If You Give a Judge a Risk Score: Evidence from Kentucky Bail Decisions[*]

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Abstract

High-stakes decisions are increasingly informed by predictive tools. Many assume that these tools should reduce disparities across groups by limiting human discretion, but empirical evidence on this is lacking. In this paper, I outline how interactions between prediction tool recommendations and human discretion can actually exacerbate disparities across groups. In particular, I discuss a policy change in Kentucky that set a recommended default for judge bail decisions based on risk scores. Counter to expectations, the policy caused an increase in raw racial disparities in initial bond, first illustrated by Stevenson (2017). Using case-level data, I show that this increase was not simply a consequence of different risk scores by race. Rather, the recommended default was also more likely to be overridden (in favor of harsher bond conditions) for black defendants than similar white defendants. I discuss two forces behind this result. First, judges varied in their policy responsiveness; judges in whiter counties responded more to the new default than judges in blacker counties. Second, even within judge and time, judges were more likely to override the recommended default for moderate risk black defendants than similar moderate risk white defendants. This result suggests that interaction with the same predictive score may lead to different predictions by race.

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1 Introduction

High-stakes decisions are increasingly informed by data-driven prediction tools. Loan officers use credit scores to help make lending decisions, managers use predictions in making hiring decisions, and judges use risk assessments to set bail (Miller 2015; Einav, Jenkins, and Levin 2013; Mamalian 2011). Despite their prevalence, usage of such predictive tools is controversial.[1] Advocates argue that their embrace could weaken the role human biases play in high-stakes decision-making (Harris and Paul 2017). Meanwhile, opponents are concerned that the tools themselves are biased against disadvantaged groups.[2] While many are focused on the predictions and biases of predictive tools in isolation,[3] these tools are usually introduced into systems chock-full of human judgments. Human discretion means that there is not necessarily a one-to-one mapping from the predictive tool to the final outcome. Despite the empirical importance of discretion, there is little evidence on how adherence to predictive tool recommendations may interact with demographic disparities.[4] Of particular policy interest is the following question: *are predictive recommendations followed similarly across racial groups?*

To address this question, I focus on an example from the criminal justice system – the usage of risk assessment recommendations in judge bail decisions. Risk assessments, generated based on individual-level characteristics, are used in bail, pretrial, or sentencing hearings in 49 of 50 US states (Traughber 2018).[5] Bail decisions determine conditions for release from jail before trial.[6] Conditions can include supervision or specific caveats such as no drinking, however, the most well-known conditions are monetary. Receiving financial bond means that a defendant needs to provide some amount of money in order to be released from jail, while non-financial bond means that the defendant does not. Empirically, in my setting, non-financial bond corresponds to a 96% chance of immediate release; financial bond corresponds to 20% chance of immediate release. My decision to focus on bail decisions is due to both policy relevance as well as methodological advantages. Pretrial detainees "account for two-thirds of jail inmates and 95% of the growth in the jail population over the last 20 years" (Stevenson and Mayson 2018), meaning they comprise a meaningful part

[1] One salient and timely example: the American Civil Liberties Union (ACLU) of California, which originally sponsored Senate Bill 10, which was passed to get rid of money bail in California, eventually came out in opposition partially due to concerns about how racial justice interacts with risk assessment tools (ACLU of California 2018).

[2] In particular, risk assessments in criminal justice have received much public criticism on this front. See Angwin and Kirchner (2016), which motivated much of the current academic work on this topic. Michelle Alexander, author of *The New Jim Crow*, has even called risk assessment scores the "Newest Jim Crow" (Alexander 2018).

[3] Concerned with bias, fairness, and predictive accuracy, current academic work on risk scores in criminal justice overwhelmingly focuses on the technical validation and generation of risk scores (Kleinberg et al. 2018, 2017; Corbett-Davies et al. 2017).

[4] Kleinberg et al. (2017) presents evidence that algorithmic prediction could reduce racial disparities in New York City. However, that finding assumes automating judges away.

[5] Furthermore, risk assessments are used in pretrial in dozens of jurisdictions and at least six entire states. They are also used in sentencing in at least twenty-eight entire states (Doleac and Stevenson 2018).

[6] For context, about 90-95% of cases are estimated to resolve in plea bargaining (rather than trial) (Devers 2011).

of the current social policy conversation on mass incarceration. Moreover, bail decisions during pretrial can have large downstream effects on future outcomes such as likelihood of conviction.[7] Methodologically, bail is a promising environment for study since, as Arnold, Dobbie, and Yang (2018) explain, bail decisions are made quickly and the legal objective is clear.[8]

My paper focuses on a policy change, House Bill 463 (HB463), in Kentucky that set bail recommendations based on defendant risk scores. During my time period of interest (2009-2013) in Kentucky, judges made initial decisions about defendants within 24 hours of the defendant's booking.[9] Before HB463, judicial consideration of a defendant's risk assessment score level, as calculated by the Kentucky Pretrial Risk Assessment (KPRA), of low, moderate, or high was optional in initial bond decisions (meaning many judges did not know the defendants' risk levels). However, when House Bill 463 (HB463) was enacted on June 8, 2011, judges became required to consider the risk score level (again, of low, moderate, or high) in their initial decision. More powerfully, judges were required to set non-financial bond for low and moderate risk defendants unless they give a reason for deviating from this "presumptive default" (Stevenson 2017).

In conceptualizing HB463 as an upward shock to the weight on risk levels in a judge's bail decision, it would be natural to think this would mechanically shrink racial disparities for low and moderate risk defendants. However, using case-level data from the Kentucky Administrative Office of the Courts, I show empirical evidence to the opposite effect. I first replicate Stevenson (2017)'s striking finding that rates of non-financial bond jump up discontinuously at the date of policy implementation, with white defendants experiencing larger gains. Given that black and white defendants differ in their underlying risk level distributions (black defendants are more likely to be scored at higher risk levels than white defendants), this could just be a mechanical consequence of judges' following the recommendations at equal rates for white and black defendants. Breaking out the picture by risk level, I show that differential trends remain when honing in on low and moderate risk defendants. Therefore, the presumptive default (of non-financial bond for low and moderate risk defendants) is more likely to be overridden for black defendants than for white defendants.

In other words, *racial disparities for low and moderate risk defendants jumped up after HB463 even though the policy recommended the same treatment (non-financial bond) for both groups with those risk levels.* This could be due to differences across populations in the underlying charge or defendant characteristics observed by judges. However, adjusting for charge and risk score component characteristics does not explain the differential policy effect on initial decisions

[7] For empirical evidence on the effects of pretrial detention, see Dobbie, Goldin, and Yang (2018) and Cowgill (2018).

[8] In their words, the objective is "to set bail conditions that allow most defendants to be released while minimizing the risk of pre-trial misconduct"(Arnold, Dobbie, and Yang 2018).

[9] There is more information about this decision in the later sections. The decision usually takes the form of a phone call between a pretrial officer and a judge, in which the pretrial officer relays relevant information about the defendant (age, name) and charges (description, class, level). Judges took such calls 1-4 times per day depending on the size of the county they work in. Ability to pay is not mandated to be in the call. Judges can ask questions and calls may differ by judge-pretrial officer pair.

across racial groups. Instead, part of the explanation is different responses by judge. Recall that while HB463 was a state-wide policy change, judges had discretion in when they deviated from the presumptive default. Extreme spatial variation in percentages of black defendants across counties meant that different policy responses had large effects on aggregate racial disparities.[10] In fact, allowing for heterogeneous policy responses by judge explains the vast majority of disparities observed among low risk defendants.[11] *This finding highlights the potential for geographic variation in policy responsiveness to generate seemingly counterintuitive gaps in treatment for those facing the same recommendation.* I discuss a few theories for why variation in policy response may correlate with defendant demographics; future work will investigate this empirically.

Even within judge and time, *black moderate risk defendants are treated more harshly than similar white moderate risk defendants after but not before HB463.* Judges are 10% more likely to deviate from the non-financial bond recommendation for moderate black rather than similar moderate white defendants. (The same is not true for low risk defendants.) This is suggestive evidence that judges interpret risk score levels differently based on defendant race.[12] In terms of mechanism, if judges want to be more cautious than the policy default, they may shift away from non-financial bond for moderate risk defendants since they are more ambiguous than low risk defendants. If judges have some sense of the underlying continuous risk score distribution and assume that moderate risk black men are still higher risk than moderate risk white men, this could explain the results. This result suggests that interaction with the same predictive score may lead to different predictions by race, which is consistent with the theory of disparate interactions, introduced by Green and Chen (2019). Further work is required to better pin down this result.

On the whole, this paper demonstrates how interactions between human discretion and prediction tool recommendations (both across and within decision-makers) can mean unequal policy effects across racial groups. This work contributes to a slim but growing literature on risk assessment policies and risk assessment adherence (Sloan, Naufal, and Caspers 2018; Stevenson 2017; Doleac and Stevenson 2018; Main 2016; Garrett and Monahan 2018; DeMichele et al. 2018). Most related to my paper is Stevenson (2017), which also focuses on HB463. In her thorough investigation, Stevenson uses graphical time-trends to show that while HB463 had effects on bail setting behavior, the effects on pretrial detention were minimal in comparison. She also addresses racial disparities and explains that HB463 had no effects on racial disparities in release after 3 days of booking. The object of interest in my paper differs in two ways. Recall I am interested in whether judges' initial bond decisions deviated from the non-financial bond recommendation. This approach (1) focuses on the initial judge decisions themselves rather detention consequences[13] and (2) takes into

[10]Stevenson (2017) hypothesized this mechanism when discussing racial disparities in release within 3 days of booking.

[11]This finding is highly reminiscent of Goncalves and Mello (2017)'s recent work which finds that a large share of the disparity in treatment of minority drivers by police officers "is due to the fact that minorities drive in areas where officers are less lenient to all motorists."

[12]The result is also consistent with Cowgill (2018)'s findings that black defendants' outcomes are more sensitive to risk thresholds.

[13]Detention consequences are a function of the initial (and followup) judge decisions as well as ability to

account the associated risk score levels, which allows me to investigate heterogeneity in responses over risk levels (low, moderate, high). On a methodological level, I use case-level data to decompose the aggregate increase in non-financial bond racial disparities.

My paper also contributes to the literature on the demographics and judicial decision-making (Arnold, Dobbie, and Yang 2018; Abrams, Bertrand, and Mullainathan 2012; Cohen and Yang 2019). A few recent studies even investigate the role of demographics when it comes to how humans use risk assessments. Green and Chen (2019) uses an Amazon Mechanical Turk experiment (rather than observational data on judge decisions) to investigate human interactions with risk scores. They find "risk assessments led to higher risk predictions about black defendants and lower risk predictions about white defendants."[14] Running an experiment with real judges, Skeem, Scurich, and Monahan (2019) finds that the same risk assessment information produces different judicial decisions based on socioeconomic class of the defendant. Using data from Broward county, Cowgill (2018) find that outcomes for black defendants are more sensitive to risk score thresholds than are outcomes for white defendants.[15] On the theoretical side, Kleinberg and Mullainathan (2019) shows that simplified prediction functions (e.g., risk assessments) create incentives for decision-makers to consider group membership information.

