden shock, which we proxy for with an indicator for whether the debtor has experienced a recent drop in monthly income of more than \$500 (`incdropbig`), and the reasonableness of the debtor's budget, which we measure as the gap between the debtor's actual expenses and the IRS local standard expenses (`expense_gap`). Finally, we include indicators for whether the case was a pro se filing (without an attorney) and for whether the case was a joint filing. Online Appendix Tables A2 and A3 provide detailed variable definitions.

The BAPCPA's means test is captured by the γ_d coefficients. Recall that below-median-income debtors automatically pass the means test, while above-median-income debtors may fail the means test if their disposable income is too high and they are unable to rebut the presumption of abuse. We capture these rules by including an indicator for above-median income, `AMI`, and interacting this indicator with all covariates included under the totality test.[19] We also interact `AMI` with `amt_above_means`, the gap between the debtor's income and the state median, to allow for the fact that the means test may be more binding for individuals farther from the median income.

Our interpretation of the γ_d parameters attributes any *within-district* differences in eligibility screening for above-median-income debtors (i.e., $\gamma_d \neq 0$) to the means test and any *cross-district* differences (i.e., $\gamma_d \neq \gamma_{d'}$ for $d \neq d'$) to differences in the implementation of the means test. Our interpretation of β_d is analogous except for the totality test. However, estimating separate models for each chapter (and district) provides a check of this interpretation. Since the means test does not screen eligibility for Chapter 13, the above-median-income variables should have little effect on Chapter 13 eligibility.

3.2 Chapter Choice Model

In the first-stage chapter choice model, debtors decide in which chapter to file taking the preceding model of eligibility screening as given. We assume that debtors (and/or their attorneys) are aware of the eligibility rules in their district (β_d, γ_d) and account for expected eligibility, $Q_C(X^E; \beta_d, \gamma_d)$, when deciding between Chapter 7 and Chapter 13. Dismissals are costly so debtors and their attorneys seek to avoid them. For debtors, the costs include delays and additional attorney fees if they wish to refile. For attorneys, the costs include uncompensated work (e.g., justifying an exception to standard practices) and professional repercussions.[20]

Consider the choice of a debtor in district d with characteristics $X = (X^E, X^C)$, where X^C are observed characteristics relevant for the debtor's payoffs in Chapter 7 or Chapter 13. X^C may overlap with X^E, the eligibility characteristics. Let U_7 and U_{13} be the debtor's utility from Chapter 7 and Chapter 13, respectively. The debtor compares the expected utility of each chapter, accounting for the probability of dismissal, and files under Chapter 7 if

$$Q_7^d(X^E)U_7(X^C) + \left[1 - Q_7^d(X^E)\right] U_0(X^C) \geq Q_{13}^d(X^E)U_{13}(X^C) + \left[1 - Q_{13}^d(X^E)\right] U_0(X^C) \quad (2)$$

[19] As discussed in Section 4, we apply the single-person household median income for single filers and the two-person-household median income for joint filers because we do not observe household size. Online Appendix C investigates the robustness of our estimates to several other measures of above-median income.

[20] Legal research emphasizes the close connections with the bankruptcy bar and that trustees and judges can influence or punish lawyers with clients filing under the "wrong" chapter (Sullivan *et al.*, 1994; Braucher, 1993). For example, Braucher (1993) discusses how attorneys learn the informal minimum requirements for Chapter 13 plans and then rarely file plans that do not meet these minimums.

where $Q^d_C(X^E) \equiv Q_C(X^E; \beta_d, \gamma_d)$ and U_0 represents the outside option of debtors – exiting the bankruptcy system, converting the case by refiling under the other chapter, or postponing a refiling until a future date – minus any upfront costs of the dismissal (such as additional fees, time delays, and financial and professional costs borne by the representing attorney).

We parametrize these utilities as linear functions of observed characteristics X^C and unobserved factors ϵ

$$
\begin{aligned}
U_7(X^C) &= X^C \delta^7, \\
U_{13}(X^C) &= X^C \delta^{13} + \epsilon \\
U_0(X^C) &= 0
\end{aligned}
\tag{3}
$$

where the utility of the outside option is normalized to zero and

$$
\begin{aligned}
X^C \delta^C = \delta^C_0 &+ \delta^C_1 \texttt{avgmnthi} + \delta^C_2 \texttt{cntmnthi} + \delta^C_3 \texttt{debt\_to\_income} + \delta^C_4 \texttt{assets\_to\_income} \\
&+ \delta^C_5 \texttt{unsec} + \delta^C_6 \texttt{sh\_secured} + \delta^C_7 \texttt{sh\_nondischarge} \\
&+ \delta^C_8 \texttt{homeowner} + \delta^C_9 \texttt{sh\_real} + \delta^C_{10} \texttt{pos\_equity} + \delta^C_{11} \texttt{neg\_equity} + \delta^C_{12} \texttt{nonexempt\_equity} \\
&+ \delta^C_{13} \texttt{pct\_black} + \delta^C_{14} \texttt{joint\_file} + \delta^C_{15} \texttt{incdropbig} + \delta^C_{16} \texttt{AMI}.
\end{aligned}
\tag{4}
$$

This parametrization captures the main financial incentives – homeownership, secured debt, nonexempt equity, and nondischargeable debts – that cause some debtors to prefer Chapter 13 (see Section 4) and largely follow the existing models of chapter choice (Domowitz and Sartain, 1999; Lefgren *et al.*, 2010; Zhu, 2011; Lawless and Littwin, 2017).[21] We include a debtor's "average" (`avgmnthi`) and "current" (`cntmnthi`) monthly income. These are the two calculations of income defined in the bankruptcy code; they measure the debtor's average income over the last six months and the debtor's income at the time of filing, respectively. We also include general characteristics about the debtor's debts and assets – secured debt, homeownership, nondischargeable debts, and nonexempt assets – that may cause a debtor to prefer Chapter 13. Given some evidence of racial steering

[21] The exact variables and functional forms vary across the models in the literature, but key aspects are the debtor's income, the breakdown between secured and unsecured credit, and homeownership. The important chapter choice variables that we lack are whether the debtor uses a specialist attorney (Lefgren *et al.*, 2010) and the amount of medical debt (Zhu, 2011).

in bankruptcy, we include the share of residents in a zip code that is black. (`pct_black`) Finally, we add a subset of the variables from the eligibility model that may also affect chapter choice: the indicator for joint filings (`joint_file`), an indicator for an income drop (`incdropbig`), and the indicator for above-median income (`AMI`). The `AMI` indicator captures the BAPCPA's direct changes on above-median-income debtors apart from eligibility.[22]

The error term ϵ represents factors that are unobserved to the econometrician but are known by the debtors and affect the value of Chapter 13 relative to Chapter 7 (and the outside option). We assume that these consist of district-specific factors affecting all debtors, such as other aspects of local legal culture, and an idiosyncratic error so that $\epsilon = -\delta_d - \tilde{\epsilon}$, where δ_d is a full set of district fixed effects, and $\tilde{\epsilon}$ follows a standard logistic distribution. By including district fixed effects, we expand on chapter choice models that impose a common intercept across districts, and match Lawless and Littwin (2017) who use district-specific fixed effects to capture important aspects of local legal culture.

Applying these functional forms to the expected utility comparison in equation (2), debtor i in district d with characteristics (X_i^E, X_i^C) chooses Chapter 7 if the following holds:[23]

$$Q_{id}(\beta_d, \gamma_d) \times X_i^C \delta_7 - X_i^C \delta_{13} + \delta_d + \tilde{\epsilon}_{id} > 0 \tag{5}$$

where $Q_{id}(\beta_d, \gamma_d) \equiv \frac{Q_7(X_i^E;\beta_d,\gamma_d)}{Q_{13}(X_i^E;\beta_d,\gamma_d)}$ is the ratio of expected eligibility in Chapter 7 to Chapter 13 for individual i in district d. Higher values of Q_{id} indicate greater expected eligibility for Chapter 7 relative to Chapter 13. Note that Q_{id} is interacted with each of the variables affecting the debtor's utility in Chapter 7 or Chapter 13. If $Q_{id}(\beta_d, \gamma_d)$ is known, equation 5 can be estimated using a standard logit model with parameters δ_7, δ_{13}, and district fixed effects δ_d. As discussed below, the inclusion of district fixed effects does not create an incidental parameters problem.

Our goal is to understand how chapter choice responds to eligibility screening. The object of interest, therefore, is the marginal effect of the eligibility ratio $Q_{id}(\beta_d, \gamma_d)$ on chapter choice, $\frac{\partial \Pr(C=7)}{\partial Q}$. We also consider the elasticity of chapter choice with respect to the eligibility ratio,

[22] Post-BAPCPA, above-median-income debtors sometimes face higher attorney fees because they must complete more bankruptcy forms and may face more scrutiny, and they also must file a five-year Chapter 13 plan (a three-year plan is not an option) and use the IRS allowable standards when determining their payment amounts.

[23] This equation substitutes into equation (2) the parametrization in equation (3) and divides all terms by $Q_{13}^d(X^E)$.

$\frac{\partial \Pr(C=7)}{\partial Q} \frac{Q}{\Pr(C=7)}$.[24] As $Q_{id}(\beta_d, \gamma_d)$ captures debtors' expectations about their eligibility for Chapter 7 relative to Chapter 13 given the local eligibility screening rules reflected in (β_d, γ_d), the marginal effect captures how heterogeneity in the district eligibility screening process filters through to alter debtors' chapter choice decisions.

3.3 Identification and Estimation

We estimate the model by maximum likelihood in two stages.[25] First, we estimate separate eligibility logit models for each district-chapter combination following equation (1). The dependent variable is a binary indicator equal to one if a filing under Chapter C is allowed to proceed and zero if it is dismissed or converted. Thus, a positive outcome indicates that a filing is deemed eligible for that chapter. We estimate β_d^7 and γ_d^7 using eligibility outcomes for the subsample of Chapter 7 bankruptcy filings in district d and β_d^{13} and γ_d^{13} using the eligibility outcomes for the subsample of Chapter 13 debtors in district d. From these estimates, we generate $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$, the eligibility ratio for debtor i in district d.

Note, $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$ depends on the full vector of parameters: β_d^7, γ_d^7, β_d^{13}, and γ_d^{13}. Consequently, this step uses the model estimated on Chapter 7 filers to form counterfactual eligibility predictions for Chapter 13 filers, and vice versa. For example, debtor i in district d who files under Chapter 7 is part of the subsample used to estimate β_d^7 and γ_d^7. $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$ for this debtor also depends on β_d^{13} and γ_d^{13}, which are estimated using the subsample of Chapter 13 filers in district d. Thus, we are assuming exogenous selection into each chapter conditional on the observed covariates. Specifically, we are assuming there are no unobserved determinants of debtor chapter choice, ϵ, that are correlated with the stochastic portion of the eligibility screening process. While districts observe more information about debtors than contained in the data, we observe the factors known

[24] Assume $\tilde{\epsilon}$ follows a standard logistic distribution. For brevity, we suppress the dependence of chapter choice $P \equiv \Pr(C = 7)$ and the eligibility ratio Q on characteristics (X^C, X^E). The marginal effect from a change in the eligibility ratio is given by $\frac{\partial P}{\partial Q} = X^C \delta_7 P(1 - P)$ and averaging this over all debtors produces the average marginal effect. Similarly, the elasticity of chapter choice with respect to eligibility is $\epsilon_Q = \frac{\partial P}{\partial Q} \frac{Q}{P} = X^C \delta_7 (1 - P) Q$, which is then averaged over all debtors. Because the elasticity of Q with respect to Q_7 is 1, and the elasticity with respect to Q_{13} is -1, ϵ_Q can be interpreted as the elasticity of chapter choice with respect to either Chapter 7 eligibility or, if multiplied by negative 1, Chapter 13 eligibility.

[25] In principle, we could jointly estimate the first stage and second stage jointly, which could lead to efficiency gains and potentially allow for correlated errors. The first stage, however, includes district-specific coefficients for each of 83 districts, and the predicted values for each debtor are then used in the second stage. By estimating the first stage independently, we gain the significant computational advantage of separately estimating the first stage for each district and then recombining the data when estimating the second stage. Moreover, given the sample size, efficiency is not a concern.

to be most salient in the eligibility screening process. As a result, we believe the role of any unobserved attributes that affect *both* chapter choice and the outcome of the eligibility screening process to be extremely limited.

Second, we estimate a single logit model of chapter choice pooling data from all districts following equation (5). The dependent variable is a binary indicator equal to one if a debtor files under Chapter 7 and zero if under Chapter 13. Letting $G(\cdot)$ be the cumulative distribution function of a standard logistic distribution and $X_i = (X_i^E, X_i^C)$, equation (5) implies that the probability of choosing Chapter 7 is

$$\Pr(C_i = 7|X_i, d) = G\left[Q_{id}(\beta_d, \gamma_d) X_i^C \delta^7 - X_i^C \delta^{13} + \delta_d\right]. \tag{6}$$

where $Q_{id}(\beta_d, \gamma_d)$ is replaced with the predicted eligibility ratios generated from the first-stage estimates, $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$.

A few comments are warranted. First, there is no challenge in terms of separately identifying δ^7 and δ^{13} as long as $Q_{id}(\cdot)$ is not constant in the entire sample. If one followed existing models by assuming debtors are always eligible for both chapters, then $Q_7^d(X_i^E) = Q_{13}^d(X_i^E) = 1$, the model would reduce to the usual chapter choice model, and only $\delta \equiv \delta^7 - \delta^{13}$ would be identified. Empirically, this restriction is rejected in the data as $Q_{id}(\cdot)$ varies across debtors due to the covariates X^E and across districts due to $(\hat{\beta}_d, \hat{\gamma}_d)$. In addition, while not necessary, there are exclusion restrictions: variables in X^E not contained in X^C.[26] Second, estimation of the district fixed effects, δ_d, by including district dummies does not lead to the incidental parameters problem. In our case, d is small (83) and i is large. Thus, allowing the number of debtors to go to infinity for a fixed number of districts is natural and ensures that the district fixed effects are consistently estimated. Third, to ensure that the estimated ratio, $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$, does not explode, we winsorize the lower range of $Q^{13}(X_{id}; \hat{\beta}_d, \hat{\gamma}_d)$ at 0.1. This only affects 0.22% of observations. Fourth, standard errors are obtained via bootstrap using a procedure to account for the fact that $Q_{id}(\hat{\beta}_d, \hat{\gamma}_d)$ is a generated regressor. Details are provided in Online Appendix D.

Finally, as mentioned at the outset, we do not model the initial decision to file. Two prior

[26] To see why an exclusions restriction is not needed for identification, consider the case where $Q_{id}(\cdot) = X_i^C \theta$ and θ is estimated from a first-step model. In this case $\Pr(C_i = 7|X_i, d) = G\left[(X_i^C \otimes X_i^C)(\hat{\theta} \otimes \delta^7) - X_i^C \delta^{13} + \delta_d\right]$ and δ^7 and δ^{13} remain identified.

studies model the decision to file and chapter choice conditional on filing using a nested logit model and data from the Survey of Consumer Finances (SCF) (Domowitz and Sartain, 1999; Zhu, 2011). The advantage of the SCF data is that it includes both filers and nonfilers, allowing for estimation of the complete nested model. The drawback is that the SCF does not contain the detailed data from filings that districts see when screening for eligibility. Nor does it allow for estimation of the debtor- and district-specific ratio of eligibility probabilities that is the focus of our model. The number of filers in the SCF is also relatively small. In contrast, as discussed in Section 4, we have data on the universe of filers, see the exact information submitted to the court, and see the exact outcome of each filing. This is the trade-off for not having data on nonfilers. That said, within a nested logit model structure, one can obtain consistent estimates through sequential estimation where the lower-level nest (in this case, chapter choice) is estimated separately using a standard conditional logit (Hensher, 1986; Greene, 2003). Thus, our procedure can be viewed as the second stage in this sequential decision-making process which, under the assumptions of the nested logit model, remains consistent even when estimated in isolation. However, while the parameter estimates are consistent for the population parameters, our counterfactual analysis will take the set of bankruptcy filers as fixed. As such, our counterfactual findings should be interpreted as the impact of a policy change on preferences for Chapter 7 and Chapter 13 among the current set of filers. To the extent that the policy change affects the initial decision to file, this will not be captured. Such a partial analysis still generates new and important insights into chapter choice decisions and sources of geographic heterogeneity.