This article generally relates to the role of discretion in decision-making, relevant to many environments beyond criminal justice. Sarsons (2017) discusses how decision-makers (physicians) interpret the same signal (a patient outcome) differently based on demographics (the performing surgeon's gender). Very similar to my setting, Hoffman, Kahn, and Li (2017) look at how decision-makers overrule a score-based recommendation; they focus on managers making hiring decisions in the labor market. Deviation from a presumptive default is a binary decision of interest for understanding the implications of providing experts (e.g., managers, judges) with prediction-based recommendations. I build on Hoffman, Kahn, and Li (2017) by considering the importance of demographics in those deviations from a recommendation.[16]

On a broader note, discussions of racial disparities are inherently intertwined with sociological and economics literatures on discrimination. Related papers span intentional experimental studies (e.g., Pager, Bonikowski, and Western 2009) as well as natural experiments (e.g., Goldin and Rouse 2000). Any context (such as Kentucky judge calls) that reveals names[17] is reminiscent of the well-known Bertrand and Mullainathan (2004) audit

pay. See Appendix A for more on marrying bond decision and detention trends in Kentucky. Note that the first-stage decision is quick and economically meaningful for predicting immediate release – non-financial bond corresponds with 95.6% chance of immediate release while financial bond corresponds with a 20.4% chance of immediate release.

[14] This is conceptually related to the "shifting standards" model outlined by Biernat and Manis (1994).

[15] Cowgill (2018)'s outcome data corresponds to length of jail stay rather than judge decision. Length of stay is a downstream consequence from the judicial decision-making itself. See Appendix A for more on that distinction.

[16] They are unable to investigate results by demographics due to data limitations.

[17] Kentucky judges are provided with defendant names, meaning they could infer information about race regardless of if it is explicitly provided. Race and ethnicity were on judge forms about cases during my studied time period of interest, meaning they could be explicitly observed when judges used said forms in

study. Bertrand and Mullainathan (2004) randomly assigned resumes to black or white names and then observed call back rates, providing evidence that call-back rates were higher for the hypothetical applicants with white names despite identical credentials. The recent Bartoš et al. (2013) study provides a possible mechanism for these results; they provide evidence of "attention discrimination," meaning a minority-sounding name could lead possible employers to pay less attention to the candidate as a prospective employee. Usually, names are used in the discrimination literature as features to be manipulated for the sake of field experiments, but variation in racial signaling from names can also be used in observational studies. For instance, Broockman and Soltas (2017) look into how name variation reveals taste-based discrimination in voting behaviors.

The remainder of the paper proceeds as follows. Section 2 provides a conceptual framework for understanding how discretion complicates the effects of risk score recommendations. Section 3 introduces the Kentucky pretrial environment. Section 4 describes the data. Section 5 presents the main results by empirically exploring disparities in deviation behavior. Section 6 discusses mechanisms behind variation in judge responsiveness and the lingering racial disparity for moderate risk defendants. Section 6 concludes and discusses avenues for future work.

2 Conceptual Framework

In order to discuss how discretion and predictive tools interact, I consider the salient example of risk scores in bail decisions that maps onto my empirical environment. In such contexts, risk scores do not mechanically determine final outcomes. Rather, they are decision-making aids that are provided to final human decision-makers – judges.[18] I describe two types of deviations from risk score recommendations can create larger or smaller racial disparities than mechanical adherence.

In this set-up, judges can set either financial or non-financial bond. Financial bond is more restrictive so judges will want to set it for defendants who are more likely to commit pretrial misconduct.[19] Consider a risk score policy that recommends 85% of black defendants receive non-financial bond and 90% of white defendants receive non-financial bond. (The risk score policy has been constructed to help increase non-financial bond rates, meaning before the policy judges set non-financial bond at low rates.) Mechanically, this would mean a racial disparity (in favor of whites) of 5 percentage points.[20] The true observed disparity will likely be complicated by one or both of the following two types of deviations.

Deviation by Judge: Judges need not respond to policy recommendations identically since they retain individual discretion. Judges serve different populations of defendants, often

their decision-making. However, these details have since been removed from judge forms.

[18] Note that pretrial decisions can also be made by other criminal justice system actors such as magistrates.

[19] Assume they do not have information about defendants' abilities to pay.

[20] Whether this is an improvement or exacerbation of the status quo depends on the specific policy context. For instance, Kleinberg et al. (2017) presents evidence that algorithmic prediction could reduce racial disparities in New York City pretrial decisions.

based on geography. Assume each judge deviates similarly by race, meaning deviation from the risk score policy recommendation is independent of race. If variation in response across judges is uncorrelated with defendant characteristics then the observed racial disparities should approximate those generated by mechanical adherence. If judges who respond more (increasing non-financial bond rates) serve a defendant population that is a relatively higher percentage black, then racial disparities (in favor of whites) will be smaller than that generated by mechanical adherence. If judges who response more serve a defendant population that is relatively lower percentage black, the opposite is true.[21] In short, differences in deviations *across judges even if they are agnostic to race of the defendant* can affect aggregate racial disparities.

Deviation by Defendant Race: While the above deviation was across judges, the second sort of deviation is *within judges*. Judges may interpret risk score recommendations differently based on defendant race. In a decision-making system with simplified predictive scores, Kleinberg and Mullainathan (2019) explains there are additional incentives for decision-makers to consider group traits such as race. If judges believe black defendants are more risky than white defendants with identical risk scores, this could lead to larger racial disparities (in favor of whites) than generated by mechanical adherence.[22] If the opposite is true (as judges could, for instance, take into account the increased likelihood of low level arrests and subsequent convictions for black people[23]), then this could lead to smaller racial disparities than generated by mechanical adherence.

In theory, these two behavioral deviations (race-invariant deviations across judges or race-correlated deviations within judge) could go in either direction and thus mean either larger or smaller racial disparities than those generated by mechanical adherence. In this paper, I specifically discuss the Kentucky pretrial system and show how both of these two forces pushed in the direction of larger racial disparities in favor of whites.

3 Empirical Environment

In response to large increases in the incarcerated population between 2000 and 2010[24], Kentucky House Bill 463 (HB463) went into effect on June 8, 2011. The law made pretrial risk assessment a mandatory part of bail decision-making and set the default decision for low or moderate risk defendants to be non-financial bond.[25] If judges wanted to defect from this recommendation, they had to provide a reason.[26] As such, HB463 mandated the

[21] This is related to Goncalves and Mello (2017)'s finding that minorities drive in areas where officers are less lenient overall.

[22] This would be in line with both Skeem, Scurich, and Monahan (2019) and Green and Chen (2019).

[23] Risk scores do not currently attempt to take into account possible biases generated by criminal history data though this has been proposed by AI (2019).

[24] According to Stevenson (2017), between "2000 and 2010, Kentucky's incarcerated population – both jail and prison – grew by 45%, more than three times the U.S. average."

[25] See bullet 3 in Figure 1.

[26] In practice, this could be as simple as saying a few words (e.g. "flight risk") to the pretrial officer.

use of risk levels and set a recommended default based on those levels.

3.1 Kentucky Pretrial Overview

Kentucky is well-known for its pretrial services for a few reasons. For one, it was the first state to ban commercial bail bonds in 1976.[27] Kentucky boasts one unified pretrial services that serves all 120 counties in the state, meaning that data management and collection is unified and well-organized. Unlike in other states, Kentucky Pretrial Services is part of the judicial branch; it is a state entity that works for the courts (and is state-funded).[28] While pretrial employees are housed in individual counties, they do not work for the individual counties.[29] Kentucky Pretrial Services even has a virtual tour of their pretrial services system online for other jurisdictions to use in ongoing bail reform efforts. Kentucky was also the first jurisdiction to pilot the Public Safety Assessment (PSA) risk assessment.

During 2009-2013 in Kentucky, after defendants were booked into jail, pretrial services officers in that county conducted risk assessments using the Kentucky Pretrial Risk Assessment framework (discussed in the next subsection). Within 24 hours of booking, these officers presented information about the defendant and incident in bail hearings with a judge.[30] The bail hearing usually takes place via a phone call (see Figure 1) between a pretrial officer and a judge.[31]

After receiving information about the defendant and case from the pretrial officer,[32] the judge decides on bond type and amount (if financial) as well as supervision and other conditions of release. In this paper, I focus on whether that initial bond decision was non-financial or financial since HB463 specifically suggested judges set non-financial bond

[27] It was one of four states with this ban as of 2018.

[28] Much of the information in the following paragraphs is from an interview with the Executive Officer of Kentucky Pretrial Services, Tara Blair.

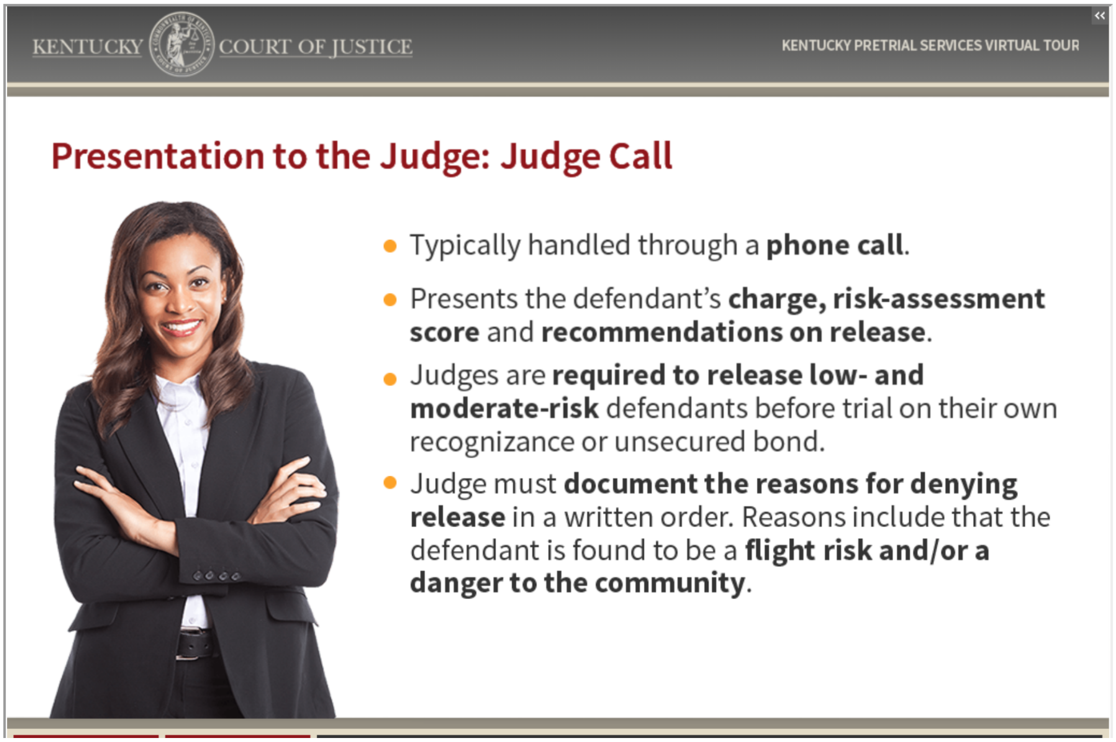
[29] As of January 2019, there were about 251 employees in Pretrial Services in Kentucky. Approximately 202 employees are pretrial officers and/or supervisors and 49 are risk assessment specialists and/or coordinators.