4 Data and Descriptive Statistics

Our data are from the Federal Judicial Center's (FJC) Integrated Database, which contains detailed case-level information on the universe of bankruptcy filings since fiscal year 2009. We impose several sample restrictions. First, we restrict the sample to new consumer Chapter 7 or Chapter 13 cases filed in fiscal years 2011-2015. By stopping in 2015, we are able to observe whether Chapter 13 plans initiated during the sample period were successfully completed. Second, we exclude eleven of the 94 federal court districts; those operating in U.S. territories and the two states where cases are not administered by the U.S. Trustee Program.[27] Third, we exclude cases with missing data, extreme outliers, and those that cannot file certain chapters because of debt limits or recent filings.[28]

Finally, we restrict the sample to debtors reporting positive disposable income on the bankruptcy forms. We do so to focus on debtors who can potentially choose either Chapter 7 or Chapter 13. As those with non-positive disposable income are unable to repay creditors, such debtors are likely restricted to Chapter 7. In practice, nearly all debtors (96.6%) with non-positive disposable income file under Chapter 7 (see Figure 1(b)). We also focus on debtors with positive disposable income since our goal is to examine geographic heterogeneity in chapter choice, and nearly all of the cross-district variation originates from this group. Online Appendix Figure A3 shows the cross-district variation in chapter choice for those with positive and negative disposable income; the variance is 40 times larger among debtors among debtors with positive disposable income. Restricting the sample to those with positive disposable income leaves 2,525,077 debtors' cases (61.7% of all filers) that, unless deemed ineligible by the means test or the totality test, had the option of choosing either Chapter 7 or Chapter 13. Of the debtors in our sample, 52.5% filed under Chapter 7.[29]

The dependent variables in the two stages of the empirical model are a binary indicator for eligibility and a binary indicator for chapter choice. The latter is clear. For the former, we define a case as eligible for a specific chapter (eligibility equal to one) if it was filed under that chapter and the case was allowed to continue in that chapter. A case is ineligible for a specific chapter (eligibility equal to zero) if it was filed under that chapter but dismissed or converted shortly after filing.[30]

[27] We exclude cases filed in North Carolina and Alabama, since these states are not under the jurisdiction of the U.S. Trustee Program, and these trustees are the agents primarily responsible for screening cases for eligibility (Wells *et al.*, 1991). Alabama and North Carolina have a separate group, bankruptcy administrators, that oversee the cases. Less is known about the information used by administrators to assess eligibility. We also exclude cases filed in Washington D.C. and the U.S. territories, which have small sample sizes.

[28] Specifically, we exclude cases with missing data on characteristics (5.4% of cases). We then filter the sample to include only records where total liabilities and total assets range between \$1,000 and \$5,000,000, average monthly income and expenses are greater than zero and less than \$50,000. Additionally, debts must be below the Chapter 13 debt limits as of 2013. These restrictions exclude 4.3% of cases. We drop extreme outliers in monthly disposable income: those where disposable income is outside of $[-\$2000, \$2000]$ (3.9% of cases).

[29] A separate, computational reason for restricting the sample to debtors with positive disposable income is that including negative disposable income debtors often leads to nonconvergence within discrete choice models. The nonconvergence is because of how strongly negative disposable is associated with filing under chapter 7.

[30] As mentioned in Section 2, ineligible cases are typically given the option to convert or be dismissed. We focus on cases dismissed soon after filing because eligibility is determined at the time of the filing. In Chapter 7, where cases only last a few months, any dismissal or conversion is included. In Chapter 13, more than half of cases are dismissed or converted at some point during the three-to-five-year plan, mostly due to the debtor missing plan payments. To focus on dismissals and conversions related to ineligibility for Chapter 13, therefore, we only include dismissals or conversions that occur within four months of the Chapter 13 filing date. We do observe some information on the

We include conversions in this measure of ineligibility because ineligible debtors are typically given the option to convert their case to the other chapter to avoid dismissal. Overall, the large majority of cases are eligible for the chapter under which they file, with only 2-3% of cases being dismissed or converted. However, this does not imply that eligibility screening is unimportant. First, Figure 1(a) shows that there are subgroups of debtors where dismissals are common. Second, our model suggests that forward-looking debtors (and/or their attorneys) take eligibility screening into account when making their chapter choice decision to avoid the costs associated with filing under a chapter for which they may be ineligible. Figure 1(b) also suggests that debtors avoid filing under a chapter for which they may be ineligible.

The remaining variables used in the analysis are listed in Table 1. The table also reports summary statistics for Chapter 7 and Chapter 13 debtors in our main sample. To reduce the influence of extreme outliers, all financial variables are winsorized at the $99^{\mathtt{th}}$ percentile, and the $1^{\mathtt{st}}$ and $99^{\mathtt{th}}$ percentile for disposable income. The first section covers variables related to eligibility for Chapter 7 and Chapter 13. For the totality test, the two primary determinants according to case law (see Section 2), are (i) the debtor's disposable income and (ii) the percent of unsecured debt that could be repaid out of this disposable income over a five-year plan.[31] Our measure of disposable income from bankruptcy Schedules I and J is the exact measure commonly used to assess ability to pay in the totality test (see Wells *et al.* (1991)).[32] The remaining variables proxy for the broader criteria used in the totality test of some districts. For BAPCPA's means test, the key factor is whether the debtor's income, adjusted for household size, exceeds the median in the debtor's state. We do not observe the household size, and instead we assume each household has zero non-filing members. The variable `AMI` is an indicator for whether the debtor's income is above the state median, using a one-person household for single filings and a two-person household for joint cases.[33] In Online Appendix C, we provide additional justification for this measure of above-median income, and also show that the results are robust to several alternatives.

reason for dismissals, but the majority of dismissals do not specify a reason (Online Appendix Table A1).

[31]Disposable income is defined as Schedule I income less Schedule J expenses, adjusted for conduit districts as discussed in Appendix B. Debt repaid in a 60-month plan is calculated as $\frac{60 \cdot \text{disp\_income} - \text{priority unsecured}}{\text{nonpriority unsecured}}$.

[32]We also verified this through discussions and material from bankruptcy attorneys about how trustees assess disposable income.

[33]Above-median income is constructed using the filer's "current monthly income" which is the six-month average used in the means test. Because we do not observe debtors' household size, we classify debtors as below-median income if their income is below the lowest possible state median income that could apply, i.e., the median income for a single-person household in single-filer cases and the median income for a two-person household in joint cases.

The second section in Table 1 covers variables that affect debtors' chapter choice, apart from eligibility. These cover the debtor's overall financial situation, several variables reflecting homeownership and home equity, as well as nonexempt assets.[34] For nonexempt assets, we calculate each filer's nonexempt equity following Pattison and Hynes (2020). We also include the value of the filer's personal (non-real-estate) assets to income as a proxy for other nonexempt assets.[35] Consistent with expectations, Chapter 7 filers have lower disposable income, are less likely to be homeowners, have less secured debts, and have less nonexempt equity. Racial differences in chapter choice are also evident, with Chapter 7 filers more likely to reside in zip codes with a lower share of Black residents.

5 Results

5.1 Eligibility Model

To begin, we discuss the results from the model for chapter eligibility given in equation (1). We focus our discussion around two questions. First, how important are the totality test and means test in determining eligibility? Second, how much does the implementation of eligibility screening under the two tests vary across different federal court districts? The first question is answered through examination of the statistical and economic significance of the (β_d, γ_d) estimates. The second question is answered through examination of the cross-district heterogeneity in the (β_d, γ_d) estimates.

Table 2 reports the coefficient estimates and marginal effects (MEs). Panel A reports the coefficients for below-median-income debtors, i.e., the β estimates and the associated MEs. These represent the effect of the totality test alone because below-median-income debtors automatically pass the means test. Panel B reports the coefficients for above-median-income debtors, i.e., the estimates of $\beta + \gamma$ and the associated MEs. These represent the combined effect of the totality test and the means test. In both panels, the MEs are for a hypothetical debtor with an eligibility probability of $\hat{Q}_C = 0.95$ for $C = 7, 13$, which matches (approximately) the mean eligibility rates

[34] We thank Sasha Indarte for making the exemption data from Indarte (2023) publicly available.

[35] Specifically, nonexempt equity is defined as $\max\{\text{real property value} - \text{secured debt} - \text{homestead exemption}, 0\}$, applying the married homestead exemption to joint filers and the single homestead exemption to single filers. If both federal and state exemptions are available, we take the maximum of the two. Pattison and Hynes (2020) finds that this approximation for home equity is highly correlated with actual home equity reported on bankruptcy forms.

in the full sample ($\bar{\hat{Q}}_7 = 0.95$ and $\bar{\hat{Q}}_{13} = 0.96$).

As a benchmark, we begin with the Chapter 7 eligibility results from a model estimated on the full national sample (i.e., pooling all districts together). We find that both the totality test (applied to all debtors) and the means test (applied to above-median income debtors) restrict eligibility in Chapter 7. The totality test primarily screens on ability to pay, measured by monthly disposable income (`disp_income`) and the percentage of debt that would be repaid over a five-year plan (`pct_repay5`). In Panel A column (1), both of these variables are statistically significant at below the 1% level. The corresponding MEs indicate that an additional $1,000 in monthly disposable income or the ability to repay 100% of unsecured debt over a five-year plan (relative to repaying 0%) both reduce eligibility by four percentage points (pp). The magnitudes are large when compared to the mean probability of dismissal or conversion of 2.1% for debtors who choose Chapter 7. Among the other variables in Panel A, filing pro se is most important; it sharply reduces the probability of eligibility, consistent with some prior estimates (Norberg and Velkey, 2005). Panel B reports estimates for above-median debtors, who are subject to both the totality test and the means test. The coefficients and MEs of `disp_income` and `pct_repay5` are more negative for above-median debtors than below-median debtors, reflecting the additional restrictions of the means test. The differences in the coefficient magnitudes between above- and below-median-income debtors are statistically significant at the 5% level.

We next turn to geographic heterogeneity in the implementation of the totality test and means test. Columns (3) and (4) report the 10^{th} and 90^{th} percentiles of the MEs across the 83 district-specific Chapter 7 eligibility models. The results reveal significant differences in implementation across districts. In Panel A, the MEs of the two ability to pay measures under the totality test vary by an order of magnitude across districts, ranging a reduction in eligibility of 7-9pp (10^{th} percentile) to a reduction of only 1pp (90^{th} percentile). In Panel B, there is similar heterogeneity for above-median debtors, which reflects the combined impact of the totality test and the means test.

Panel C isolates the net effect of the means test. Specifically, we report the average marginal effect (AME) of the means test, defined as the average difference in predicted eligibility when `AMI` = 1 compared to when `AMI` = 0. The average is taken over the above-median-income debtors in the national sample. Thus, the AME reflects the impact of the means test on those subject to it. In the national model, the means test reduces expected eligibility for Chapter 7 by 6.6pp. But allowing for heterogeneity across districts, the AME varies from -15pp to -3pp. Note, we calculate the *district-specific* AMEs by taking the average over the *national* sample of above-median debtors. As a result, any cross-district differences in the AMEs arise solely due to heterogeneity in the estimated parameters and not debtor characteristics, X^E. Thus, even though the means test is mostly formulaic, there is room for variation in its implementation across districts (see Section 2). These estimates of the means test's impact on eligibility, particularly in Chapter 7, will be central to the policy analysis later in the paper.[36]

Lastly, we consider estimates and MEs from the Chapter 13 eligibility model in columns (5)-(8). The signs and magnitudes of the estimates corroborate assumptions in our model. First, the Chapter 13 model estimates provide a falsification check of our model. Because the means test does not alter eligibility for Chapter 13, the variables capturing this screening mechanism should have little impact on Chapter 13 eligibility. This is confirmed in the results of Panel C columns (6) through (8), supporting our interpretation of the above-median indicator `AMI` and its interactions as capturing the effect of the means test. Specifically, the estimated effect of the means test in Chapter 13 is essentially zero in the national model and the district-specific estimates are also small and clustered around zero (Panel C columns (6) through (8)). Second, consistent with how districts evaluate Chapter 13 plan feasibility, the ability to repay a greater percentage of debt is associated with increased eligibility under Chapter 13 in the majority of districts, while the effect of disposable income is much more variable. In contrast, the ability to repay and disposable income both reduce eligibility under Chapter 7. In summary, our analysis of eligibility screening is consistent with the expected applications of the totality test and the means test, but also highlights significant heterogeneity across districts in the implementation of these tests.

[36]One potential concern with our analysis is that above-median-income status (`AMI`), the key variable identifying the effect of the means test, is measured with error since we do not perfectly observe household size. In Online Appendix C, we examine this concern and find that the results are robust to several alternative measures of above-median income status, including applying different thresholds for the means tests and using an independent measure available for a subset of districts. The district-specific estimates of the means test are highly similar across all measures; the correlation of the district-specific AMEs of the means test across measures ranges from 0.86 to 0.98.

5.2 Chapter Choice Model

We now turn to the results from the model for chapter choice given in equation (6). Again, we focus our discussion around two questions. First, do debtor characteristics differentially affect the benefits from filing under Chapter 7 versus under Chapter 13? Second, are debtors forward-looking and incorporate eligibility into their chapter choice decision calculus? The first question is answered through examination of examination of the heterogeneity in the estimates of (δ^7, δ^{13}). The second question is answered through the statistical and economic significance of the marginal effect of the eligibility ratio, Q.

The estimates are reported in Table 3. The table contains the coefficient estimates, $(\hat{\delta}^7, \hat{\delta}^{13})$, along with their difference and the statistical significance of the difference. We also report the AMEs of the covariates and the eligibility ratio. In nearly all cases, we easily reject the null of equality between δ^7 and δ^{13}. This is noteworthy for two reasons. First, prior students have only estimated the difference, $\delta^7 - \delta^{13}$. Based on our structural model, we are able to separately identify the parameters. Second, because of the separate identification of δ^7 and δ^{13} we are able to confirm alignment between the estimates and the expected effects. Specifically, the coefficients in column (1) and column (2) reflect the change in the value of Chapter 7 and Chapter 13, respectively, relative to the outside option of dismissal. Column (3) reports the difference $(\delta^7 - \delta^{13})$ which reflects the variable's impact on the benefits of Chapter 7 relative to Chapter 13. As expected, secured debt, nondischargeable debt, having real property, and having nonexempt home equity are all associated with a greater preference for filing under Chapter 13. However, the fact that $\hat{\delta}^7$ and $\hat{\delta}^{13}$ are both negative for these variables indicates that higher values are associated with lower value of either chapter relative to the outside option. Moreover, filers from zip codes with a higher share of residents that is Black have a higher value of both Chapter 7 and Chapter 13 relative to the outside option. However, the AME is negative, indicating that such filers are more likely to file under Chapter 13.