[30] Appendix B for more information on judges.

[31] This is abnormal in the US as most jurisdictions use in-person bail hearings. If pretrial officers and judges are in the same place, this could be an in-person meeting instead. The data does not specify whether initial bond decisions are via judge calls or not, so it is unclear to me how many initial bond decisions I observe are via phone calls. Kentucky has been using calls for pretrial services since 1976 – this is especially efficient in areas of the state where people are very spread out and there would be significant time costs for in-person bail hearings.

[32] The eight example judge calls that available online on the Kentucky pretrial website include the following information: name, age, risk score information, list of charges, and incident description. The incident description quotes information from the police report. In Kentucky, police have full authority to charge; there is no prosecutorial review before the judge call. Note that while demographic information on race or gender can be missing explicitly in the call, these details are implicitly included. Gender is revealed through usage of pronouns (e.g. "he" and "she") when the pretrial officer discusses the defendant. Meanwhile, names (especially in combination with the county) can signal information about race. Moreover, race and ethnicity were on judge forms about cases during my studied time period of interest, meaning they could be explicitly observed when judges used said forms in their decision-making. (However, these details have since been removed from judge forms.)

Figure 1: Judge Call Information



for low and moderate risk defendants.[33] While there are many smaller bail outcomes, the key overarching decision is whether to set financial conditions or not, as illustrated by Figure 2.[34]

3.2 Kentucky Pretrial Risk Assessment

Kentucky has used a few different risk assessment tools over the years. At first, Kentucky used a six-question tool developed by the Vera Institute.[35] In 2006, Kentucky moved to its own Kentucky Pretrial Risk Assessment (KPRA) tool[36] – this is the tool used during my

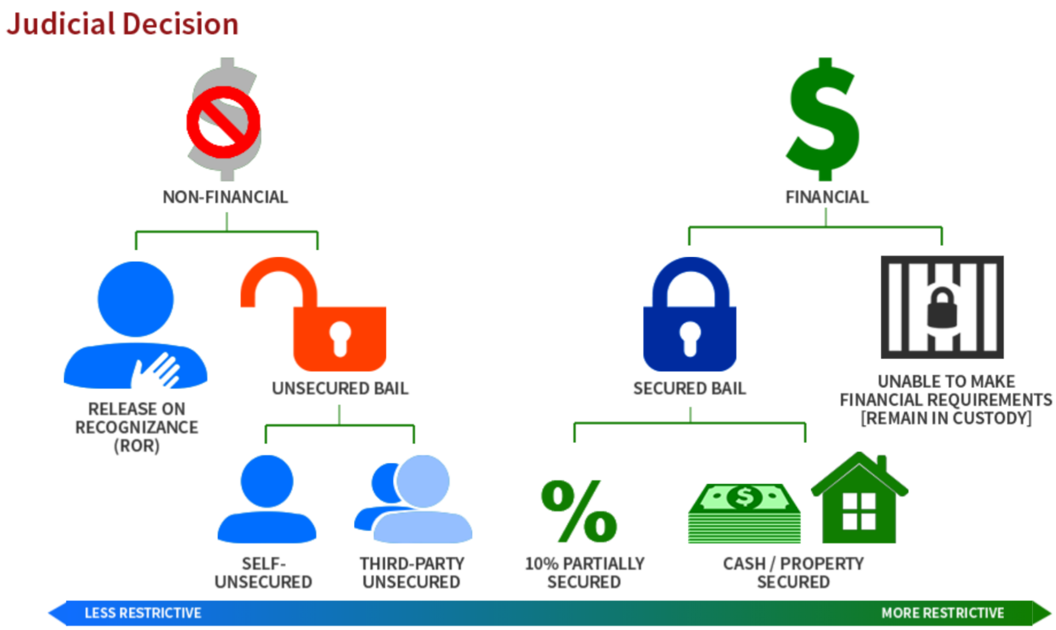
[33]In the data, non-financial and financial bond correspond to a 95.6% or 20.4% chance of initial release (release on that bond), respectively. If the defendant has not posted bail within 24 hours of the initial decision, the pretrial officer informs the court and the judge can change the bond to increase the chance that they can be released pretrial. If the defendant remains detained pretrial, the next time bond could be reconsidered is usually first appearance (Stevenson 2017).

[34]Note that there is no non-refundable piece to bond (as there is in many states), so bond is fully returned to defendants at the disposition of the case regardless of outcome. All offenses are bailable except capital offenses in Kentucky, meaning judges can rarely simply detain defendants as they can in Washington DC or New Jersey (12-15% are denied bail in Washington D.C.) (Santo 2015).

[35]Information on the history of risk assessment in Kentucky is via communication with Executive Officer of Pretrial Tara Blair.

[36]The tool was created in-house, fitting a regression model to predict pretrial misconduct using the existing Kentucky data at the time.

Figure 2: Bond Types



time period of interest. In June 2013, Kentucky began to use the Public Safety Assessment (PSA), which was developed by the Laura John Arnold Foundation.[37]

The KPRA tool was not a complex black-box machine learning tool.[38] Rather, it was a check-list tool that added up points based on Yes/No answers to a series of questions. It was modified slightly on March 18, 2011. Figure 3 documents the weights that various components are given in both the 7/1/09-3/17/11 and 3/18/11-6/30/13 version of the scores (Austin, Ocker, and Bhati 2010).

The factors in the KPRA are mostly criminal history elements (e.g., prior failure to appear, pending case) but there is also information about the current charge (e.g., whether the charge is a felony of class A, B, or C) and defendant personal history (e.g., verified local address, means of support). To calculate a risk score level, the weights shown in Figure 3 are added up and then mapped to a low, moderate, or high score level. Before 3/18/11, totals of 0-5, 6-12, and 13-23 correspond to low, moderate, and high levels, respectively. As of 3/18/11, totals of 0-5, 6-13, and 14-24 correspond to low, moderate, and high levels, respectively. During the time period of interest (around the HB463 policy change), judges were informed of risk score levels rather than total number of points. Recall the 2011 law

[37]The PSA is used exclusively in the pretrial stage of the criminal justice system; its formula is open and meant to be shared publicly (Schuppe 2017). It was initially developed in 2013 (and altered slightly in 2014) by investigating 746,525 cases in which defendants had been released pretrial (over 300 jurisdictions) to determine which defendant characteristics were most predictive of new crime, new violent crime, and failure to appear pretrial (Laura & John Arnold Foundation 2013). As of late 2018, “over 40 jurisdictions have either adopted the PSA or is engaged in implementation with LJAF technical assistance” (John Arnold Foundation 2018).

[38]The Angwin and Kirchner (2016) article that generated lots of press about risk assessment scores was about a black-box machine learning tool called COMPAS.

Figure 3: Weighting Rules for Kentucky Pretrial Risk Assessment

	Scoring Items	Current		Modified	
		Yes	No	Yes	No
1	Does the defendant have a verified local address and has the defendant lived in the area for the past twelve months?		1		2
2	Does the defendant have verified sufficient means of support?		1		1
3	Did a reference verify that he or she would be willing to attend court with the defendant or sign a surety bond?		1	Removed	
4	Is the defendant's current charge a Class A, B, or C Felony?	1		1	
5	Is the defendant charged with a new offense while there is a pending case?	5		7	
6	Does the defendant have an active warrant(s) for Failure to Appear prior to disposition? If no, does the defendant have a prior FTA for felony or misdemeanor?	4		2	
7	Does the defendant have prior FTA on his or her record for a criminal traffic violation?	1		1	
8	Does the defendant have prior misdemeanor convictions?	1		2	
9	Does the defendant have prior felony convictions?	1		1	
10	Does the defendant have prior violent crime convictions?	2		1	
11	Does the defendant have a history of drug/alcohol abuse?	2		2	
12	Does the defendant have a prior conviction for felony escape?	1		3	
13	Is the defendant currently on probation/ parole from a felony conviction?	2		1	

did not introduce the KPRA levels for the first time; rather, it mandated their consideration in bail decisions.

4 Data and Descriptive Statistics

I use data from the Kentucky Administrative Office of the Courts (KY AOC) on initial bond decisions for misdemeanors and felonies.[39] I consider all initial bond decisions about male defendants from July 1, 2009 to June 30, 2013 (the time period that featured the KPRA tool).[40] The final dataset consists of 383,080 initial bond decisions, which cover decisions for 192,758 distinct defendants by 563 distinct judges.[41][42]

4.1 Charges

An important part of the initial decision is the set of charges brought against a defendant. Recall that I am focusing on misdemeanors and felonies.[43] In terms of charge severity, I plot the most severe (highest level and charge combination) charge for each initial decision in Figure 4. This illustrates that 79.5% top-charges are class A or class B misdemeanors, and 20.5% are class D felonies. Only 8.5% of initial decisions include a top-charge that is a class A, B, or C felony. In terms of specific charge characteristics, 1.2% of initial decisions involved weapon-related charges, 4.9% of initial decisions involved violence-related charges, and 8.3% of initial decisions involved drug-related (excluding alcohol) charges.[44]

[39] On a technical note, I use R Markdown for my data cleaning and analysis. The R packages I use are: Wickham, Chang, et al. (2018), Wickham (2018), Hlavac (2015), Dowle and Srinivasan (2018), Firke (2018), Wickham (2017), and Wickham, François, et al. (2018).

[40] Recall that Kentucky switched its risk score system to the PSA on July 1, 2013.

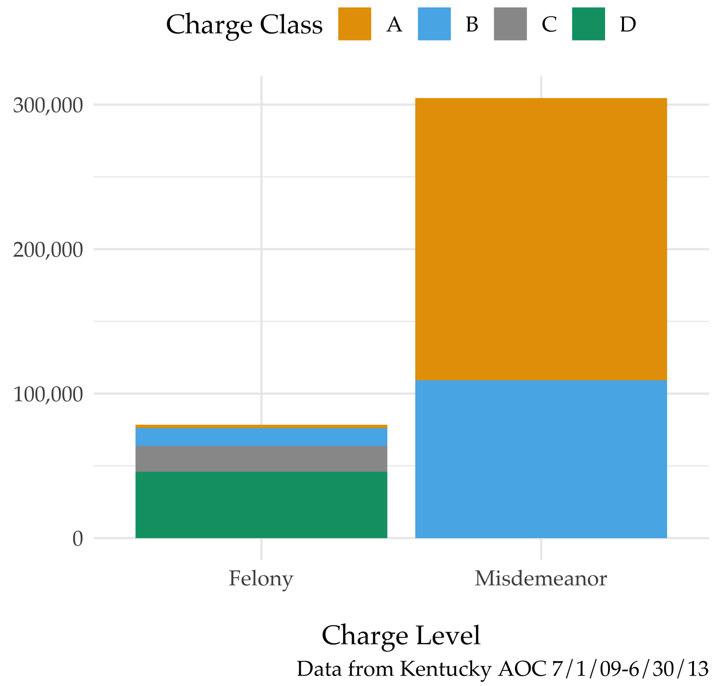
[41] I first consider all 1.56 million initial bond decisions for 7/1/09-12/30/17 and then subset to misdemeanor and felonies (with a known class) within the 7/1/09-6/30/13 time period with known age, gender, judge, race, risk level, and risk level components – this leads to a sample of 524,229 initial bond decisions. After subsetting to those decisions about male defendants, I have 383,080 initial bond decisions; this is 73% of the sample that includes both genders.

[42] For more on judge types see Appendix B.

[43] Most violation offenses, which are lower level, do not result in a bond hearing. In fact, they are so rarely associated with a bond hearing that if I don't mechanically exclude violation and other offenses, they comprise only 2% of the sample.

[44] I define weapon-related charges as those with descriptions including the words "gun", "firearm", or "weapon". I define violence-related charges as those with descriptions including the words "violence", "assault", "rape", or "murder". I define drug-related charges as those with descriptions including the words "cocaine", "heroin", "marijuana", "drug", or "meth", but excluding charges that include "under/infl" since those are agnostic to alcohol/drugs.

Figure 4: Top Charges by Level and Class



4.2 Bond Types

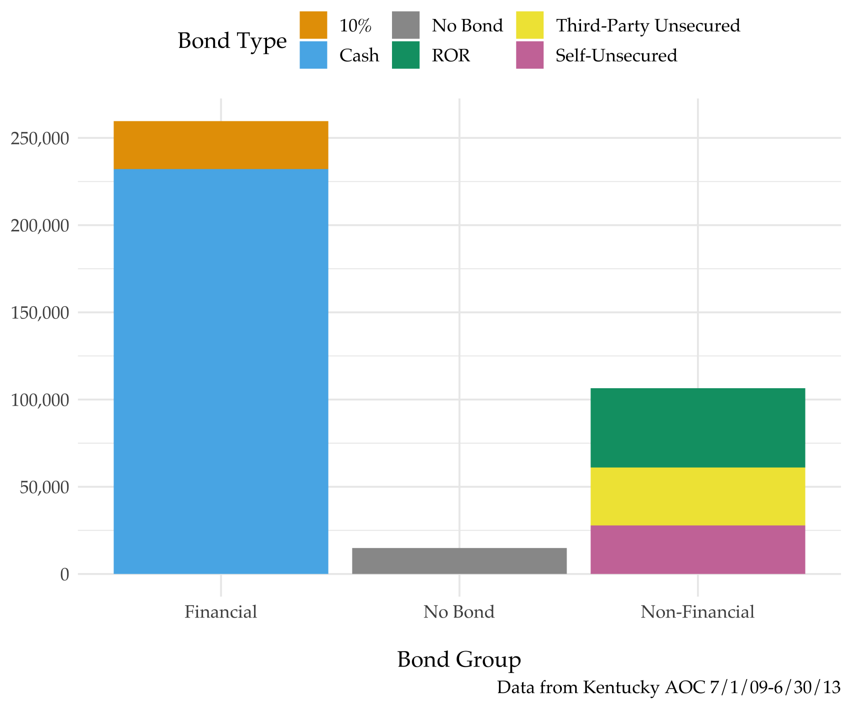
Bond comprises conditions for release from jail. While there are a range of possible conditions, the most salient conditions are monetary. Recall from Figure 2 that the initial bond decision by the judge can be financial or non-financial. Financial bond means there are financial conditions that must be met before release; there are no such financial conditions for non-financial bond. As such, non-financial bonds are less financially restrictive for defendants. Figure 5 shows the frequency of the specific types of initial bond outcomes. Bond can be refused only for capital crimes (e.g. murder) for Kentucky, so "no bond" is observed in only around 3.9% of observations. Bond is financial in 68.3% of the initial bond hearings and is mostly cash bond.[45] In 27.8% of initial bond hearings, the bond type is non-financial, which is pretty evenly split across release on recognizance, self-unsecured, and third-party unsecured bonds ("surety").[46][47]

[45] Cash bond means the entire amount of the bail must be posted in cash. A 10% bond means that only 10% of the amount must be posted.

[46] Unsecured bond means that the defendant would owe some amount of money if the defendant fails to appear.

[47] This is consistent with Stevenson (2017)'s finding (using Kentucky data from a different time range) that "[i]f judges followed the recommendations associated with the risk assessment, 90% of defendants would be granted immediate non-financial release" but "[i]n practice, only 29% are released on non-monetary bond at the first bail-setting."

Figure 5: Bond Outcomes by Group and Type



4.3 Race

I am limiting my discussion to male defendants. In terms of race, defendants are white in 79.1% of these initial bond hearings and black in 20.6% of them.[48] For context, the 2017 Kentucky state population was 87.8% white and 8.4% black.[49][50]

Racial composition varies spatially over the state of Kentucky. Figure 6 shows that while a handful of counties have over 30% black defendants, most counties have less than 5% black defendants. This variation is due to preexisting spatial racial segregation in the state. The choropleth in Figure 6 illustrates the variation across the state by coloring counties based on their percentages of black defendants. Christian, Jefferson, and Fayette counties are the counties with the highest percentages of black defendants in my data.[51] Meanwhile, most counties in the east are dark purple, meaning their percentages of black defendants are near zero.

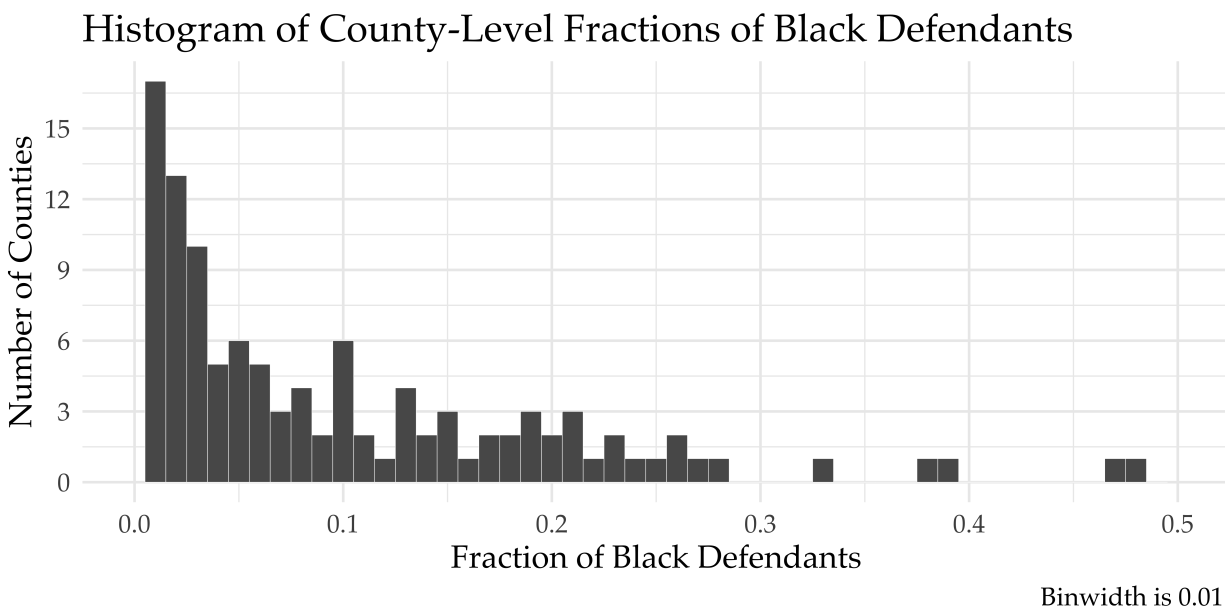
[48] Defendants are Asian in 0.24% of initial bond hearings.

[49] This is from the Census QuickFacts data.

[50] In terms of ethnicity, defendants are recorded as Hispanic in only 2% of these initial bond hearings. In 70% of initial decisions, defendants are recorded as non-Hispanic and in 27.9% of initial decisions, ethnicity is recorded as unknown. Due to the small sample size, I will not be discussing disparities by ethnicity.

[51] For context, the largest cities in Kentucky are Louisville, located in Jefferson county, and Lexington, located in Fayette county.

Figure 6: County-Level Fractions of Black Defendants



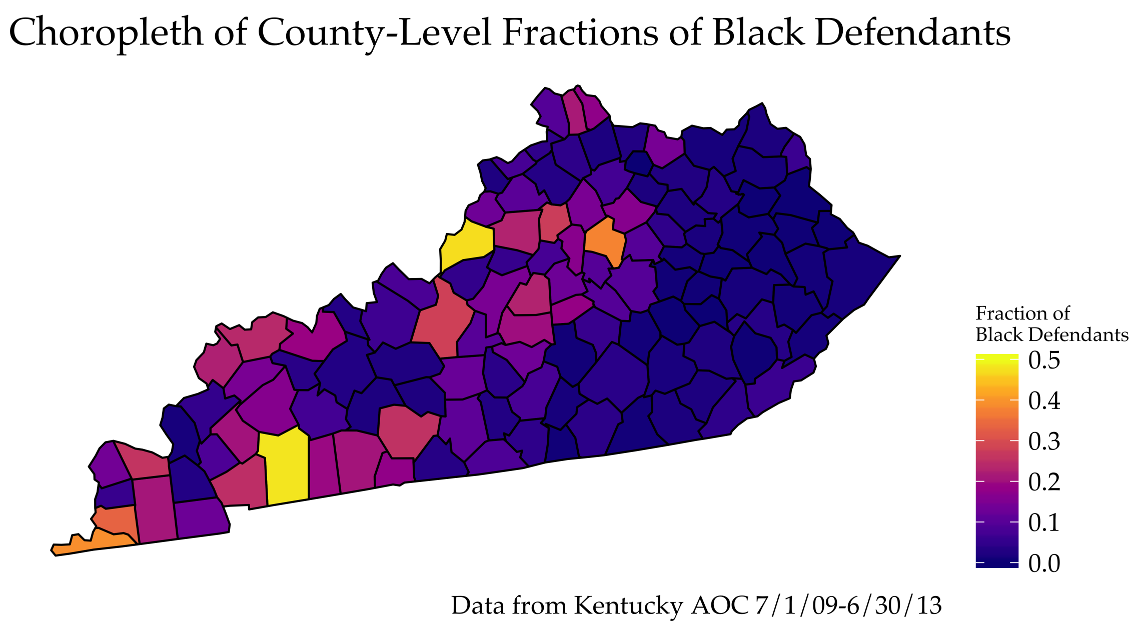
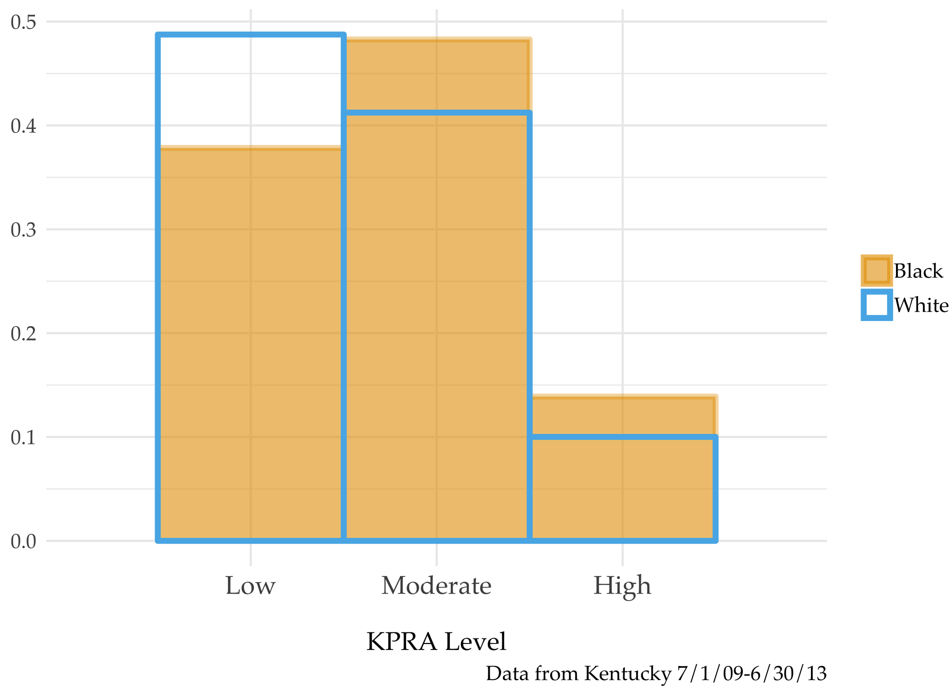