While the individual estimates are of interest, our primary focus is on the responsiveness of chapter choice to changes in expected eligibility. The bottom row in Table 3 reports the AME of a change in the eligibility ratio, Q, which is the ratio of expected eligibility under Chapter 7 to expected eligibility under Chapter 13.[37] The estimate indicates that a one unit increase in Q, which, for the average filer, is roughly a 1pp increase in expected Chapter 7 eligibility, increases the probability of filing Chapter 7 by 3.17pp. This effect translates to an average elasticity of chapter choice with respect to Q of 8.91, indicating that a 1% increase in Chapter 7 eligibility (or a 1% decrease in Chapter 13 eligibility) raises the probability of filing for Chapter 7 by 8.91%. Thus, chapter choice decisions are highly responsive to expected eligibility.

Given how responsive chapter choice is to expected eligibility, heterogeneity in how eligibility screening is implemented across districts will strongly influence chapter choice. Figure 2 illustrates the variation in eligibility across districts and how it affects chapter choice. Figure 2(a) shows the cross-district differences in the eligibility ratio for a debtor with the average characteristics from the national sample, $\bar{X}$. The predicted eligibility ratio, Q, ranges from 0.916 to 1.12, indicating that some districts view this representative debtor as more suited for Chapter 13 (ratio < 1), whereas others view the debtor as more suited for Chapter 7 (ratio > 1). Figure 2(b) shows the effect of these changes in eligibility screening on chapter choice. Holding other factors constant, the variation in the eligibility ratio across districts would change the probability that a debtor with characteristics $\bar{X}$ files under Chapter 7 from less than 40% (when $Q = 0.916$) to more than 70% (when $Q = 1.12$).

The large response to eligibility may seem surprising. This is especially true given that case dismissal or conversion is relatively rare; as mentioned previously, Table 1 shows that only 2-3% of bankruptcy cases are dismissed or converted. However, in the context of the model, this can arise if there are large costs to dismissal or conversion, and thus debtors (and/or their attorneys) choose the chapter that minimizes the risk of dismissal. Thus, it is precisely *because* debtors are responsive to eligibility probabilities that helps explain why dismissals and conversions occur so infrequently. As evidence of this, we find that while dismissals or conversions are unlikely for those who actually file under Chapter 7, with a mean expected eligibility $\bar{Q}_7$ of 97.9%, our model predicts that if those who actually filed under Chapter 13 had *instead* filed under Chapter 7, they would have faced a much larger dismissal rate, with a mean eligibility $\bar{Q}_7$ of only 88.7%. This sorting reflects the central role that eligibility screening plays in chapter choice.

[37] The formulas for the marginal effect of Q and the elasticity of chapter choice with respect to Q are in Section 3.

6 Policy Analysis

With the model estimates in hand, we turn to the examination of two major bankruptcy policies. First, we examine the impact of the BAPCPA's flagship feature – the means test – which aimed to encourage Chapter 13 by restricting high-income debtors' access to Chapter 7. Second, we examine how increased uniformity in eligibility screening would affect the longstanding geographic disparities in chapter choice. In both policy analyses, we rely on our model of chapter choice conditional on filing. Thus, our analyses capture the effects of these two policies on the current set of bankruptcy filers. We leave an exploration of selection into filing and general equilibrium effects for future work.

6.1 Policy I: BAPCPA's Means Test

BAPCPA, which introduced the means test, was implemented in 2005 and was the largest change to the U.S. bankruptcy code since the 1980s. The means test aimed to shift filings into Chapter 13, but evidence on its effects is mixed. Several quantitative macroeconomic models suggest that the means test has large effects on filings and credit markets (Chandra and Staiger, 2007; Mitman, 2016; Nakajima, 2017). However, empirical studies have found little impact. Instead of restricting access to Chapter 7 for high-income debtors, research has consistently found minimal change in the income distribution of Chapter 7 filers from the pre-BAPCPA period (Lawless and Littwin, 2017; Albanesi and Nosal, 2022; Gross *et al.*, 2021).[38] That said, identification of the causal effect of the means test is challenging since it represents a change at the national level and BAPCPA introduced more than just the means test.[39] We overcome this challenge by using new variation identified by our model to generate counterfactual, district-specific predictions of the impact of the means test on chapter choice. We then compare these model-generated predictions to the actual district-specific changes that occurred around BAPCPA. Since the model is estimated using data from the post-BAPCPA period of 2011-2015, assessing the BAPCPA's effects in 2005 provides an out-of-sample validation test of the model's ability to predict the impact of policy changes.

[38] Cornwell and Xu (2014) is an exception. The authors find some evidence that the means test is more binding in eight states with income distributions more concentrated around the state median income, presumably causing more debtors to be affected by the means test. We show that our results are robust to controlling for this channel.

[39] For example, one explanation for the stable income distribution of filers may be that the means test reduced filings among high-income filers, but the BAPCPA's impact on attorney fees also reduced filings among low-income debtors (Albanesi and Nosal, 2022).

Counterfactual Impact of the Means Test

Using the estimated model, we generate counterfactual predictions for each debtor's chapter eligibility and chapter choice if the means test was not in place, which represents the pre-BAPCPA environment. Aggregating these counterfactual predictions to the district-level and comparing them with the observed data (with the means test) allows us to estimate district-specific effects of the means test. To proceed, recall that the district-level eligibility rules for chapter C are captured by $Q_C(\cdot)$, the probability of choosing Chapter 7 is given by $G(\cdot)$, and the impact of the means test in the eligibility model is captured by γ_d in equation (1). As a result, the effect of the means test for debtor i in district d on Chapter C eligibility is $\Delta Q^d_{iC} = Q_C(X_i, \hat{\beta}_d, \hat{\gamma}_d) - Q_C(X_i, \hat{\beta}_d, 0)$, where the second term removes the means test by setting $\gamma_d = 0$. The corresponding district-level average is $\Delta Q^d_C = \frac{1}{N_d}\sum_{i=1}^{N_d} \Delta Q^d_{iC}$ where N_d is the number of filers in district d. Similarly, the impact of the means test for individual i in district d on the probability of filing under Chapter 7 is $\Delta G_{id} = G(X_i, \hat{\beta}_d, \hat{\gamma}_d, \hat{\delta}) - G(X_i, \hat{\beta}_d, 0, \hat{\delta})$. The corresponding district-level average is $\Delta G_d = \frac{1}{N_d}\sum_{i=1}^{N_d} \Delta G_{id}$.

Two details require mentioning. First, when generating the probability of filing under Chapter 7 without the means test, $G(X_i, \hat{\beta}_d, 0, \hat{\delta})$, we also set to zero the coefficient on `AMI`, given by δ^C_{16} in equation 1, to capture the BAPCPA's restrictions on Chapter 13 plans. Second, because the model is estimated only on debtors with positive disposable income and only these debtors are likely to be affected by the means test, the predicted change in *overall* chapter choice for the district is $\Delta G^O_d = DI_d \Delta G_d$, where DI_d is the share of debtors in district d with positive disposable income.[40]

To summarize, in our exercise we remove the means test in the eligibility screening models, thereby generating counterfactual district-level predictions for the impact of the means test on eligibility. Moreover, since the changes in eligibility impact chapter choice, we also generate counterfactual district-level predictions for the impact of the means test on chapter choice.

Figure 3 reports the predicted changes in district-level *eligibility*, ΔQ^d_C, and overall chapter choice ΔG^O_d. Figure (a) shows that, as expected, the means test decreases eligibility for Chapter 7, but has essentially zero effect on Chapter 13 eligibility. Chapter 7 eligibility decreases in all districts,

[40]We assume that debtors with negative disposable income are unaffected by the means test because 96.6% file under Chapter 7, 74.9% are below-median income, and those with above-median income would almost certainly qualify for Chapter 7 under the expense-based portion of the means test. The predicted change in a district's share of bankruptcies under Chapter 7 from the removal of the means test is, therefore, $\Delta G^O_d = DI_d \Delta G_d + (1 - DI_d) \times 0 = DI_d \Delta G_d$.

with a mean change of -3pp, and ranging from -0.16pp to -8pp across districts. Conversely, Chapter 13 eligibility is unaffected in most districts, with a mean change of 0.18pp and changes larger than 2pp in absolute value in only 2 districts. Although Chapter 7 eligibility declines, the effects are relatively small for two reasons. First, most filers are below the median income and thus unaffected by the means test. Second, the totality test, captured by the β_d coefficients, is as strict as the means test in some districts. When this occurs, the means test does not provide any additional screening for above-median-income debtors. While these findings are new to the literature (to our knowledge), both of these explanations are consistent with anecdotes from bankruptcy judges and attorneys about the limited impact of the means test in light of the pre-existing totality test (Wedoff, 2005; Littwin, 2016).

Figure 3(b) shows the district-specific changes in *chapter choice*. The model predicts that adding the means test decreases a district's share of bankruptcies filed under Chapter 7 by 11pp on average. However, there is considerable variation across districts; the predicted change ranges from less than 5pp to more than 20pp. This variation is due to (i) differences across districts in the implementation of the means test relative to the pre-BAPCPA eligibility screening process that relied on the totality test, among others, and (ii) differences in the characteristics of debtors across districts. In summary, our model indicates that the means test *did affect* chapter eligibility and chapter choice in meaningful ways. Moreover, the effects are highly variable across districts.

Comparison to Observed Changes in Chapter Choice

In the previous section, we use the model estimates – obtained using a sample from the 2011-2015 post-BAPCPA period in which the means test is in effect – to generate counterfactual predictions of the impact BAPCPA's means test on each district's average chapter choice. In this section, we use a *different* data set at the district-quarter-level to compare these counterfactual predictions to the observed district-specific changes in chapter choice that occurred when the BAPCPA's means test was implemented in 2005.[41] Thus, evaluating the model's predictions using data from the pre-BAPCPA period in which the means test was not in effect provides a test of the model's ability to generate out-of-sample predictions under a different policy environment.

To proceed, we use the model-predicted value, ΔG_d^O, from the prior section as a covariate in

[41]Case-level bankruptcy data published by the FJC are only available for the post-BAPCPA period.

the following specification

$$\texttt{Ch.7}_{dt} = \beta_0 + \beta_1 \texttt{Post}_t \times \Delta G_d^O + \delta_d + \tau_t + \texttt{controls}_{dt} + u_{dt} \tag{7}$$

where $\texttt{Ch.7}_{dt}$ is the share of bankruptcies under Chapter 7 in district d during quarter t, $\texttt{Post}_t$ is an indicator for being in the post-BAPCPA period (fourth quarter of 2005 and later), δ_d and τ_t are district and time fixed effects, and $\texttt{controls}_{dt}$ is a vector of controls. The coefficient of interest, β_1, captures the fraction of the observed (conditional) change in Chapter 7 rates around the introduction of BAPCPA accounted for by our predicted change in Chapter 7 rates, ΔG_d^O. If the predictions are perfect, β_1 will equal one. If our model captures some, but not all, of the (condtional) changes, β_1 will be less than one. We use data on quarterly district bankruptcies from 2001-2019, stopping before the onset of the Covid-19 pandemic.[42]

Before turning to the results, it should be noted that we do not expect our model to capture the full extent of changes around the introduction of BAPCPA as there are several aspects of BAPCPA and the economic environment that we abstract from in our model. First, chapter choice may vary geographically due to other provisions in BAPCPA which we do not model or due to heterogeneous economic conditions during the Great Recession and subsequent recovery. Second, our model assumes that the composition of bankruptcy filers is constant. As a result, we will not capture changes in chapter choice due to changes in the composition of filers; for example, compositional changes during the spike in Chapter 7 bankruptcies immediately before BAPCPA (Morgan *et al.*, 2012). Finally, measurement error in ΔG_d^O, due to the fact that it is estimated, will likely lead to attenuation bias. To the extent possible, we examine the sensitivity of our estimates to these factors by controlling for other aspects of bankruptcy taken from the literature and through additional fixed effects. We also estimate an event study version of equation (7) to investigate whether the timing of the changes in chapter choice correspond with the enactment of the means test.

Table 4 reports the estimation results. Column (1) reports estimates from a model containing only the variable of interest $\texttt{Post}_t \times \Delta G_d^O$, controls for the state-level unemployment rate and log of home prices, and district and year fixed effects. Since the means test was intended to reduce

[42] We also remove Arkansas from the sample because the quarterly bankruptcy data does not separate the Eastern and Western districts.

filings under Chapter 7, the estimates indicate that a model-predicted 1pp decrease in the share of filings under Chapter 7 is associated with a 0.46pp decline in the actual share of bankruptcies under Chapter 7. The estimate is significant at the 1% level. That is, districts where our model predicts larger declines in Chapter 7 usage did, in fact, experience larger declines.

While the relationship between the model-predicted and actual shares of filings under Chapter 7 is statistically significant, the estimate is less than one. As mentioned, one reason for this may be that BAPCPA affected several aspects of bankruptcy apart from the means test and these changes are not modeled. The remaining columns explore the sensitivity of the estimates to additional controls for other effects of BAPCPA. The literature suggests that BAPCPA's impact varied geographically due to several features of bankruptcy law including homestead exemptions (Morgan *et al.*, 2012), states' income distributions (Cornwell and Xu, 2014), attorney fees (Albanesi and Nosal, 2022), and the historical use of Chapter 13 (Chakrabarti and Pattison, 2019). We add the key variables from these papers, controlling for the interaction of the post-BAPCPA indicator with homestead exemptions (column 2), an indicator, `means test`, for the states Cornwell and Xu (2014) argues are more affected by the means test because of the state's income distribution (column 3), changes in Chapter 7 and Chapter 13 attorney fees from Lupica (2012), and controls for the pre-BAPCPA (2003-2004 average) share under Chapter 7 similar to Chakrabarti and Pattison (2019) (column 4).[43] We include all of these covariates in column (5). The point estimates for our coefficient of interest, β_1, generally increase in magnitude as we control for these additional effects. The largest impact results from including the pre-BAPCPA (2003-2004) Chapter 7 share, which proxies for other aspects of local legal culture that altered the impact of BAPCPA (Chakrabarti and Pattison, 2019).[44] Thus, as expected, controlling for unmodeled heterogeneity in BAPCPA's impact increases the alignment between the model-generated predictions and the observed changes.

Our preferred specification in column (6) controls for these other aspects of BAPCPA-induced heterogeneity and also allows for flexible, time-varying geographic differences by including region-

[43] Note, the covariate measuring the pre-BAPCPA (2003-2004 average) share under Chapter 7 is similar to a lagged dependent variable model. As such, we do not expect this covariate to be strictly exogeneous which is necessary due to the inclusion of district fixed effects. However, the bias – referred to as Nickell (1981) bias – disappears asymptotically for large T. Because $T = 76$ in our estimation, the issue can be ignored.

[44] The pre-BAPCPA Chapter 7 share proxies for the areas persistent legal culture around chapter choice, which altered the impact of BAPCPA provisions. The channel highlighted in Chakrabarti and Pattison (2019) is that, in areas with a low Chapter 7 share (high Chapter 13 share), a change to the treatment of auto loans in Chapter 13 had a larger effect. Another important channel is that the means test and increases in Chapter 7 attorney fees will have a larger impact in areas where, because of the local legal culture, Chapter 7 is more common.

by-quarter fixed effects for the four Census regions. These controls address concerns that the results are driven by broader shocks to geographic regions, such as the South, where Chapter 13 is most common. With these controls, the coefficient on $\texttt{Post}_t \times \Delta G_d^O$ indicates that a 1pp increase in the predicted impact of the means test on the share of bankruptcies in Chapter 7 is associated with a 0.76pp increase in the district's actual share of bankruptcies under Chapter 7. Moreover, we cannot reject the null that β_1 equals one at conventional levels of statistical significance. In column (7) we also control for the share of bankruptcies with negative disposable income in each district $(1 - DI_d)$. The point estimate on $\texttt{Post}_t \Delta G_d^O$ remains above 0.60pp, indicating that the correlation is driven by the predicted changes among the positive-disposable-income debtors affected by the means test.

Finally, we estimate an event study to examine the timing of the changes in chapter choice around BAPCPA.[45] Figure 4 plots the coefficients from this event study specification. The interpretation of the figure is as follows. First, prior to 2004, there is essentially no relationship between ΔG_d^O and district changes in $\texttt{Ch.7}_{dt}$. The coefficient estimates are close to zero and typically statistically insignificant. There is, however, a slight seasonality that is correlated with ΔG_d^O, as the coefficients in quarters 3 and 4 of each year tend to be slightly larger and sometimes statistically significant. This seasonality is similar in both the pre-BAPCPA and post-BAPCPA periods. Second, in quarters two through four of 2005 we obtain large negative estimates, indicating that districts for which our model predicts a large decline in Chapter 7 filings *after* the introduction of the means test, experience an increase in the Chapter 7 cases immediately *before* the law went into effect. This pattern reflects the well-known rush to filing under Chapter 7 for districts where our model predicts the means test to be most binding (Morgan *et al.*, 2012). Finally, once BAPCPA is in effect, the predicted change aligns well with the actual changes, as the estimates vary from roughly 0.25 to 0.75. Overall, the figure shows the timing of the changes in chapter choice predicted by our model align closely with the timing of BAPCPA. This helps to validate the ability of the model to

[45] Based on the specification in column (1), we estimate

$$\texttt{Ch.7}_{dt} = \alpha_0 + \sum_{k \neq 2003Q1} \gamma_k \Delta G_d^O \times 1[t = k] + \delta_d + \tau_t + \texttt{controls}_{dt} + u_{dt}$$

where we interact the district-specific predicted change ΔG_d^O with quarter fixed effects, omitting the first quarter of 2003 as a reference group. We omit this quarter to make it easier to observe the well-known anticipation effects that occurred in 2005 before BAPCPA went into effect.

generate informative out-of-sample predictions about the single most important policy change in U.S. bankruptcy over the past 40 years.

6.2 Policy II: Uniform Screening

Although the U.S. bankruptcy code is primarily a uniform federal law, there is tremendous geographic variation in the relative use of the two bankruptcy chapters. Across districts, the average share of bankruptcies filed under Chapter 7 varies from 25% to more than 90%. This heterogeneity is persistent and leads to significant variation in debt relief and creditor repayment across states.[46] Concerned by these stark cross-district differences, many have called for greater uniformity in bankruptcy practices across districts.[47] However, it is unclear which features of the bankruptcy system or local legal culture policymakers should target to increase uniformity. For instance, existing evidence shows that well-known features such as asset exemptions and garnishment laws are not strongly correlated with the geographic patterns (Keys *et al.*, 2020).

Here, we use our model to quantify the importance of a previously unexamined feature of bankruptcy in explaining geographic heterogeneity: heterogeneous eligibility screening. To proceed, we replace each district's eligibility screening process with a uniform process estimated from the full national sample. Next, we examine how this uniform eligibility screen would affect the geographic variation in chapter choice. We continue to restrict the analysis to positive disposable income debtors who, as discussed in Section 4, account for nearly all of the cross-district variation in chapter choice.

To measure the cross-district variation, we first compute with the difference between each district's observed share of Chapter 7 filings and the national average. We then determine the portion of this difference that would be eliminated if the district adopted the uniform, national eligibility screening process. Recall that the probability that debtor i in district d files under Chapter 7 is given in equation (6) and is a function of debtor characteristics, X_i, district fixed effects, and the district's eligibility screening process which depends on the parameters β_d and γ_d.

[46]For evidence on the correlation of states' discharges and recoveries with their chapter choice averages, see Online Appendix Figure A4. We aggregate to the state-level because the calculations rely on trustee-specific data and trustees are often shared across districts within a state.

[47]For example, the American Bankruptcy Institute's 2017-2019 Commission on Consumer Bankruptcy, a committee of bankruptcy judges, trustees, and attorneys concluded that "nonuniform practices are a problem in the bankruptcy system that should be minimized to the greatest extent possible" (American Bankruptcy Institute, 2019).

District d's observed share of bankruptcies under Chapter 7, $\texttt{Ch.7}_d$, can be expressed as

$$\texttt{Ch.7}_d = \frac{1}{N_d} \sum_{i=1}^{N_d} G(X_i, \hat{\beta}_d, \hat{\gamma}_d, \hat{\delta})$$

where the probability that a debtor chooses Chapter 7 is denoted by $G(X_i, \hat{\beta}_d, \hat{\gamma}_d, \hat{\delta})$. Similarly, the national share of bankruptcies under Chapter 7 is

$$\texttt{Ch.7}_N = \frac{1}{N} \sum_{d=1}^{D} \sum_{i=1}^{N_d} G(X_i, \hat{\beta}_N, \hat{\gamma}_N, \hat{\delta}) + r_N$$

where D is the number of districts, $N \equiv \sum_d N_d$, and $(\hat{\beta}_N, \hat{\gamma}_N)$ are the estimated coefficients from the national eligibility model in Table 2 columns (1) and (5). The residual in the national model, r_N, reflects the small gap between the sample mean $\texttt{Ch.7}_N$ and the mean predicted value. The residual arises because the national chapter choice model was estimated using the district-specific eligibility rules $(\hat{\beta}_d, \hat{\gamma}_d)$ to form Q_{id} while, in this policy analysis, we generate Q_{id} using the uniform eligibility rules from the national model, $(\hat{\beta}_N, \hat{\gamma}_N)$. In practice, r_N is very small; the sample mean and mean predicted value differ by only 1.4pp. Both the district and national models use the same estimated chapter choice coefficients $\hat{\delta}$ from Table 3.

Let district d's "total gap", $\Delta_d^T = \texttt{Ch.7}_d - \texttt{Ch.7}_N$, measure the difference between district d's share under Chapter 7 and the national share under Chapter 7. We decompose the gap into three components as follows

$$\begin{aligned} \underbrace{\Delta_d^T}_{\text{Total Gap}} &= \underbrace{\frac{1}{N_d} \left[\sum_{i=1}^{N_d} G(X_i, \hat{\beta}_d, \hat{\gamma}_d, \hat{\delta}) - G(X_i, \hat{\beta}_N, \hat{\gamma}_N, \hat{\delta}) \right]}_{\text{Eligibility Gap } (\Delta_d^E)} \\ &+ \underbrace{\frac{1}{N_d} \sum_{i=1}^{N_d} G(X_i, \hat{\beta}_N, \hat{\gamma}_N, \hat{\delta}) - \frac{1}{N} \sum_{i=1}^{N} G(X_i, \hat{\beta}_N, \hat{\gamma}_N, \hat{\delta})}_{\text{Covariate Gap } (\Delta_d^X)} \\ &- \underbrace{r_N}_{\text{Residual Gap } (\Delta_d^R)} . \end{aligned} \tag{8}$$

The Eligibility Gap, Δ_d^E, captures the difference between the district's share under Chapter 7 and the national share under Chapter 7 due to the district following its own eligibility screening process rather than the uniform eligibility screening from the national model. In other words, the Eligibility Gap is the portion of the variation that would be eliminated if district d adopted the uniform national eligibility rules. The Covariate Gap, Δ_d^X, captures the difference caused by heterogeneity in the covariate distributions (inclusive of the district fixed effects) between district d and the national sample. The residual gap, Δ_d^R, captures the small difference between the national model's sample mean and mean fitted value, which is the same for all districts d. These three components account for all variation in the total gap as $\Delta_d^T = \Delta_d^E + \Delta_d^X + \Delta_d^R$.

We summarize the role of each component in the total variation across all districts using an exact variance decomposition. Similar exact variance decompositions have been used to decompose other sources of geographic variation, such as geographic variation in economic conditions (Fadinger *et al.*, 2022; Bilal, 2023) and firm size (Eaton *et al.*, 2004; Bernard *et al.*, 2022). The variance in Δ_d^T across districts can be decomposed into the portion due to the Eligibility Gap, Covariate Gap, and Residual Gap. This is given by

$$\mathrm{Var}[\Delta_d^T] = \mathrm{Cov}[\Delta_d^E, \Delta_d^T] + \mathrm{Cov}[\Delta_d^X, \Delta_d^T] + \mathrm{Cov}[\Delta_d^R, \Delta_d^T]$$

Therefore, share of the variation attributed to each component $j = E, X, R$ is $S^j = \frac{\mathrm{Cov}[\Delta_d^j, \Delta_d^T]}{\mathrm{Var}[\Delta_d^T]}$, with the shares summing to 100%.[48] The portion attributed to the residual R will mechanically equal zero in this exact variance decomposition because Δ_d^R is entirely due to the national model and is therefore constant across districts. We explore alternative decomposition methods in Online Appendix E, conducting a standard variance decomposition and a decomposition using absolute value ratios. These alternatives produce similar results.

Table 5 reports the shares from the decomposition. Heterogeneity in eligibility screening, Δ_d^E, explains 24% of the cross-district variation in chapter choice. Thus, about one quarter of the geographic variation is due to differential implementation of eligibility screening across districts. This is a significant share given that eligibility screening is just one of many potential aspects of local legal culture that vary across districts. The remaining 76% of the geographic variation is due to heterogeneity in filer characteristics and other unmodeled aspects of local legal culture captured by the district fixed effects. Thus, much of the geographic variation is due to differences in the

[48] The share attributed to component j is also equal to the coefficient estimate from a district-level regression of component j on Δ_d^T.

characteristics of debtors that make them more or less suited for Chapter 7 and thus are largely beyond the reach of policy reform. Nonetheless, the fact that differences in eligibility screening explain a quarter of the variation provides critical insights into the potential impact of making eligibility screening more uniform across districts. Policies that eliminate discretion could reduce the geographic variation by up to a quarter. However, note two caveats. First, as mentioned previously, our analysis neglects any general equilibrium effects of a policy change or changes in selection into bankruptcy. Second, our analysis is positive not normative. We cannot speak to whether increased uniformity is welfare-enhancing.

7 Conclusion

This paper develops a model of consumer bankruptcy chapter choice that incorporates two new, realistic features of eligibility screening in bankruptcy: (i) the multiple eligibility tests used by trustees and judges, and (ii) geographic heterogeneity in how these tests are implemented. Using case-level data from 83 court districts, we estimate the parameters governing the eligibility screen tests in each district. The estimates from the chapter choice model indicate that debtors and their attorneys are highly responsive to eligibility screening when making their initial chapter choice decisions.

We then use the model to examine two policy counterfactuals. First, we examine the impact of BAPCPA's flagship feature - the means test - which aimed to encourage Chapter 13 by restricting high-income debtors' access to Chapter 7. We use the model to generate the predicted impact of the means test on chapter choice in each district, and then show that these model-generated predictions are strongly correlated with observed changes in chapter choice around the enactment of BAPCPA. Not only do these estimates quantify the policy impact of the means test, but they demonstrate the model's ability to generate out-of-sample policy predictions that align closely with observed outcomes. Second, we examine how increased uniformity in eligibility screening would affect the longstanding geographic disparities in chapter choice, finding that heterogeneity in eligibility screening explains about one quarter of the existing geographic variation. This provides some guidance to policies that aim to alter chapter choice by making eligibility screening more uniform (American Bankruptcy Institute, 2019). A limitation in both policy counterfactuals is that we hold the decision to file fixed, and so do not examine the impact of these policy decisions on selection into bankruptcy.

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Table 1: Summary Statistics

variable	definition	Chapter 7 mean	Chapter 7 std. dev.	Chapter 13 mean	Chapter 13 std. dev.	difference
	(1)	(2)	(3)	(4)	(5)	(6)
Eligibility Variables						
elig	eligible (%)	97.9	14.4	97.1	16.8	0.8
converted_early	convert early (%)	0.8	9.0	0.8	9.0	0.0
dism_early	dismiss early (%)	1.3	11.3	2.1	14.3	-0.8
disp_income	disposable income ($1,000s)	0.1	0.2	0.5	0.4	-0.4
pct_repay5	debt repaid in 60-month plan (%)	13.3	23.7	64.5	37.4	-51.2
incdropbig	income drop at least $200 (%)	43.6	49.6	45.8	49.8	-2.2
expense_gap	actual exp. - IRS standards ($1,000s)	-0.4	1.3	-0.1	1.5	-0.3
prose	pro se filer (%)	5.1	21.9	1.8	13.3	3.3
joint_file	joint filing (%)	31.0	46.2	31.7	46.5	-0.8
AMI	income above median (%)	29.5	45.6	44.9	49.7	-15.4
amt_above_means	amount above median ($1,000s)	5.1	11.7	12.2	19.8	-7.0
Chapter Choice Variables						
avgmnthi	average monthly income ($1,000s)	3.0	1.4	3.7	1.8	-0.7
cntmnthi	avg. monthly inc. past 6 months ($1,000s)	3.2	2.1	4.0	2.7	-0.8
debt_to_income	debt to income	4.2	4.4	4.0	3.4	0.2
assets_to_income	assets to income	2.4	3.1	3.0	3.0	-0.6
unsec	unsecured debt ($1,000s)	60.1	56.3	47.8	53.0	12.2
sh_secured	share secured debt (%)	39.2	34.9	60.8	32.2	-21.6
sh_nondischarge	share non-dischargeable debt (%)	6.2	16.1	7.7	17.6	-1.5
homeowner	homeowner (%)	48.1	50.0	67.0	47.0	-18.9
sh_real	real property to assets (%)	38.0	41.6	53.7	40.4	-15.7
pos_equity	pos. home equity ($1,000s)	5.0	18.2	8.5	25.8	-3.6
neg_equity	neg. home equity ($1,000s)	18.2	42.9	32.1	57.7	-13.9
nonexempt_equity	nonexempt home equity ($1,000s)	0.8	6.9	2.8	13.0	-2.0
pct_black	zip percent Black	13.0	19.6	23.8	27.3	-10.7
irs_expense	IRS local standard exp. ($1,000s)	3.3	0.8	3.3	0.8	0.0
Observations		1,325,977		1,199,100		

Notes: Summary statistics for the consumer bankruptcy cases in the analysis sample. Column 6 reports the difference in means between column (2) and column (4). Online Appendix Tables A2 and A3 provide detailed variable definitions.