Figure 7: Risk Level Density by Race



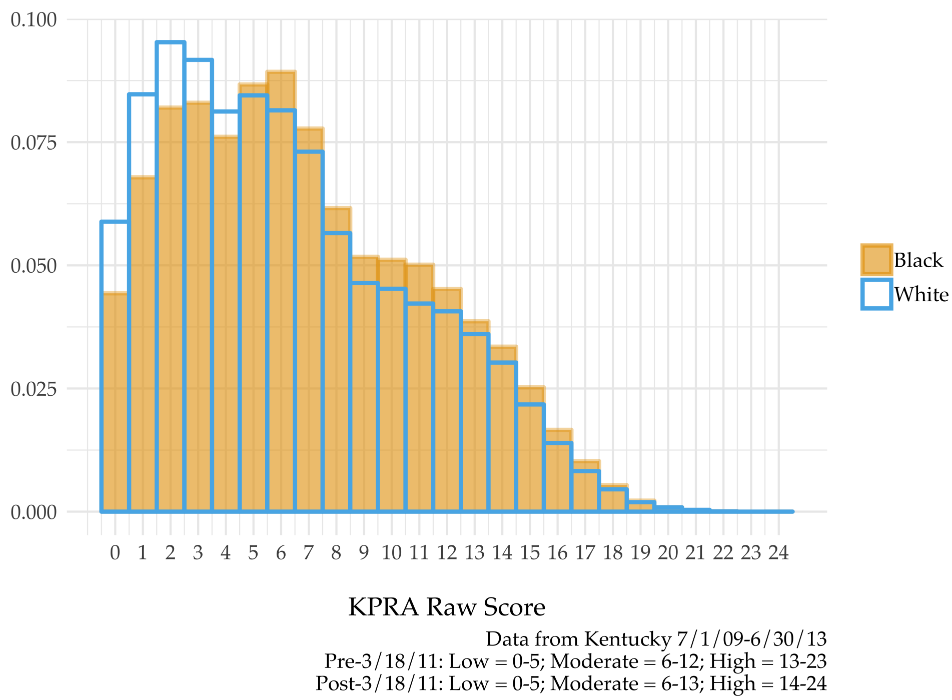
4.3.1 Risk Scores and Race

Risk assessment score distributions may differ across racial groups. This is the primary mechanism through which the current literature discusses how risk scores may impact racial disparities. In Angwin and Kirchner (2016)'s piece about the COMPAS algorithm, the score distributions by race are strikingly different – white defendants are notably skewed towards lower-risk categories (1 out of 10, in particular), while black defendants scores are evenly distributed across the full 1-10 range. Figure 7 compares the risk score densities for black and white defendants for KPRA risk assessment levels. The distributions are substantially more similar across races than in the case of COMPAS. However, Figure 7 does show that white defendants are more heavily skewed towards the lower-risk levels, while black defendants are more heavily skewed towards the higher-risk levels.

The three levels (low, moderate, and high) are what is communicated to judges during the time period of interest. However, as mentioned before, there are more specific raw scores calculated for each defendant, which are then converted into these coarse (low, moderate, high) categories. See Figure 8 for a more detailed comparison of score distributions.[52]

[52] For the time period up until 3/17/11, the scores ranged from 0-23. After 3/18/11, the scores ranged from 0-24.

Figure 8: Raw Risk Score Density by Race



5 Disparities in Deviations

In this paper, I am focused on how judges respond to risk score recommendations. Specifically, I focus on the decision to set non-financial bond since HB463 made non-financial bond the presumptive default for low and moderate risk defendants.[53] Judges had to give pretrial officers a reason for defecting from this recommendation, as seen in Figure 1.[54]

HB463 had a clear and immediate effect. Figure 9 shows the simplified effect of HB463 on non-financial bond outcomes across all defendants, black and white. The percentage of male defendants receiving non-financial bond jumped in a clearly discontinuous manner at the effective date of HB463, increading from a pre-HB463 mean of 22.5% to a post-HB463 mean of 36.5%. However, all defendants did not equally benefit. Following Stevenson (2017), Figure 10 breaks the picture out by race to show that rates of non-financial bond jump up discontinuously at the date of policy implementation but white defendants experience larger gains. Both groups are more likely to receive non-financial bond after HB463, however, the gap between the two increases from 3 percentage points (in the pre-period) to around 8.8 percentage points (in the post-period).

[53] Appendix A speaks to the realm of financial bond decisions as well as how these combine with non-financial bond decisions to explain trends in pretrial release on initial bond. That appendix builds on Stevenson (2017)'s prior findings, marrying non-financial bond findings and pretrial detention trends after HB463.

[54] However, the reason could be as simple as saying "flight risk," meaning the cost to deviation was not very high for judges.

Figure 9: Bond Outcomes Before and After HB463

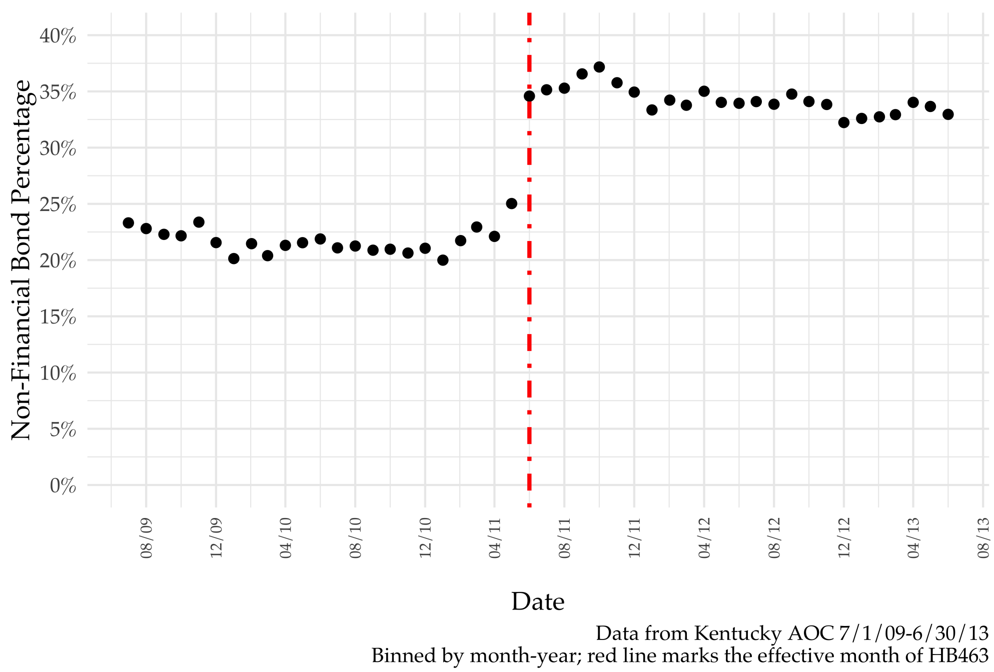


Figure 10: Bond Outcomes Before and After HB463 by Race

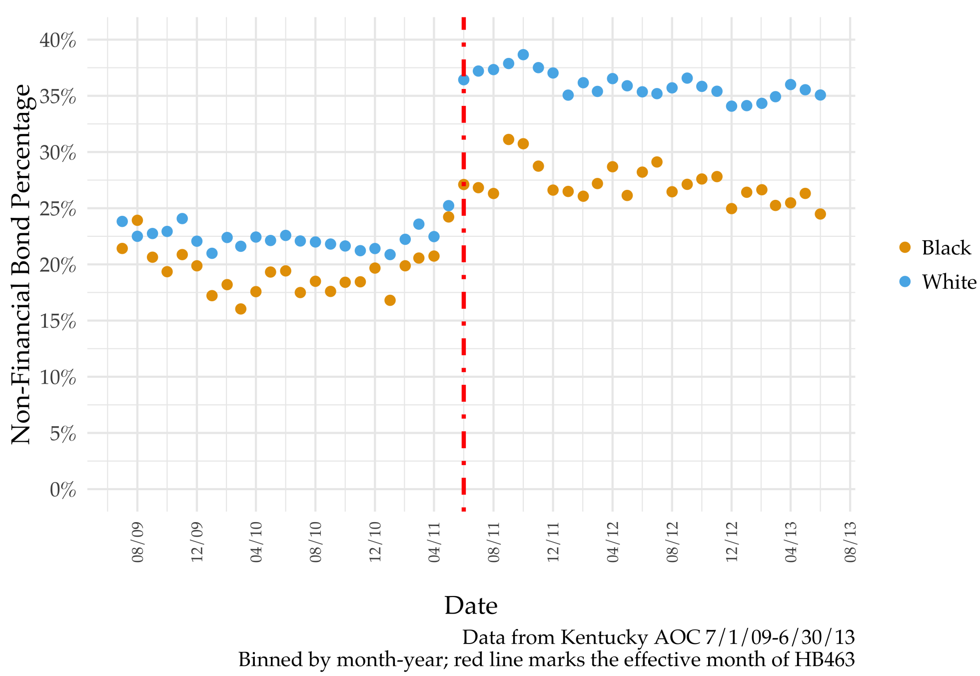
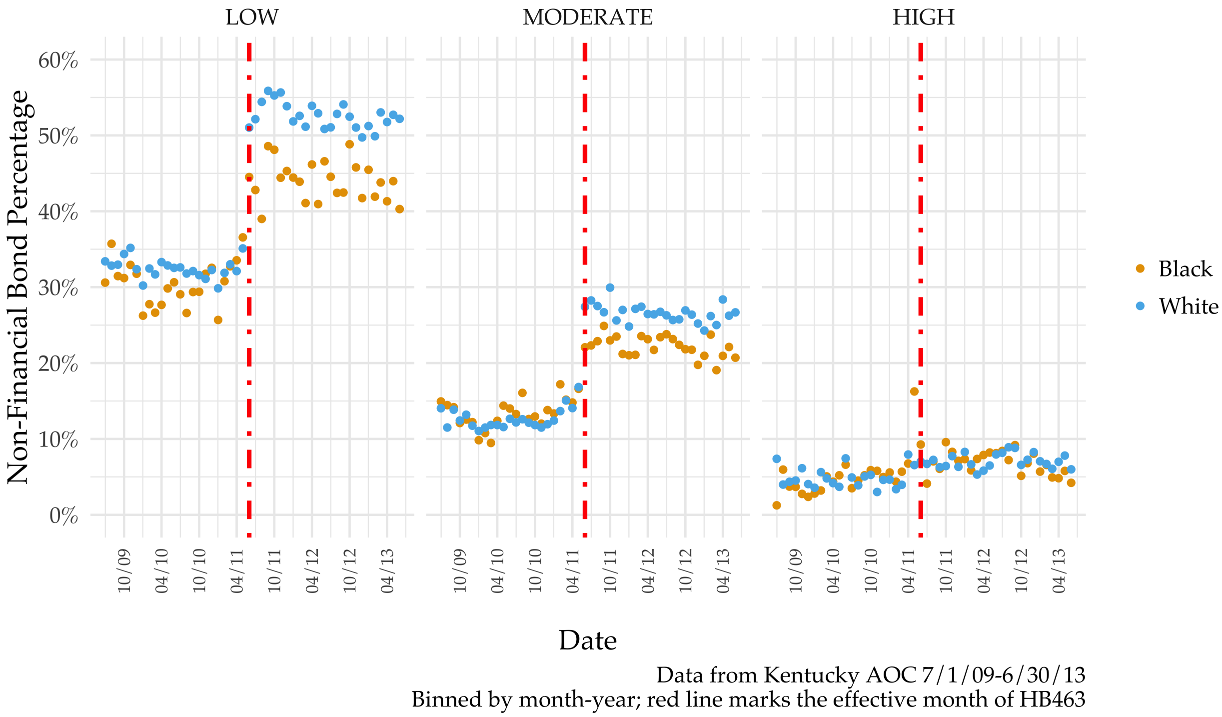


Figure 11: Bond Outcomes Before and After HB463 by Race and Risk Level



Given that black and white defendants differ in their underlying risk level distributions (Figure 7 showed black defendants are more likely to be at higher risk levels than white defendants), this could be a natural consequence of judges' following the score recommendations (setting non-financial bond for low and moderate defendants) at equal rates for white and black defendants. In other words, it is possible that the judicial deviations look the same across racial groups but different risk level distributions cause the disparity increase visible in Figure 10. To address this possibility, I break the picture out by risk level in Figure 11. There are differential shifts in non-financial bond rates by race within the low and moderate risk levels. Therefore, the aggregated picture is not simply a consequence of black defendants' higher risk levels – *rather, there are racial disparities in deviation from the recommendation.*

The following sections aim to investigate the underlying reasons for the disparities in deviations, which are of policy importance as researchers and policy-makers evaluate the growing field of risk score policies across the country.

5.1 Theoretical Framework and Empirical Methodology

Figure 11 demonstrates that the gaps in racial disparities in non-financial bond rates widen after HB463 for low and moderate risk defendants. While the risk levels themselves cannot be driving these results, the results could be driven by a myriad of other factors that are important to judges in bail decisions.[55] To motivate my empirical approach to identifying why there are these disparities in deviations, I provide a theoretical framework of judge bail decision-making and illustrate the equivalent empirical specifications.

5.1.1 Homogeneity in Policy Response

Assume judge j makes the binary decision to set non-financial bond ($b_{ictj} = 1$) or not ($b_{ictj} = 0$) for defendant i with charges c at time t. Since the probability of release without financial conditions is 95.6%, while probability of release drops meaningfully to 20.4% once any financial conditions are imposed,[56] I assume the judge interprets this binary decision as equivalent to the decision between releasing or detaining the defendant.[57] Following Arnold, Dobbie, and Yang (2018)'s framework, the judge will set non-financial bond for the defendant if and only if the expected cost of release is less than benefit. The cost can be conceptualized as the expected probability of pretrial misconduct, as perceived by judge j – that is, $E_j[p_{ic}]$.[58] I assume the benefit before HB463 is some fixed threshold ζ.[59] After HB463, there is a small cost to deviating from the presumptive default of non-financial bond for low and moderate risk defendants, η. By setting non-financial bond for low and moderate defendants, judges avoid this cost.

Given information about present charges κ_c, defendant characteristics δ_i (e.g., age, criminal history, etc.), defendant risk level $KPRA_i$, and defendant race $race_i$,[60] a judge will set non-financial bond if and only if:

$$E_{jt}[p_{ic}|\kappa_c, KPRA_i, \delta_i, race_i] < \zeta + \eta \times I[t \geq 6/8/11] \times I[KPRA_i \in \{Low, Moderate\}]$$

In this set-up, judges' unique decision thresholds all move to the same extent after HB463. That is, there is no variance in policy responsiveness across judges. This maps empirically onto estimating the following specification (I present results by each of the three $KPRA_i$ risk levels):

$$b_{ijct} = \alpha + \phi_1 HB463_t + \phi_2 Black_i + \phi_3 (Black_i \times HB463_t) + \beta_1 \kappa_c + \beta_2 \delta_i + \omega_j + x_t + \epsilon_{ijct} \quad (1)$$

[55] In bail decisions in Kentucky, attorneys are not a part of the equation, so attorney quality is not a concern, as it would be for evaluating disparities in sentencing.

[56] Financial conditions often mean detention due to inability to pay.

[57] Other papers often focus on the release outcome rather than the bond decision. Doleac and Stevenson (2018) looks into release rates over the entire pretrial period while Dobbie, Goldin, and Yang (2018) focus on whether defendants were released within 3 days.

[58] Pretrial misconduct in this discussion contains both probability of new crime and failure to appear.

[59] In other words, I do not assume benefit to vary by case. However, it would be natural to extend this assumption, as Arnold, Dobbie, and Yang (2018) do.

[60] Race could be observed indirectly through names in calls or directly through forms or in-person meetings.

In this framework, b_{ijct} is a dummy variable that takes the value 1 if judge j set non-financial bond for defendant i with charges c during time t. $HB463_t$ is an indicator for if the decision takes place before or after the effective date of HB463. $Black_i$ is an indicator for if the defendant is black, and δ_i is a vector of defendant characteristics (age, criminal history variables, including dummies for prior FTAs, prior convictions, and pending cases). The vector of charge variables κ_c includes: (i) dummies for all combinations of charge levels (misdemeanor, felony, violation, other) and charge letter classes and (ii) dummies for if the charge description is related to drugs, weapons, or violence.[61][62] Given that judges are known to be heterogeneous in their decision-rules,[63] it is crucial to consider judge fixed-effects ω_j.[64] I also include month-year fixed effects x_t.

After attempting to approximate for the judge's information set, the coefficient of interest is ϕ_3 since this speaks to the change in the racial gap in non-financial bond that occurs after HB463.[65]

5.1.2 Heterogeneity in Policy Response

Judges were not regulated in their response to HB463 in Kentucky. As such, it would be more realistic to assume they varied in their costs of deviation η_j. Allowing for variation in policy responsiveness, the decision rule is subtly changed to the following:

$$E_{jt}[p_{ic}|\kappa_c, KPRA_i, \delta_i, race_i] < \zeta + \eta_j \times I[t \geq 6/8/11] \times I[KPRA_i \in \{Low, Moderate\}]$$

This then maps onto the following empirical specification:

[61] The weapon dummy is 1 when descriptions include the word "gun", "firearm", or "weapon". The violence dummy is 1 when descriptions include the word "violence", "assault", "rape", or "murder". The drug dummy is 1 when descriptions include the word "cocaine", "heroin", "marijuana", "drug", or "meth", but excluding charges that include "under/infl" since those are agnostic to alcohol/drugs.

[62] The reason for including these charge description dummies is that gun, violence, or drug-related offenses could be treated differently even if they share an offense level and class with a property crime offense. Without these variables, differences in charge specifics within charge severity bins by race for low risk defendants could drive observed disparities even after controlling for charge level and class.

[63] Thus the ability of researchers to exploit such variation with "judge designs" for causal inference.

[64] Moreover, recall the spatial variation in black defendants observed in Figure 6. Without fixed effects, I might be concerned that if judges in more populous counties, such as Christian and Fayette, are both harsher to everyone and working in counties where most black defendants are booked, then estimates of racial disparities will be biased upwards. For that reason, it is important to adjust for judge fixed-effects so that I compare bail decisions within given judges since I do not want differences that are stable within judges to drive results.

[65] In focusing on the interaction between race and time ($HB463_t$), the analysis relies on the assumption that any differences in important variables to the initial bond decision before and after HB463 are not statistically different by defendant race. (I.e., case characteristics before and after HB463 are not unbalanced by race.) My approach does not require that there are no differences in important variables by race across all time; this is similar to the assumptions required by Cohen and Yang (2018). While it seems unlikely that case characteristics discontinuously changed by race at the point of HB463, I should still prove this is the case empirically in future drafts.

$$b_{ijct} = \alpha + \phi_1 HB463_t + \phi_2 Black_i + \phi_3(Black_i \times HB463_t) + \beta_1\kappa_c + \beta_2\delta_i + \omega_{jt} + \epsilon_{ijct} \quad (2)$$

The single difference between equations 1 and 2 is that the latter includes time-varying (defined as month-year) judge fixed-effects, ω_{jt}. The comparison between the estimates of ϕ_3 in the two equations highlights the power of heterogeneous responses across judges to HB463 in driving changes in racial disparities.[66] Judge-specific responses are important to consider given the notable spatial variation in percentage of black defendants across the state. In other words, if judge responses are correlated with judge populations (fraction of black defendants), this could drive ϕ_3 in Equation 1 to be notably higher than ϕ_3 in Equation 2.

5.2 Empirical Results

I now estimate the specifications discussed above in order to see how much of ϕ_3 observed in raw Figure 11 is explained by differences in (i) judge information sets, (ii) variation in policy response across judges. Table 1 presents estimates for low risk defendants in columns 1 and 2, moderate risk defendants in columns 3 and 4, and high risk defendants in columns 5 and 6. The odd columns present results without any covariates, thus showing the regression equivalent of the visual trends in Figure 11. The even columns present results from specification 1.