Table 2: Eligibility Models

	Chapter 7				Chapter 13			
	National Model		District Models		National Model		District Models	
	Est.	ME	ME (10th)	ME (90th)	Est.	ME	ME (10th)	ME (90th)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Estimates (β) and Marginal Effects for Below-Median Inc. (AMI= 0)								
disp_income	-0.78	-0.040	-0.070	-0.010	-0.41	-0.020	-0.040	0.092
	(0.031)				(0.021)			
pct_repay5	-0.79	-0.040	-0.090	-0.010	0.66	0.031	-0.010	0.062
	(0.032)				(0.019)			
incdropbig	0.47	0.018	0.000	0.027	0.34	0.014	-0.010	0.031
	(0.021)				(0.022)			
expense_gap	-0.02	0.000	-0.010	0.005	-0.01	0.000	-0.010	0.010
	(0.0077)				(0.0066)			
prose	-1.62	-0.160	-0.380	-0.080	-2.86	-0.430	-0.590	-0.240
	(0.016)				(0.017)			
joint_file	0.19	0.008	-0.020	0.018	0.41	0.016	-0.020	0.026
	(0.019)				(0.02)			
(Intercept)	4.33				3.28			
	(0.013)				(0.016)			
B: Estimates ($\beta + \gamma$) and Marginal Effects for Above-Median Inc. (AMI= 1)								
disp_income	-1.18	-0.060	-0.100	-0.030	-0.16	-0.010	-0.040	0.052
	(0.034)†				(0.023)†			
pct_repay5	-1.11	-0.050	-0.100	-0.010	0.64	0.030	-0.010	0.084
	(0.042)†				(0.026)			
incdropbig	0.13	0.006	-0.060	0.023	0.56	0.021	-0.050	0.035
	(0.032)†				(0.027)†			
expense_gap	-0.08	0.000	-0.010	0.007	-0.03	0.000	-0.010	0.013
	(0.0099)†				(0.0094)†			
joint_file	-0.02	0.000	-0.030	0.013	0.42	0.017	-0.010	0.027
	(0.021)†				(0.021)			
amt_AMI	-0.03	0.000	0.000	0.000	0	0.000	0.000	0.001
	(0.00068)†				(0.00071)			
(Intercept)	4.83				3.046			
	(0.032)†				(0.026)†			
C: Average Marginal Effects of Means Test								
Sample: Above-Median		-0.066	-0.151	-0.033		0.000	-0.014	0.013
Observations	1,325,977				1,199,100			

Notes: Estimates from logit models following equation (1) for Chapter 7 (columns 1-4) and Chapter 13 (columns 5-6). For each chapter, the first two columns report estimates and marginal effects (MEs) from the model estimated on the national sample, while the next two columns report the 10$^{\text{th}}$ percentile and the 90$^{\text{th}}$ percentile from the 83 district-chapter-specific models. Marginal effects are for a debtor with an eligibility probability of $\hat{Q} = 0.95$ (the sample mean). Panel A reports estimates (β) and MEs for below-median debtors. Panel B reports estimates ($\beta + \gamma$) and MEs for the above-median debtors. Standard errors are reported below estimates with † indicating the γ coefficient is statistically different from zero at the 5%-level. Panel C reports the average marginal effect of the `AMI` variable (the means test), averaging marginal effects over the (i) full sample and (ii) the sample of above-median debtors.

Table 3: Chapter Choice Model

	Ch.7 coef. (δ_7)		Ch.13 coef. (δ_{13})		$\delta_7 - \delta_{13}$	p-value	AME
	est.	std. err.	est.	std. err.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
avgmnthi	-0.84	(0.07)	-0.85	(0.07)	0.00	0.846	0.00
cntmnthi	-1.06	(0.06)	-1.13	(0.06)	0.07	<0.001	0.01
debt_to_income	-0.14	(0.02)	-0.24	(0.02)	0.10	<0.001	0.01
assets_to_income	-0.10	(0.02)	-0.06	(0.02)	-0.04	<0.001	-0.01
unsec	0.85	(1.58)	3.60	(1.58)	-2.75	<0.001	-0.43
sh_secured	-5.31	(0.52)	-3.42	(0.52)	-1.89	<0.001	-0.29
sh_nondischarge	-3.10	(0.56)	-1.45	(0.57)	-1.65	<0.001	-0.26
homeowner	16.03	(0.96)	15.42	(0.96)	0.61	<0.001	0.08
sh_real	-20.45	(1.03)	-20.03	(1.03)	-0.42	<0.001	-0.06
pos_equity	-22.25	(3.15)	-17.36	(3.16)	-4.89	<0.001	-0.76
neg_equity	-11.72	(0.84)	-6.99	(0.85)	-4.74	<0.001	-0.73
nonexempt_equity	-23.72	(6.21)	-9.86	(6.18)	-13.86	<0.001	-2.14
pct_black	0.07	(0.01)	0.08	(0.01)	-0.01	<0.001	-0.00
joint_file	19.06	(0.51)	18.76	(0.51)	0.30	<0.001	0.04
incdropbig	10.56	(0.37)	10.29	(0.37)	0.27	<0.001	0.04
irs_expense	-5.90	(0.23)	-5.85	(0.24)	-0.05	<0.001	-0.01
AMI	4.22	(0.35)	4.32	(0.36)	-0.10	<0.001	-0.01
(Intercept)	38.21	(0.98)	36.17	(1.05)	2.04	<0.001	
AME: Eligibility Ratio $\frac{Q_7}{Q_{13}}$							3.17
Observations			2,525,077				

Notes: Estimates from chapter choice logit model following equation (5), where the dependent variable is an indicator for filing under Chapter 7. The model also includes district-specific fixed effects. Columns (1) through (4) report the coefficient estimates δ_7 and δ_{13} and bootstrap standard errors. Column (5) reports the difference in these coefficients, i.e., the effect on chapter choice, and column (6) reports the bootstrap p-value of this difference. The bootstrap procedure uses 500 bootstrap samples to account for the estimated regressors as described in Online Appendix D. Column (7) reports the average marginal effect on the probability of choosing Chapter 7 over Chapter 13 from a one unit increase in the variable. The row labeled "AME: Eligibility Ratio" reports the marginal effect from a one-unit change in the eligibility ratio $Q = \frac{Q_7}{Q_{13}}$. Average monthly income and current monthly income are measured in thousands of dollars. Unsecured debt, nonexempt equity, positive equity, and negative equity are in millions of dollars. Percent black ranges from 0 (0%) to 100 (100%).

Table 4: Testing Validity of Predicted Means Test Impact

	Dependent variable:						
	District's Ch. 7 Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`Post` $\times$ ΔG^O_d	0.459***	0.490***	0.414***	0.882***	0.842***	0.764***	0.632***
	(0.134)	(0.136)	(0.140)	(0.220)	(0.223)	(0.225)	(0.200)
`unemp. rate`	0.548**	0.560**	0.575**	0.404	0.423	0.495**	0.400*
	(0.262)	(0.262)	(0.259)	(0.259)	(0.257)	(0.237)	(0.234)
`ln(HPI)`	−0.043	−0.045	−0.035	−0.045	−0.042	−0.088***	−0.076**
	(0.036)	(0.036)	(0.035)	(0.034)	(0.033)	(0.036)	(0.035)
`Post` $\times$ `homestead`		−0.012			−0.011	−0.015	−0.018*
		(0.012)			(0.012)	(0.012)	(0.011)
`Post` $\times$ `unl. exemption`		0.001			−0.0003	0.023	0.040*
		(0.014)			(0.016)	(0.022)	(0.021)
`Post` $\times$ `means test`			−0.021		−0.023	−0.028	−0.035**
			(0.016)		(0.019)	(0.019)	(0.017)
`Post` $\times$ Δ`fee 7`				0.015	0.047	0.038	−0.005
				(0.040)	(0.047)	(0.053)	(0.044)
`Post` $\times$ Δ`fee 13`				−0.024*	−0.025*	−0.023	−0.014
				(0.013)	(0.014)	(0.017)	(0.014)
`Post` $\times$ `pre-Ch.7 sh.`				−0.206**	−0.202**	−0.246***	−0.308***
				(0.092)	(0.085)	(0.077)	(0.059)
`Post` $\times$ `neg. DI sh.`							0.254***
							(0.066)
Mean Dependent Variable	0.71	0.71	0.71	0.71	0.71	0.71	0.71
District FE	X	X	X	X	X	X	X
YQ FE	X	X	X	X	X	X	X
Reg-YQ FE						X	X
Observations	6,004	6,004	6,004	6,004	6,004	6,004	6,004
Note:							*p<0.1; **p<0.05; ***p<0.01

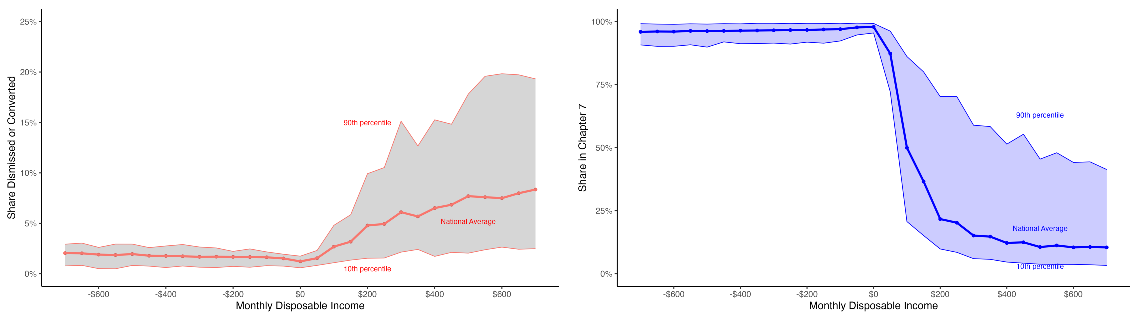
Notes: Table reports estimated from linear regressions on quarterly, district-level data from 2001-2019 following equation (7). Columns 2-5 add the post-BAPCPA indicator interacted with state homestead exemptions (column 2), an indicator `means test` for the states Cornwell and Xu (2014) argues are more affected by the means test (column 3), the districts' changes attorney fees from Lupica (2012) and the pre-BAPCPA (2003-2004) share in Chapter 7 similar to Chakrabarti and Pattison (2019) (column 4), and all controls together (column 5). Column 6 add region-by-year fixed effects, and column 7 adds a control for the share of debtors with negative disposable income in each district. Bootstrap standard errors are from 500 bootstrap samples in a procedure that accounts for both clustered observations at the district level and the estimated regressor ΔG^O_d. Details are in Appendix D.

Table 5: Exact Variance Decomposition of District Variation in Chapter Choice

component	share explained (%) (1)	std. err. (2)	95% CI (3)	95% BC-CI (4)
Eligibility (Δ^E)	24.1	1.4	$[21.4, 26.9]$	$[24.1, 25.4]$
Covariates (Δ^X)	75.9	1.4	$[73.1, 78.6]$	$[74.6, 75.9]$

Notes: This table reports the results from and exact variance decomposition of differences in districts' Chapter 7 filing rates. Column (1) reports the share of the total geographic variation in districts' chapter choice (share of bankruptcies under Chapter 7) that is explained by heterogeneity in eligibility screening, covariates, and the residual term. Column (2) reports the bootstrap standard errors $s_{\hat{\theta}}^{\text{boot}}$ from 500 bootstrap samples. Column (3) reports normal-approximation confidence intervals constructed as $\hat{\theta} \pm 1.96 \times s_{\hat{\theta}}^{\text{boot}}$, where $\hat{\theta}$ is the estimated decomposition share and $s_{\hat{\theta}}^{\text{boot}}$. Column (4) reports the Bias-Corrected (BC) Percentile Interval of Efron (1982). Note that bias-corrected confidence intervals need not be symmetric or centered on the estimate. Online Appendix D details the bootstrap procedure.

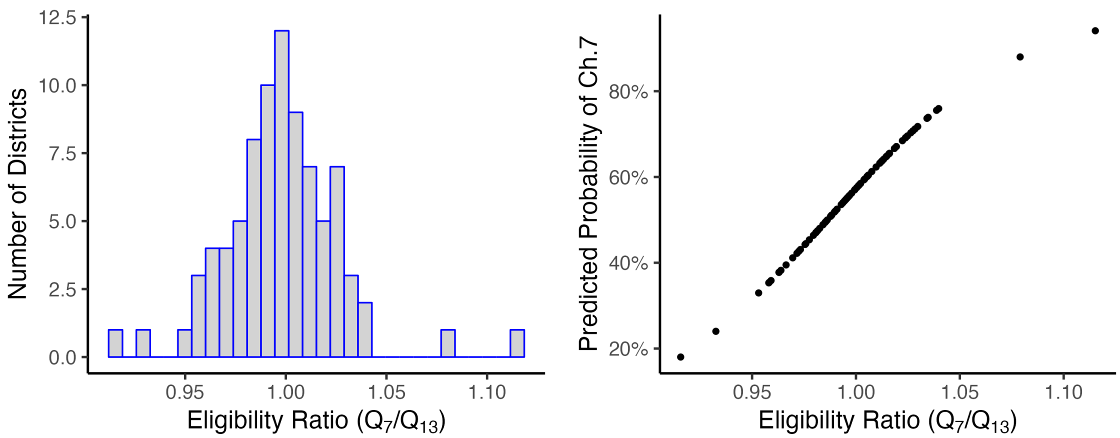
Figure 1: Disposable Income and Chapter Choice



(a) Ch.7 Eligibility (b) Chapter Choice

Sample consists of cases filed in FY2009-2019 within the 83 districts included in the main analysis. Debtors are grouped into \$50 bins based on their disposable income. Panel (a) shows the share of Chapter 7 cases that were dismissed or converted in each bin. The shaded region shows the $10^{\mathtt{th}}$ percentile and $90^{\mathtt{th}}$ percentile of the cross-district distributions. Panel (b) shows the share of cases in Chapter 7, along with the $10^{\mathtt{th}}$ and $90^{\mathtt{th}}$ percentiles of the cross-district distributions in the shaded region.

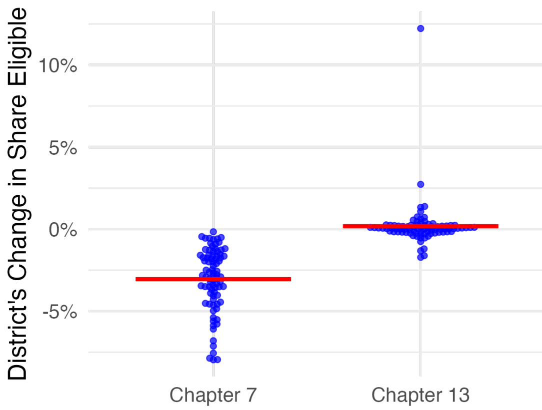
Figure 2: Heterogeneity in Screening the Average Debtor



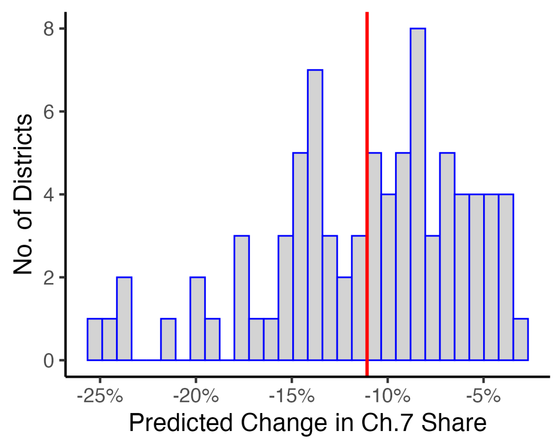
(a) Eligibility across Districts (b) Chapter Choice across Districts

These figures show, for the average filer, the heterogeneity in screening across districts and its impact on chapter choice. To generate the figures, we use the mean characteristics debtors in the national sample, $\bar{X}$. Figure (a) the histogram of predicted eligibility ratios for each district. Figure (b) shows the predicted chapter choice as a function of the predicted eligibility for each district.