Table 1 shows that after adjusting for judge information sets,[67] there are not observable racial disparities favoring white defendants in the pre-HB463 period. (The negative coefficient in the low specification in column (1) disappears once conditioning on the information set.) If anything, as seen in column 4, moderate risk black defendants are more likely (2.2 percentage points more) to receive non-financial bond than similar white defendants. However, in the post-period white defendants appear to be significantly advantaged after adjusting for the judge's information set. Low and moderate risk black defendants experienced 30% and 62% less of the short-term gains in non-financial bond setting than similar white defendants, respectively.[68]

Different responses by judge are important to consider given that judges work within specific counties and there is notable spatial variation in percentage of black defendants across the state (see Figure 6). With Table 2, I test for whether the results on ϕ_3 from Table 1

[66]Given Stevenson (2017)'s hypothesis of differential judge behavioral response, this is important to further investigate.

[67]Specifically, in line with the prior subsection, I approximate judge information sets with the following covariates: defendant age, number of charges, top charge severity (level and class), characteristics (whether it is related to weapons, drugs, or violence), risk level components (see Figure 3 for full list), and separate fixed effects for judge and month-year.

[68]For low risk defendants, in column 2, the $Black \times Post$ coefficient is 4.8 percentage points and the $Post$ coefficient is 15 percentage points. ($4.8/15 \approx .30$.) For moderate risk defendants, in column 4, the $Black \times Post$ coefficient is 4.9 percentage points and the $Post$ coefficient is 7.9 percentage points. ($4.9/7.9 \approx .62$.)

Table 1: Disparities in Non-Financial Bond Deviations before/after HB463

	Dependent Variable = Non-Financial Bond					
	Low		Moderate		High	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.022^{***}	0.004	0.007^{**}	0.022^{***}	0.002	0.005
	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.005)
Post	0.201^{***}	0.150^{***}	0.138^{***}	0.079^{***}	0.021^{***}	0.039^{*}
	(0.003)	(0.020)	(0.002)	(0.020)	(0.003)	(0.020)
Black x Post	-0.065^{***}	-0.048^{***}	-0.051^{***}	-0.049^{***}	-0.004	-0.007
	(0.006)	(0.011)	(0.005)	(0.008)	(0.005)	(0.007)
Covariates?	No	Yes	No	Yes	No	Yes
Pre-White Mean	0.326	0.326	0.128	0.128	0.050	0.050
Cluster SE?	NA	Judge	NA	Judge	NA	Judge
N	178,238	178,238	163,479	163,479	41,363	41,363
R^2	0.039	0.220	0.027	0.144	0.002	0.068
Adjusted R^2	0.039	0.217	0.027	0.141	0.002	0.058

OLS estimates. *** p<0.01; ** p<0.05; * p<0.1.

are robust to allowing for time-varying judge fixed-effects.[69] In fact, the disparities for low risk defendants become indistinguishable from zero once judges are allowed to vary in their responsiveness.[70] The disparities in deviations for low risk defendants were driven by heterogeneous behavioral responses to HB463 across judges. However, moderate risk black defendants remain less likely than similar white defendants to receive non-financial bond even after allowing for time-varying judge fixed-effects – they experience a boost from the policy that is 25% less than the boost for similar white defendants.[71] In short, while the low risk defendant disparities are a consequence of variation in judge response, there are lingering unexplained results for moderate risk defendants.

These results are at odds with the often assumed story that score usage should necessarily equalize outcomes across racial groups with scores. Policy changes that are subject to judicial discretion may not be equally adopted across geographies. If responsiveness is correlated with demographic features of the population, risk score policies which intend to render more similar decisions across races but within risk scores may lead to counterintuitive patterns. Moreover, even within judge-time, there is suggestive evidence that moderate risk levels may interact with race to produce different judicial decisions.

[69] Again, I approximate judge information sets with the following covariates: defendant age, number of charges, top charge severity (level and class), characteristics (whether it is related to weapons, drugs, or violence), risk level components (see Figure 3 for full list). Now, I use time-varying (month-year) judge fixed-effects (as opposed to separate judge and time fixed-effects).

[70] See the change from column 2 to column 3.

[71] In column 6, for moderate risk defendants, the *Black* $\times$ *Post* coefficient is 2 percentage points and the *Post* coefficient is 8.1 percentage points. ($2/8.1 \approx .25$.)

Table 2: Disparities in Non-Financial Bond Deviations before/after HB463

	Dependent Variable = Non-Financial Bond								
		Low			Moderate			High	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	-0.022^{***}	0.004	-0.011^{**}	0.007^{**}	0.022^{***}	0.006^{*}	0.002	0.005	0.006
	(0.004)	(0.006)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.005)	(0.005)
Post	0.201^{***}	0.150^{***}	0.145^{***}	0.138^{***}	0.079^{***}	0.081^{***}	0.021^{***}	0.039^{*}	0.042
	(0.003)	(0.020)	(0.021)	(0.002)	(0.020)	(0.025)	(0.003)	(0.020)	(0.027)
Black x Post	-0.065^{***}	-0.048^{***}	-0.012	-0.051^{***}	-0.049^{***}	-0.020^{***}	-0.004	-0.007	-0.007
	(0.006)	(0.011)	(0.008)	(0.005)	(0.008)	(0.006)	(0.005)	(0.007)	(0.007)
Covariates?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Judge-Time FEs?	No	No	Yes	No	No	Yes	No	No	Yes
Pre-White Mean	0.326	0.326	0.326	0.128	0.128	0.128	0.050	0.050	0.050
Cluster SE?	NA	Judge	Judge	NA	Judge	Judge	NA	Judge	Judge
N	178,238	178,238	178,238	163,479	163,479	163,479	41,363	41,363	41,363
R^2	0.039	0.220	0.294	0.027	0.144	0.231	0.002	0.068	0.299
Adjusted R^2	0.039	0.217	0.242	0.027	0.141	0.166	0.002	0.058	0.091

OLS estimates. *** p<0.01; ** p<0.05; * p<0.1.

6 Mechanisms Discussion

6.1 Correlates of Judicial Responsiveness to HB463

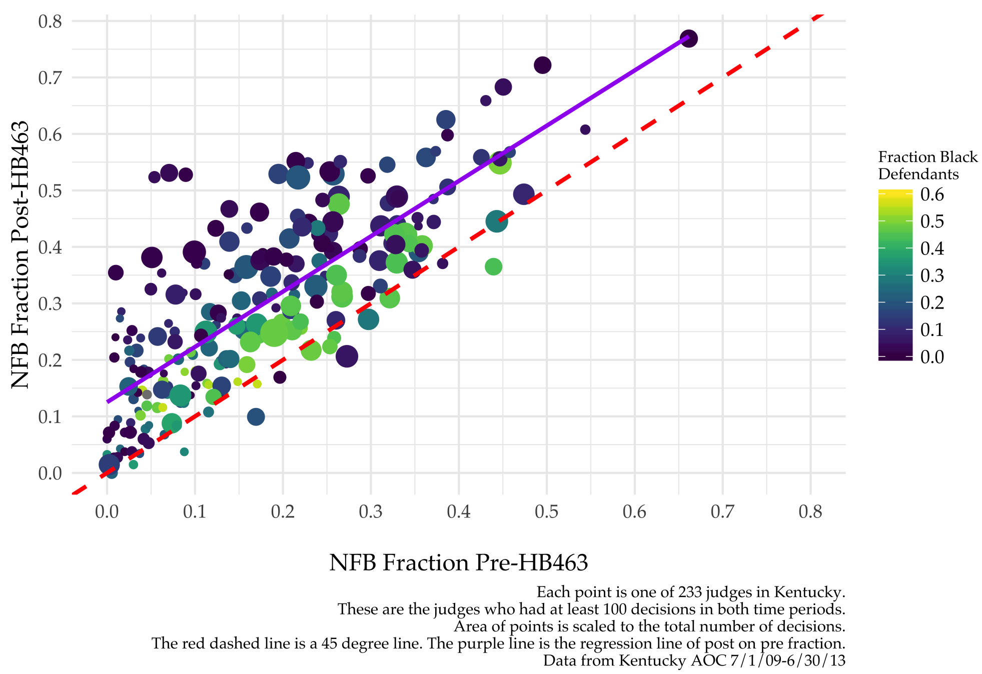
In this policy context, judge responsiveness is correlated with judge population (specifically, the fraction of black defendants). In order to provide exploratory evidence on what could be driving this reduced-form correlation, I investigate judge-level data on responses by focusing on the 233 judges who made at least 100 decisions before and after HB463. I first show visual evidence on the relationship between a judge's response and the population observed by that judge – specifically, I consider the fraction of initial bond decisions made that were about black defendants. I then suggest future work on this topic.

6.1.1 Further Reduced-Form Evidence

Figure 12 plots each judge as a point, whose size (area) corresponds to the number of decisions made over the whole time period, that demonstrates the judge's pre-HB463 and post-HB463 rates of non-financial bond decisions. The visual illustrates that the fraction of non-financial bond decisions increased after HB463, given that the overwhelming majority of points are above the 45 degree line, meaning most (though not all) judges were more likely to give non-financial bond after HB463. Interestingly, the regression line demonstrating the relationship between the pre- and post- rates is parallel to the 45 degree line, meaning that while the change in likelihood of non-financial bond is not meaningfully different dependent on the rate in the pre-period.

The color of the dots corresponds to the fraction of a judge's bail decisions that are for black defendants. The fact that the lighter yellow points are closer to the red line than the darker blue points are suggestive of the relationship between defendant population and responsiveness. Figure 13 then makes this relationship explicit by plotting each judge's response (fraction of non-financial bond decisions in the pre-period less fraction non-financial bond decisions in the post-period) by the judge's observed defendant population

Figure 12: Judge Non-Financial Bond Rates Before and After HB463



(fraction of decisions made about black defendants). The purple line displays a clear negative relationship between the two.

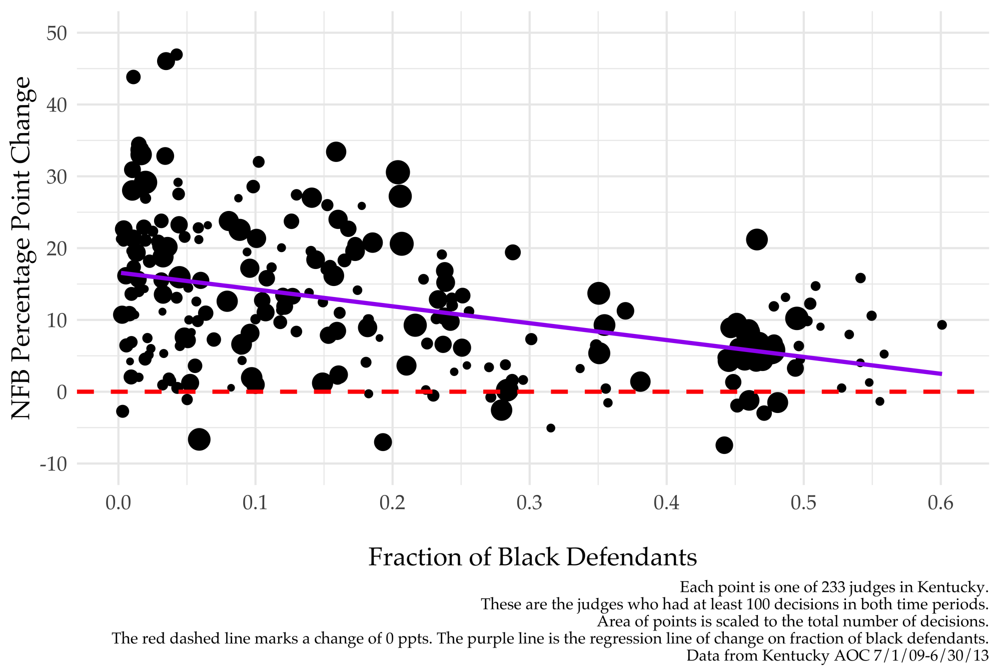
6.1.2 Explaining *Why* Judge Responsiveness Correlates with Defendant Population

While there is a large body of empirical work examining differential treatment within place-time, there is limited work on explaining why policy response might be correlated with population demographics. Given the growing set of bail reform policies, it is important to understand why and how uneven take-up of policies occurs.