Figure 3: Impact of BAPCPA's Means Test



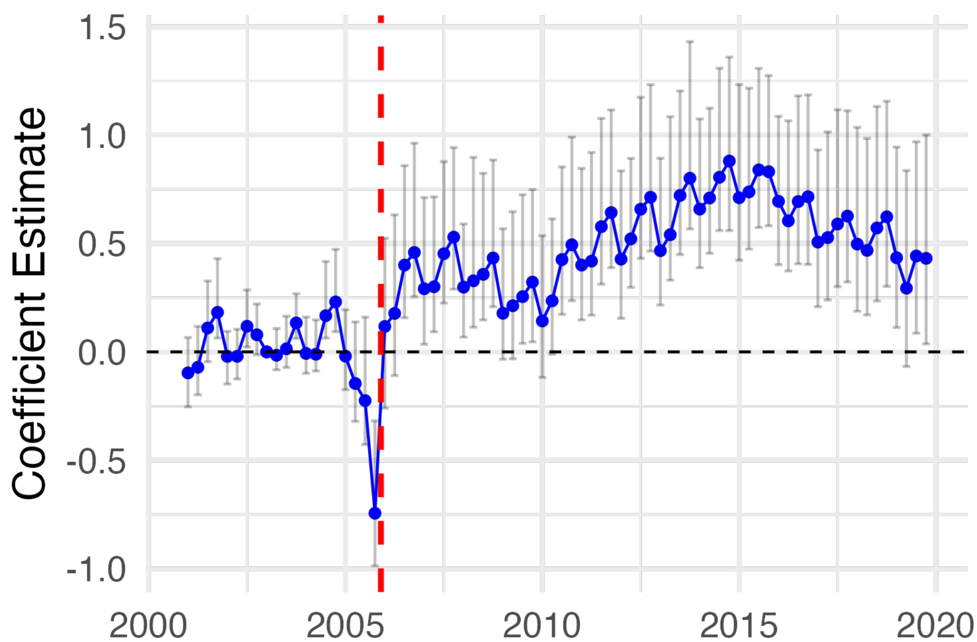
(a) Eligibility



(b) Chapter Choice

Notes: These figures report the model-generated predictions for the district-specific impact of BAPCPA's means test on eligibility and chapter choice. Figure (a) shows the effect of the means test on each district's average eligibility for Chapter 7 and Chapter 13 among positive-disposable-income debtors. Each point represents a district, and the horizontal bars show the means of the distributions. Figure (b) shows a histogram of the change in each district's overall share of bankruptcies under Chapter 7 (ΔG_d^O) as a result of adding the means test, with the vertical red line showing the mean change.

Figure 4: Event Study of Mean Test Impact



Notes: Figure reports estimates from an event study linear regression on quarterly, district-level data from 2001-2019 showing the correlation between the model's predicted impact of the means test on chapter choice ΔG_d^O and actual changes in chapter choice. The other controls match those of Table 4 column (1). The vertical line shows the enactment of BAPCPA in October 2005. Error bars show 95% Bias-Corrected bootstrap percentile intervals following Efron (1982). We use 500 bootstrap samples in a procedure that accounts for both clustered observations at the district level and the estimated regressor ΔG_d^O. Details of the bootstrap procedure are in Online Appendix D.

Online Appendix

Eligibility Screening and Means Testing in Consumer Bankruptcy

Appendix A Appendix Tables and Figures

Table A1: Case Outcomes

Case Outcome	Disposable Income < \$0	Disposable Income [\$0, \$100)	Disposable Income ≥ \$100
Initial Chapter 13			
Converted (Early) to Other Chapter (%)	51.01	68.93	21.93
Dismissed (%)	48.99	31.07	78.07
Failure to File Information (%)	18.56	8.99	13.16
Failure to Pay Filing Fee (%)	3.59	2.92	10.59
Abuse (%)	0.37	0.21	0.39
Other Reason (not specified) (%)	26.49	18.94	53.92
N	16,118	10,306	64,946
Initial Chapter 7			
Converted (Early) to Other Chapter (%)	16.19	21.68	55.80
Dismissed (%)	83.81	78.32	44.20
Failure to File Information (%)	14.50	9.87	8.93
Failure to Pay Filing Fee (%)	14.73	16.98	7.64
Abuse (%)	3.31	3.24	2.77
Other Reason (not specified) (%)	51.27	48.23	24.87
N	61,362	32,730	31,192

This table shows, for cases that were dismissed or converted shortly after filing, the distribution across conversions and reasons for dismissal. In Chapter 7, where the median case takes less than four months to receive a discharge, any dismissal or conversion is included. In Chapter 13, more than half of cases are dismissed or converted at some point during the three-to-five-year plan, mostly due to the debtor missing plan payments. To focus on dismissals and conversions related to ineligibility for Chapter 13, we only include early dismissals or conversions that occur within four months of filing. `dism_early` and `converted_early` show these rates of dismissals and conversions.

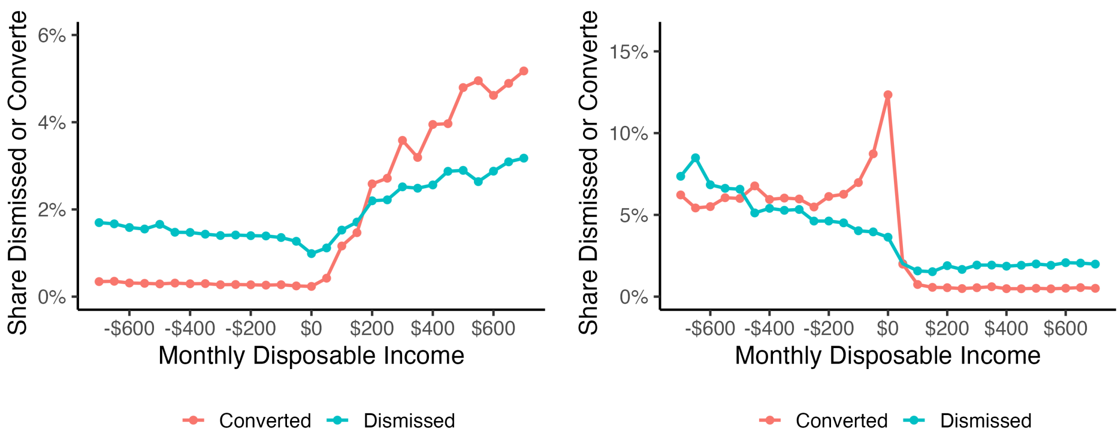
Table A2: Variable Definitions (1)

Variable	Definition
elig	Eligible to file under chosen chapter. Defined as not dismissed or converted in the months after filing. For chapter 7 filings, which only take a few months to complete, all dismissals and conversions are counted as indicators of ineligibility. For Chapter 13, we only count dismissals and conversions within the first four months of a case as indicators of ineligibility. We exclude later dismissals within Chapter 13 because the dismissals are primarily due to the debtor's failure to make plan payments, not because the debtor is deemed ineligible.
disp_income	Estimated disposable income at the time of filing, calculated as the difference between Schedule I Average Monthly Income and Schedule J Average Monthly Expenses. Average Monthly Expenses is adjusted for differential reporting in Conduit and Direct-Pay districts, as discussed in Online Appendix B.
pct_repay5	Amount of nonpriority unsecured debt that could be repaid out of disposable income over a five-year Chapter 13 repayment plan, calculated as $(60 \times \texttt{disp\_income} - \texttt{priority\_unsecured})/\texttt{nonpriority\_unsecured}$ and truncated between 0% and 100%.
incdropbig	Indicator for whether (average) monthly income at the time of filing (`avgmnthi`) is at least \$500 below average monthly income in prior six months (`cntmnthi`), i.e., $\texttt{avgmnthi} - \texttt{cntmnthi} < -\$500$
expense_gap	Actual monthly expenses minus IRS location-adjusted standard expenses. actual expenses are from Schedule J, adjusted for conduit and direct-pay districts. IRS local standards are defined below in the variable `irs_expense`
prose	Indicator for whether the first listed debtor in the bankruptcy petition was pro se (not represented by an attorney)
joint_file	Indicator for whether the bankruptcy petition is a joint petition (by spouses)
AMI	Indicator for whether `cntmnthi` exceeds the median income of the state as defined in the means test forms at the time of filing. The two-person income threshold is used for joint filings, and the single-person threshold for joint filings. Data available here: Income standards for means testing
amt_above_means	Amount by which average annual income ($12 \times \texttt{cntmnthi}$) exceeds the applicable means test threshold, as defined in `AMI`.

Table A3: Variable Definitions (2)

Variable	Definition
avgmnthi	Estimated monthly household income of debtor at the time of filing, reported as Average Monthly Income from Schedule I
cntmnthi	The monthly income of the household from all sources, averaged over the six months prior to filing; Current Monthly Income from form 22A for Chapter 7 debtors or form 22C for Chapter 13 debtors.
debt_to_income	Total liabilities over annual income. Annual income is defined as 12 $\times$ `avgmnthi`
assets_to_income	Total assets over annual income
unsec	Sum of nonprioirity and priority unsecured debt
sh_secured	Secured debt divided by total liabilities
sh_nodischarge	Nondischargeable debt divided by total liabilities; nondischargeable debt consists of domestic support obligations, taxes and certain debts owed to the government, student loan obligations, some other legal debts, and obligations to pension or profit-sharing programs.
homeowner	Indicator for whether the debtor owns real property
sh_real	Real property value divided by total assets
pos_equity	Positive home equity, defined as max $\{equity, 0\}$, where equity is defined as real property value minus total reported secured debt; See Pattison and Hynes (2020) for evidence that this accurately measures home equity.
neg_equity	Negative home equity, defined as max{-equity, $0\}$
nonexempt_equity	max$\{equity - exemption, 0\}$, where exemption is the maximum of the state and, if applicable, federal homestead exemption at the time of filing. Married homestead exemptions are used for joint filings, and single homestead exemptions for single filings. Exemption data are from (Pattison and Hynes, 2020), which also validates this measure of nonexempt equity.
pct_black	Share of residence in debtor's home zip code that are Black, from 2018 five-year ACS estimates
irs_expense	Sum of the IRS local and national standards for housing expenses (mortgage and non-mortgage), transportation expenses (operation and ownership), household expenses (food, housekeeping, apparel and service, personal care, miscellaneous), and out-of-pocket expenditures. We use two-person standards for joint-filings and one-person standards for single filings. The IRS standards depend on the debtor's location of residence (MSA or state) and the filing date. Data available here: IRS standards for means testing

Figure A1: Dismissals/Conversions and Disposable Income by Chapter

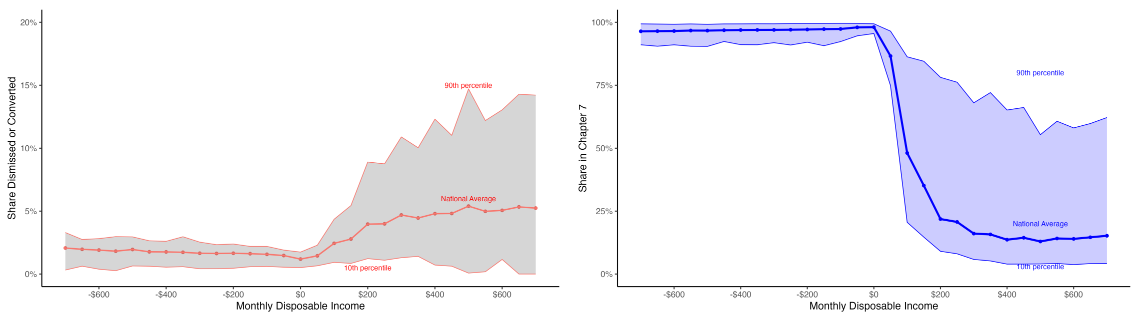


(a) Chapter 7 Cases

(b) Chapter 13 Cases

Sample consists of cases filed in FY2009-2019 within the 83 districts included in the main analysis. Debtors are grouped into $50 bins based on their disposable income. Panel (a) shows the share of Chapter 7 cases that were dismissed or converted in each bin. Panel (b) shows the share of Chapter 13 cases that were dismissed or converted in each bin.

Figure A2: Disposable Income and Chapter Choice
(Below-Median-Income Debtors)

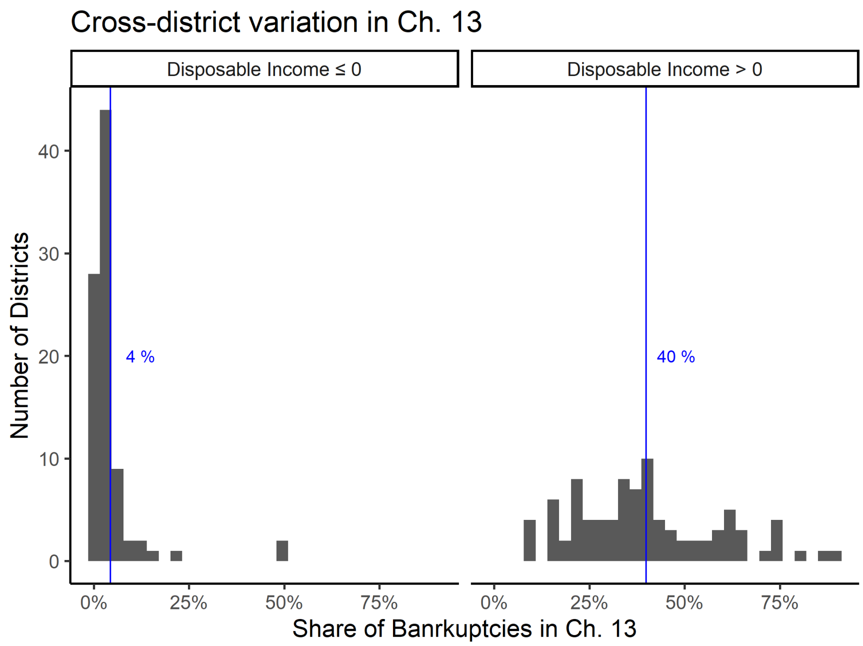


(a) Ch.7 Dismissals and Conversions

(b) Chapter Choice

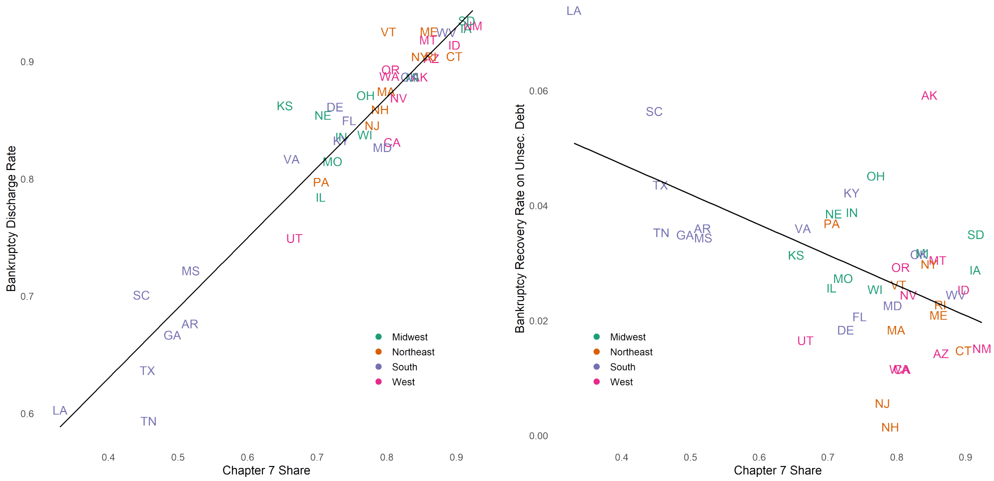
Sample consists of cases filed by below-median-income debtors in FY2009-2015 within the 83 districts included in the main analysis. . Debtors are grouped into \$50 bins based on their disposable income. Panel (a) shows the share of Chapter 7 cases that were dismissed or converted in each bin. The shaded region shows the 10^{th} percentile and 90^{th} percentile of the cross-district distributions. Panel (b) shows the share of cases in Chapter 7, along with the 10^{th} and 90^{th} percentiles of the cross-district distributions in the shaded region.

Figure A3: Cross-District Variation by Disposable Income



The figures above show the distributions of districts' share of bankruptcies in Chapter 13 across districts among debtors with negative disposable income (left histogram) and debtors with positive disposable income (right histogram). The blue line in each represents the average share of bankruptcies in Chapter 13 across districts.

Figure A4: Discharge and Repayment by Chapter 7 Share



(a) Discharge Rate

(b) Recovery Rate

Notes: The discharge rate is the share of bankruptcy filings that obtained a discharge. The recovery rate is the share of unsecured debt returned to creditors, calculated as the total amount returned by trustees to general unsecured creditors in 2010-2014 divided by the total non-priority unsecured debt of those filing in 2010-2014. Data on discharge rates and total non-priority unsecured credit are from the Federal Judicial Center's Integrated Database. Data on the amount returned are from Trustee Final Reports, which detail actual payments to creditors.

Appendix B Adjusting Disposable Income for Conduit Districts

We adjust a key variable, disposable income, to account for differences in how mortgage payments are reported in some districts. Specifically, in a subset of districts that use conduit Chapter 13 plans (defined below), mortgage payments are not reported as expenses on Schedule J. Because disposable income equals reported income less expenses, this makes disposable income artificially high for Chapter 13 debtors with mortgage payments in these districts. To correct this, we approximate mortgage payments and subtract the amount from reported disposable income. The remainder of this section provides more detail on this procedure.

Some districts use conduit plans, in which mortgage payments are made through the Chapter 13 plan, or direct payment plans, in which debtors with a mortgage pay the mortgagor directly.[49] For our purposes, this matters because (i) conduit districts typically exclude mortgage payments from Chapter 13 filers' Schedule J expenses, and (ii) these reported Schedule J expenses enter our

[49] In many conduit districts, this is implemented through the local Chapter 13 plans or the practices of the local trustee. In some places, only a subset of Chapter 13 cases will be conduit plans (e.g. unless the court allows direct payment, or depending on whether a prepetition arrearage exists) (American Bankruptcy Institute, 2019).

calculation of disposable income. We adjust for this different treatment of Chapter 13 filers with mortgages in conduit districts.

We first classify conduit districts and direct payments using the Chapter 13 Trustee Final Reports from 2008-2019. If ongoing mortgage payments account for at least 10% of total Chapter 13 disbursements, we classify that district as a conduit district. Districts in which ongoing mortgage payments make up less than 10% of total Chapter 13 disbursements are classified as direct payment districts.[50] Among conduit districts, ongoing mortgage payments average 29.2% of Chapter 13 total disbursements in the average district. Among direct-payment districts, ongoing mortgage payments average 1.8% of Chapter 13 total disbursements in the average district.

Conduit districts typically exclude mortgage payments from Schedule J expenses for Chapter 13 mortgage holders and, as a result, the bankruptcy forms overstate these debtors' disposable income. Only mortgage holders in Chapter 13 are affected by conduit reporting in these districts. To illustrate, Figure B1 compares the disposable income share, i.e. the share of income that is disposable, across those with and without mortgages in direct-payment and conduit districts.[51] The distributions of disposable income shares are similar across direct-payment and conduit districts, except for Chapter 13 filers with a mortgage. But, in conduit districts, Chapter 13 filers with a mortgage report higher disposable income (bottom-right figure). This difference in the empirical CDFs reflects that conduit districts exclude mortgage payments from Schedule J expenses.

To adjust for the different treatment of mortgage payments among Chapter 13 debtors in conduit districts, we estimate their monthly housing payment and add the amount to their monthly expenses. We compute each filer's expected monthly mortgage payment, assuming that the principal at origination equaled the reported real property value less a 6% down payment, and took out a 30-year mortgage with an annual interest rate of 7%.[52] We then adjust Schedule J expenses by adding this expected mortgage payments to all Chapter 13 filers in conduit districts with a disposable income share of at least 30%. Figure B2 plots the empirical CDFs of the disposable income

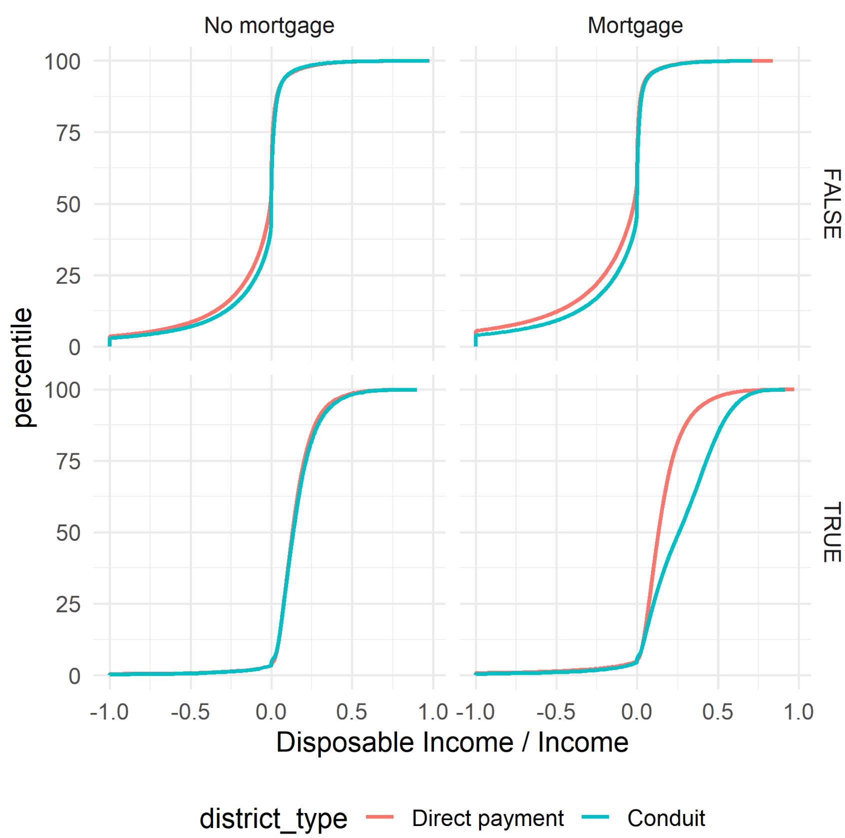
[50] Alabama and North Carolina are not present in the Trustee Final Reports. We classify Alabama as a direct payment district and North Carolina as a conduit district, based on the similarity of Schedule J expenses to the districts we classify using the Final Reports.

[51] Disposable income is defined as the difference between Schedule I average monthly income and Schedule J average monthly expenses.

[52] The 6% down payment is the average down payment (see `https://www.rocketmortgage.com/learn/what-is-the-average-down-payment-on-a-house`). The 7% interest rate equals the presumptive interest rate applied to installment debt in many Chapter 13 districts at that time (see `https://www.mssb.uscourts.gov/rulesorders-procedures/presumptive-interest-rate/`.)

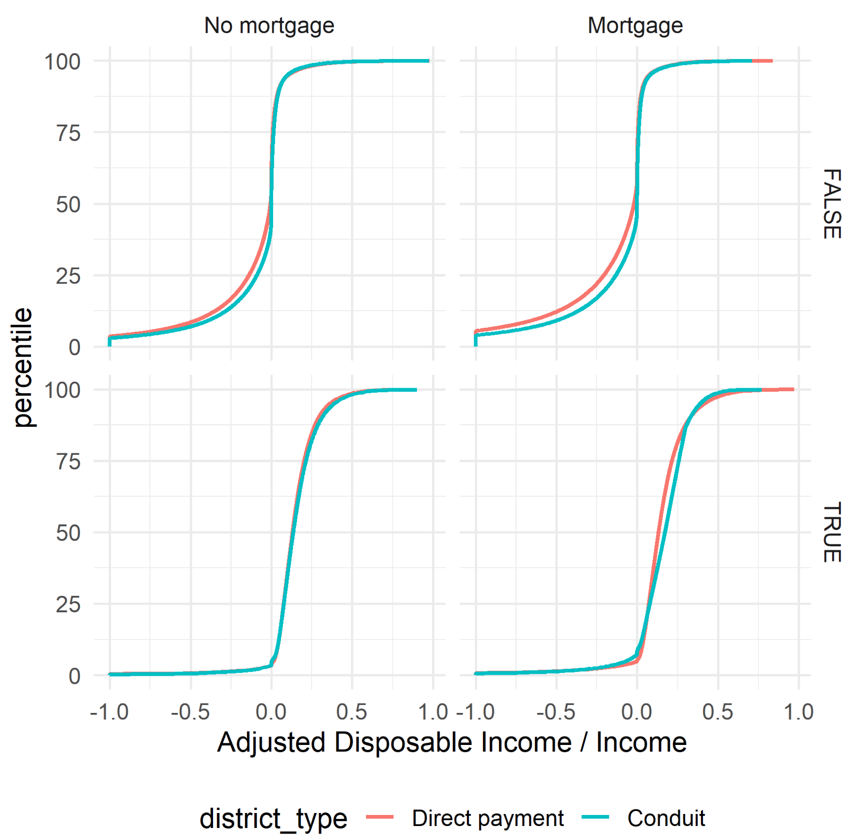
shares after making this adjustment. After adjustment, the distributions of disposable income are much more similar across conduit and non-conduit districts.

Figure B1: Before Adjustment: Disposable Income of Direct-Payment and Conduit Districts



The figure plots the empirical cumulative distribution functions of the share of income that is disposable. Shares below −1 are assigned a value of −1. Shares below −1 are assigned a value of −1.The sample excludes filers with less than $500 in reported monthly income.

Figure B2: After Adjustment: Disposable Income of Direct-Payment and Conduit Districts



The figure plots the empirical cumulative distribution functions of the share of income that is disposable, adjusted for housing expenditures for Chapter 13 filers with mortgages in conduit districts. Shares below -1 are assigned a value of -1. The sample excludes filers with less than $500 in reported monthly income.

Appendix C Measuring Above-Median Income

In this section, we discuss and investigate the sensitivity of our results to different measures of above-median-income status. Above-median status is particularly important for our analysis, because it is the variable that allows us to identify the effect of BAPCPA's means test, which applies only to above-median income debtors.

Legally, the means test applies if a debtor is above their state's median income *adjusted for household size*. We do not observe the household size, and instead, our primary measure assumes that each household has zero non-filing members and so treat all single filers as single-person households and all joint filers as two-person households. This applies the lowest possible median income threshold for each household. As a result, it creates one-sided measurement error because we will apply too low of a median-income threshold to the households with non-filing household members, and so may mistakenly count them as above-median-income when they are not.

Appendix C.1 Support for Primary Measure of Above-Median Status

First, we provide evidence about the accuracy of our primary measure of disposable income. If a debtor's income exceeds the median, the debtor faces additional restrictions in both Chapter 7 and Chapter 13 that may discourage filings in both chapters. Consistent with the accuracy of our measure, we find a sharp, discontinuous decline in both Chapter 7 and Chapter 13 filings exactly once debtors' incomes exceed our measure of the applicable median income (Appendix Figure C1). Using our main measure and counting both Chapter 7 and Chapter 13 filings, there are 8,109 cases with reported gap in the range of $[-\$199, \$0]$, but only 6,455 cases with reported incomes in the range $[\$1, \$200]$, a discontinuity of 1,654 cases.

The primary measure assumes filers have zero non-filing household members and so applies the median income threshold for one-person household for single filers and two-person households for joint filers. We refer to this as Threshold 1. For comparison, we also show the discontinuities if we assume each filer has one non-filing household member (Threshold 2) or two non-filing household members (Threshold 3). If we use Threshold 2, the discontinuity is 660 cases and if we use Threshold 3, the discontinuity is 692 cases. These discontinuities are smaller than those using Threshold 1, suggesting that our main measure captures the relevant means test threshold for most households.

As a separate test, we collect an alternative measure of debtors' above-median-income status by searching each case's court dockets for the presence of specific bankruptcy forms that are only filed by above-median debtors. Specifically, there are certain bankruptcy forms (forms 122A-2 in Chapter 7 and 122-C2 in Chapter 13) that debtors only need to complete if they report above-median income. A few districts report whether the file has submitted these forms on their bankruptcy court dockets. In many courts, this docket information from 2013 to the present has been scraped and made publicly available.[53] We are able to identify 20 districts that consistently report the presence of these forms for above-median income debtors between 2015 and 2019.[54] In these districts, 41.2% of cases we identify as above-median income have dockets with these forms, while 3.05% of cases we identify as below-median income do.[55] Thus, this independent measure corroborates our main measure of above-median-income status.

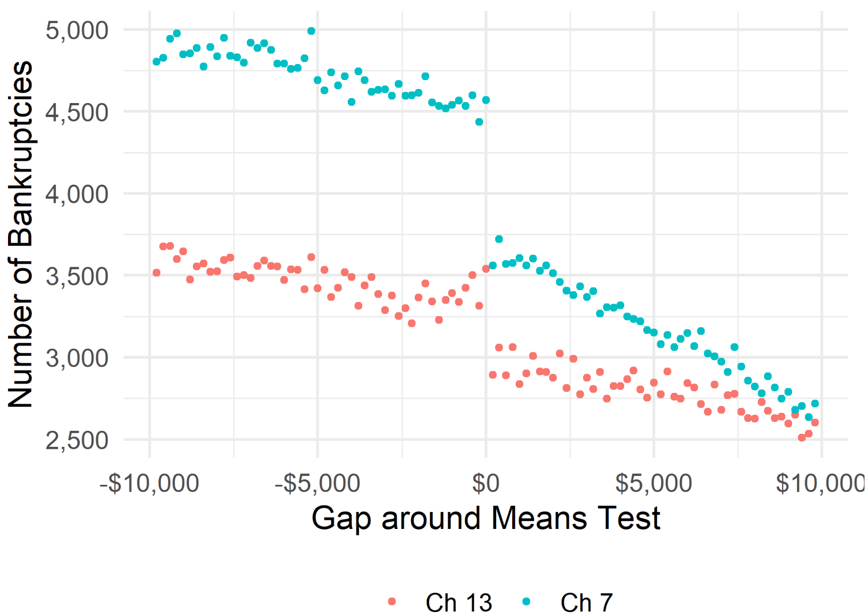
The model estimates of Section 5 also indicate that our measure accurately captures the means test. The means test restricts eligibility for Chapter 7 but not Chapter 13. Consistent with this, the AME estimates of the means test reported in Table 2 show a strong effect of the means test in Chapter 7, but virtually no effect in Chapter 13. Similarly, in the counterfactual policy analysis, our structural model is able to accurately predict changes in chapter choice that came with the introduction of the means test (Figure 3).

[53] Journalist Matt Clark made these data available here https://archive.org/details/federal-court-dockets

[54] To do so, we search the text of each docket entry for the strings "22A-2" or "22C-2". In some courts, dockets contain these entries regardless of whether the debtor actually fills out these forms. To identify districts where these forms provide a good measure of above-median status, we (i) require that over 98% of the cases on our FJC sample are matched to dockets, (ii) at least 5% of the cases marked as above-median income in the FJC data have dockets entries listing the forms, and (iii) cases marked above-median income in the FJC have at least 4 times as many reported forms as cases marked below-median income in the FJC.

[55] These "false positives" may come from measurement error in this alternative measure or from mistakes or updates to income as reported in the FJC database.

Figure C1: Discontinuity around Means Test Income Threshold



Number of filings in main sample, grouped into $200-wide bins based on the difference between the reported current monthly income (CMI) and the applicable means test income threshold. For single filers, we apply the single-person household median income for the state at the time of filing, and for joint filers we apply the two-person household threshold.

Appendix C.2 Robustness to Alternative Measures of Above-Median Status

We also examine the sensitivity of our estimates to using alternative measures of above-median status. Our primary measure assigns median income as if all debtors have zero non-filing household members. We examine three alternative measures, detailed in Table C1, which use alternative thresholds when determining the means test (Measures 2 and 3) or use the independent measure based on the docket reports as described above.

Under each measure of above-median-income status, we reestimate the district-specific eligibility models of equation (1). We then compare the estimated effect of the means test as measured by the means test's average marginal effect (AME). We report the correlation coefficient between the primary and alternative district-specific AMEs in Table C1, and show the estimates graphically in Figure C2. When using alternative thresholds, the average marginal effects of the means test on dismissal rates remain similar to those of the primary (Baseline) measure. In Chapter 7, the district-specific AMEs are highly correlated across the measures. The correlation coefficient between the baseline estimate and the alternative measures is 0.98 when assuming one non-filing household member, and 0.94 when assuming two non-filing household members. In Chapter 13, the AMEs remain tightly clustered around zero.

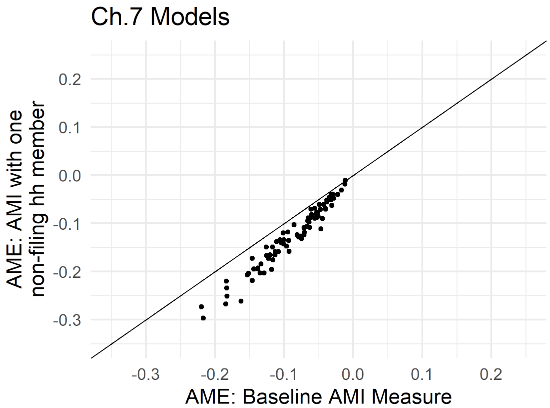
We also compare estimates when using the third alternative measure based on the presence of specific bankruptcy in the dockets, and find similar patterns. This alternative forms measure of above-median status is only available for a subset of districts for the years 2015-2019. For our comparison, we reestimate the main model on the years 2015-2019. Again, the correlation is high at 0.86. To summarize, we estimate similar district-specific effects of the means test regardless of exactly how we measure above-median-income status.

Table C1: Alternative Measures of Above-Median Status

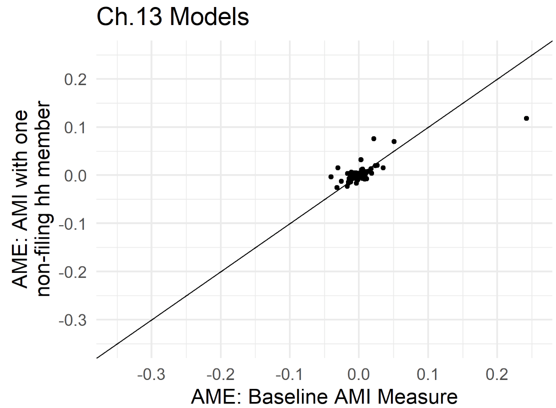
Measure (1)	Definition (2)	Correlation with Baseline AME (Ch.7) (3)
Baseline	Median Income Threshold 1. `AMI` as defined in A2. Compares current monthly income as reported in the FJC data at the time of filing to the state median income adjusted for household size. Assumes **zero** non-filing household members when assigning the applicable state median income.	1
Measure 1	Median Income Threshold 2. Compares current monthly income as reported in the FJC data at the time of filing to the state median income adjusted for household size. Assumes **one** non-filing household member when assigning the applicable state median income.	0.98
Measure 2	Median Income Threshold 3. Compares current monthly income as reported in the FJC data at the time of filing to the state median income adjusted for household size. Assumes **two** non-filing household members when assigning the applicable state median income.	0.94
Measure 3	Forms indicator. Examines case dockets, and identifies above-median debtors whether the case has filed either from 122A-2 or 122C-2, which are only filed by above-median-income debtors. This measure is only available for a subset of districts and during the period 2015-2019. For comparison with the baseline estimates, we re-estimate the baseline model on these districts using the same 2015-2019 sample of cases. Column (3) compares the average marginal effect from this reestimated baseline model to the model estimated using Measure 3.	0.86

Table reports the Baseline and three alternative measures of above-median-income status used for the robustness checks. Column (3) reports the correlation of the district-specific average marginal effects (AMEs) from the Chapter 7 models using the alternative measures. We do not report the correlation for the Chapter 13 models because nearly all AMEs are clustered near zero, but the AMEs are shown in the second column of Figure C2.

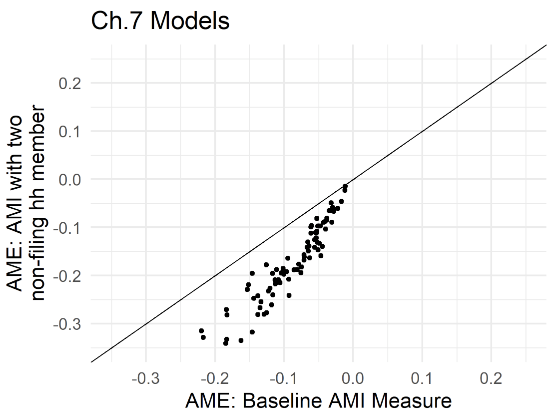
Figure C2: Alternative Measures of Above-Median Income



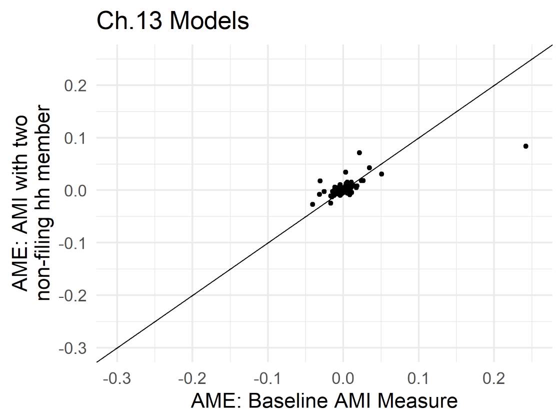
(a) Ch.7, Measure 2



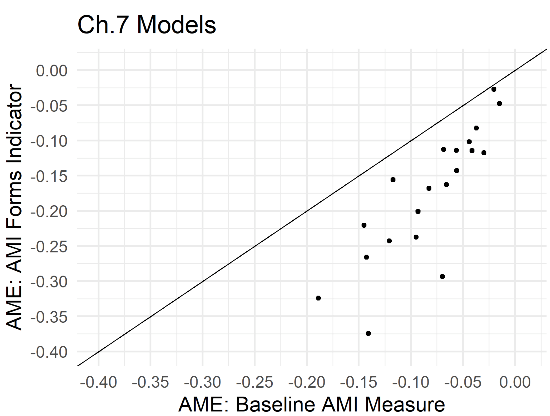
(b) Ch.13, Measure 2



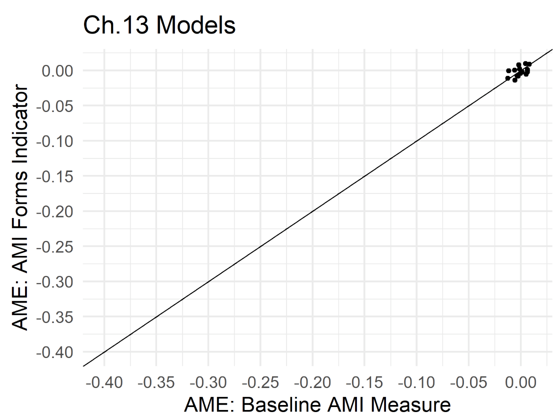
(c) Ch.7, Measure 3



(d) Ch.13, Measure 3



(e) Ch.7, Measure 4



(f) Ch.13, Measure 4

Figure plots the estimated district-specific AMEs of the means test when using alternative measures of above-median status (vertical axis), plotted against the AMEs from the baseline measure (horizontal axis).

Appendix D Bootstrap Procedure

We first detail the main bootstrap procedure used to obtain standard errors, p-values, and confidence intervals for the chapter choice model and the decomposition estimates. We then discuss a second bootstrap procedure used to account for clustering in the difference-in-difference model of equation (7).

Main Bootstrap Procedure We form our main bootstrap samples and estimates using the following procedure:

1. Let N_d denote the number of observations from district d in the original sample. For each district d, we randomly draw a bootstrap sample, with replacement, of N_d observations from the original sample.

2. Using the bootstrap sample, we then estimate

   - **Eligibility Models** Using the bootstrap sample, we estimate the district-chapter-specific eligibility models following the specification in equation (1). In some bootstrap samples, a small number of district-specific models do not converge. In these cases, we drop those districts from the remaining chapter choice, means test, and decomposition analysis.

   - **Chapter Choice Models** Using the predicted eligibility from the bootstrap-sample models estimated in the prior step, we use the same bootstrap sample to estimate the chapter choice model in equation (5).

   - **Counterfactual: Means Test** Using the bootstrap sample and bootstrap-estimated eligibility and chapter choice models, we generate the predicted change in each district's chapter choice caused by the removal of the means test, ΔG_d^b, as discussed in Section 6.1 and where b denotes that this predicted change is generated using bootstrap sample b. We then form $\Delta G_d^{O,b} = DI_d \Delta G_d^b$ to form the predicted change in the chapter choice of district d. The share of positive income debtors, DI_d, is the same across all bootstrap samples because the bootstrap procedure resamples form our main estimation sample, which includes only debtors with positive disposable income.

- **Decomposition** Using the bootstrap sample and the bootstrap-estimated eligibility and chapter choice models, we calculate the decomposition following the equations in Section 6.2..

   To summarize, for the bootstrap sample b, we obtain estimates (i) the parameters in each district-chapter-specific eligibility model, (ii) the parameters of the chapter choice model, (iii) the counterfactual change in each district's share under Chapter 13 caused by removing the means test, and (iv) the decomposition terms reflecting the share of the total geographic variation in chapter choice attributed to eligibility criteria or debtor characteristics.

3. We repeat this procedure for $b = 1, \ldots, 500$.

Bootstrap standard errors and p-values Let $B = 500$ be the number of bootstrap samples, $\hat{\theta}$ be a parameter estimated in the main sample, and $\hat{\theta}^*(b)$ be the same parameter estimated using bootstrap sample b. Following Hansen (2022), we estimate the bootstrap variance as

$$\hat{V}_{\hat{\theta}}^{\text{boot}} = \frac{1}{B-1} \sum_{b=1}^{B} \left(\hat{\theta}^*(b) - \bar{\theta}^* \right) \left(\hat{\theta}^*(b) - \bar{\theta}^* \right)'$$

$$\bar{\theta}^* = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}^*(b).$$

For the estimator $\hat{\theta}$, the *bootstrap standard error* is the square root of the bootstrap estimator of variance:

$$s_{\hat{\theta}}^{\text{boot}} = \sqrt{\hat{V}_{\hat{\theta}}^{\text{boot}}}.$$

We report bootstrap p-values for the null hypothesis that the parameter $\theta_0 = 0$ as

$$p^* = \frac{1}{B} \sum_{b=1}^{B} \mathbb{1} \left\{ |\hat{\theta}^*(b) - \hat{\theta}| > |\hat{\theta} - \theta_0| \right\}.$$

We also report bias-corrected (BC) percentile intervals of Efron (1982) as described in Hansen (2022).

Bootstrapping for Clustered Observations in BAPCPA Regression For the district-quarter level regressions in equation (7) and reported in Table 4, we adjust the bootstrap procedure to account for both the estimated regressor ΔG_d^O and the clustering of observations at the district level. Specifically, we combine a pairs cluster bootstrap for the district-quarter level observations and the earlier bootstrap procedure for ΔG_d^O outlined above.

- **Pairs Cluster Bootstrap** The original sample used to estimate equation (7) contains observations from 81 districts and each quarter from 2001-2019. To form bootstrap sample b, we randomly draw, with replacement, 81 districts. Because we draw with replacement, some districts will appear in the sample multiple times. For each district in the bootstrap sample, we include all quarterly observations from 2001-2019.

- **Bootstrap Estimated Regressor** To account for the uncertainty in the estimated regressor, ΔG_d^O, we merge each district with its bootstrap-estimated parameter ΔM_d^b. As discussed above, the variation in this parameter across bootstrap samples reflects the variation in both the eligibility models, the chapter choice models, and the distribution of variables in the sample.

- The bootstrap sample b combines the pairs cluster bootstrap with the earlier bootstrap procedure generating ΔM_d^b. We use this sample to estimate equation (7) and form bootstrap estimates of the coefficient of interest β_1^b and the other model parameters.

- Bootstrap standard errors and p-values are calculated as described above.

We use this same procedure to calculate standard errors for the event study estimates reported in Figure 4.

Appendix E Alternative Decomposition Methods

When examining uniform screening, we decompose the total variation in Chapter 7 filing rates using an exact variance decomposition. Here, we use two other decomposition methods and find similar results.

The first method is a traditional variance decomposition, where

$$\mathrm{Var}[\Delta_d^T] = \mathrm{Var}[\Delta_d^E] + \mathrm{Var}[\Delta_d^X] + \mathrm{Var}[\Delta_d^R] + \texttt{interaction terms}.$$

The share attributed to each component $j = E, X, R$ is $S_1^j = \frac{\mathrm{Var}[\Delta_d^j]}{\mathrm{Var}[\Delta_d^T]}$, which compares the variation in each component as a share of the total variation. The disadvantages of this simple measure are that the share does reflect whether the variables Δ_d^j are positively or negatively correlated with Δ_d^T and the shares will typically not sum to 100% because we ignore the interaction terms.

The second method is the absolute deviation ratio

$$S_2^j = \frac{\sum_{d=1}^{D} \texttt{sign}\left(\Delta_d^T\right) \cdot \Delta_d^j}{\sum_{d=1}^{D} \left|\Delta_d^T\right|},$$

where D is the total number of districts. The numerator for district d will be positive only if helps explain that district's deviation from the national average. Instead, if component Δ_d^j would exacerbate district d's deviation from the national average, the numerator will correctly capture that this component explains a *negative* portion of that district's deviation. Additionally, the three S_j^2 terms must sum to 100%, thereby fully accounting for the geographic variation in filing rates across districts.

Appendix Table E1 reports the decomposition of the geographic variation in chapter choice using these two measures. In both, heterogeneity in eligibility screening explains about 22.6% using S_1^E and 17.5% using S_2^E, which is slightly lower than the 24.1% found using the exact variance decomposition.

Table E1: Decomposition of Geographic Variation

component	share explained (%) (1)	std. err. (2)	95% CI (3)	95% BC-CI (4)
Panel A: S_1 (Variance Decomposition)				
Eligibility (Δ^E)	22.6	1.3	$[20.2, 25.1]$	$[22.8, 22.9]$
Covariates (Δ^X)	74.4	2.0	$[70.4, 78.3]$	$[70.9, 76.5]$
Residual (Δ^R)	0.0	0.0	$[0, 0]$	$[0, 0]$
Panel B: S_2 (Absolute Deviations)				
Eligibility (Δ^E)	17.5	1.4	$[14.7, 20.2]$	$[16.8, 19.7]$
Covariates (Δ^X)	80.0	1.4	$[77.2, 82.8]$	$[78.2, 80.6]$
Residual (Δ^R)	2.5	0.2	$[2.1, 2.9]$	$[2.4, 2.9]$

Notes: This table reports the results from decomposing the total geographic variation in chapter choice using two alternative methods. Column (1) reports the share of the total geographic variation in districts' chapter choice (share of bankruptcies under Chapter 7) that is explained by heterogeneity in eligibility screening, covariates, and the residual term. Column (2) reports the bootstrap standard errors $s_{\hat{\theta}}^{\text{boot}}$ from 500 bootstrap samples. Column (3) reports normal-approximation confidence intervals constructed as $\hat{\theta} \pm 1.96 \times s_{\hat{\theta}}^{\text{boot}}$, where $\hat{\theta}$ is the estimated decomposition share and $s_{\hat{\theta}}^{\text{boot}}$. Column (4) reports the Bias-Corrected (BC) Percentile Interval of Efron (1982). Online Appendix D details the bootstrap procedure.