There are two main hypotheses for why judges may respond differently to policy reforms. For one, judges with more experience might be less likely to respond to policy changes. If judges who work in counties with higher fraction of black counties are more experienced (perhaps because these are larger counties and thus more competitive elections for judgeships) this could generate the observed relationship.[72] Second, we suspect judges who have made decisions that are associated with higher pretrial misconduct than others would respond less since they face a higher expected cost of release in changing their threshold. If judges who experience higher failure to appear or new criminal activity in their bail decisions work in the counties with more black defendants, this could generate the observed effect.

[72]The experience explanation would tie into a model with different costs across judges η_j where costs are larger for more experienced judges.

Figure 13: Judge Responses to HB463 and Judge Population



In future work, I plan to investigate these possible explanations. I plan to run a horserace with judicial experience, pretrial misconduct in the pre-period, and judge population demographics to test if the observed relationship between responsiveness and defendant population is explained by one of these two theories. This would be descriptive work that would be useful for putting structure on understanding judge willingness to adapt to policy suggestions.

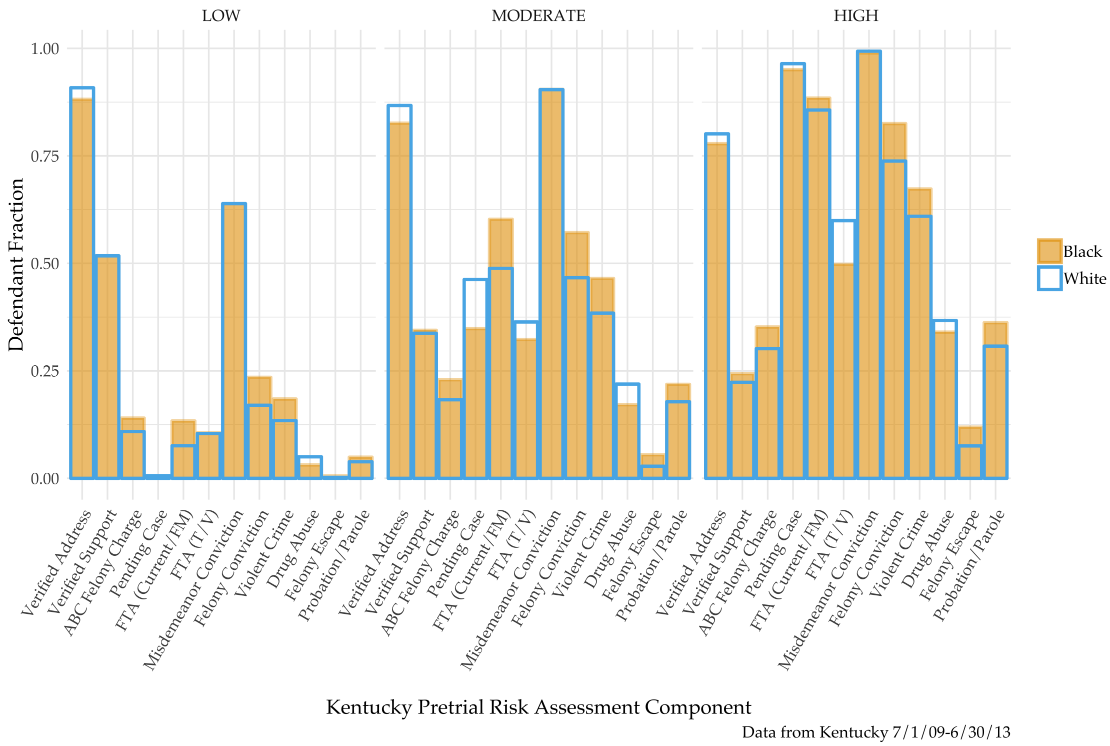
6.2 Remaining Racial Disparities for Moderate Risk Defendants

In understanding the mechanism behind the lingering disparities for moderate risk defendants, it is worth considering two possible explanations: differential weighting and disparate interactions. On differential weighting, it could be that there are criminal history characteristics already embedded in the Kentucky Pretrial Risk Assessment, as illustrated in Figure 3, that also make their way into the pretrial-judge conversation. If black and white men have different compositions of factors going into the same underlying risk score level, then this could explain why they are treated differently despite similar environments (judge-time), charge characteristics, and risk level. Figure 14 demonstrates that it is the case that component combinations look different across races within risk levels.[73]

Imagine that a judge considers a moderate risk black defendant and a moderate risk white defendant with similar charges. Despite their identical risk levels, the black defendant has

[73]The ordering of components in Figure 14 matches the ordering in Figure 3.

Figure 14: Make-up of Components within Levels Across Race



an active warrant for a failure to appear (FTA) prior to disposition (factor 6 on the list), while a low risk white defendant does not. If a prior FTA is more likely to be relayed to the judge independently of the risk level (as occurs in one of the example judge calls on the Kentucky online virtual tour), then that judge might deem that black defendant riskier than the white defendant even though the risk score already has taken this factor into account. In other words, score level and contributory factors (to the risk level) are strongly correlated but might not be identified as such, which could lead to double-counting in the vein of Enke and Zimmermann (2017). If this is the case, then allowing interaction terms between the time period and the risk components should reduce or eliminate the original result. Table 3 shows (see column 4) that despite inclusion of said interaction terms, the moderate risk result remains though it is slightly smaller in magnitude.

Differential weighting of components over time does not eliminate the moderate risk result, nor did different judge responses or judge information sets. As such, the moderate risk result must be a product of judges interpreting scores differently by race. Imagine judges have some sense of the underlying continuous risk score distribution and assume that moderate risk black men are still higher risk than moderate risk white men even though they are put in the same larger buckets. This could also explain the results and would accord well with recent findings by Green and Chen (2019) and Skeem, Scurich, and Monahan (2019).[74] Understanding this possible mechanism is broadly relevant to hiring,

[74] However, more empirical work is necessary to pin down this result.

Table 3: Do Different Weighting of Components Explain the Moderate Result?

	Dependent Variable = Non-Financial Bond					
	Low		Moderate		High	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.011^{**}	-0.012^{**}	0.006^{*}	0.005	0.006	0.006
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Post	0.145^{***}	0.106^{***}	0.081^{***}	0.106^{***}	0.042	0.035
	(0.021)	(0.022)	(0.025)	(0.026)	(0.027)	(0.065)
Black x Post	-0.012	-0.011	-0.020^{***}	-0.017^{***}	-0.007	-0.007
	(0.008)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
Components x Post	No	Yes	No	Yes	No	Yes
Covariates?	Yes	Yes	Yes	Yes	Yes	Yes
Judge-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pre-White Mean	0.326	0.326	0.128	0.128	0.050	0.050
Cluster SE?	Judge	Judge	Judge	Judge	Judge	Judge
N	178,238	178,238	163,479	163,479	41,363	41,363
R^2	0.294	0.295	0.231	0.232	0.299	0.299
Adjusted R^2	0.242	0.242	0.166	0.167	0.091	0.091

OLS estimates. *** p<0.01 ** p<0.05; * p<0.1.

loan decisions, and other important high-stakes decisions.[75]

7 Conclusion

As predictive tools continue to be integrated into high-stakes decisions, there is a growing need to understand how they are used by the human decision-makers (e.g., judges, loan officers, and hiring managers). While predictive tools often present recommendations, there is little oversight as to how decision-makers may overrule or follow them. I use this paper to show that, counter to intuition, the introduction of risk score recommendations can increase racial disparities for individuals with the same risk level.

This result is a consequence of two types of deviations by judges: across-judge and within-judge deviations. On the former, judges varied in their policy responsiveness; judges in whiter counties responded more to the new default (increasing their leniency) than judges in blacker counties. There is a striking correlation between a judge's response to the policy and a judge's defendant population. Given the growing set of bail reform policies, it is important to understand why this uneven take-up of policies occurs. Otherwise, similar patterns of judicial take-up could exacerbate racial disparities in other policy contexts.

Second, even within judge and time, I show judges are more likely to deviate from the

[75]For more on hiring, see Hoffman, Kahn, and Li (2017).

recommended default for moderate risk black defendants than for similar moderate risk white defendants. This result suggests that interaction with the same predictive score may lead to different predictions by race, which warrants further investigation. Part of the public appeal of risk assessments is the movement towards a system that is more "objective" than the status quo (Harris and Paul 2017). However, if interpretation of the scores itself interacts with defendant race, the very judicial discretion that risk score proponets sought to reduce has simply been shifted to a later stage.

A Judge Decision Dimensions and Initial Release

A.1 Mapping Judge Decisions onto Release

There is a distinction between judge actions in terms of bond setting and outcomes such as pretrial detention. The set of judge actions for the purpose of this paper is simplified down to the binary decision between non-financial and financial bond since that was the main implication of the policy of interest, HB463. However, judge actions are much more complex than this simple binary decision. Bond is broader than simply setting a money amount – bond can include non-monetary conditions (e.g., no driving) on defendants. Furthermore, within financial and non-financial bond, there are a variety of amounts that can be picked for the money amount. (The non-financial bond types, surety and unsecured bond, only come into play if the defendant does not show up for court.)

The multi-dimensional judge decision then plays into whether a defendant is released on that initial bond. Release is a consequence of the initial bond but it is not explicitly set by Kentucky judges. In the aggregate, for initial bond, when a judge setting non-financial bond (nfb) or financial bond (fb), the following is true:

$$Pr(release) = Pr(release|fb)Pr(fb) + Pr(release|nfb)Pr(nfb) \tag{3}$$

Note that since all decisions are either non-financial or financial bond, $Pr(fb) = 1 - Pr(nfb)$. While it is the case that HB463 significantly increased $Pr(nfb)$ and $Pr(release|fb) < Pr(release|nfb)$ since less financial conditions means higher probability of release, the change in $Pr(release)$ need not match that change in $Pr(nfb)$ if the probabilities of release conditional on the two bond groups are markedly changed as well. As a brief accounting exercise, see below for release probabilities decomposed for the pre- and post-HB463 periods.

Table 4: Bond and Release Probability Before and After HB463

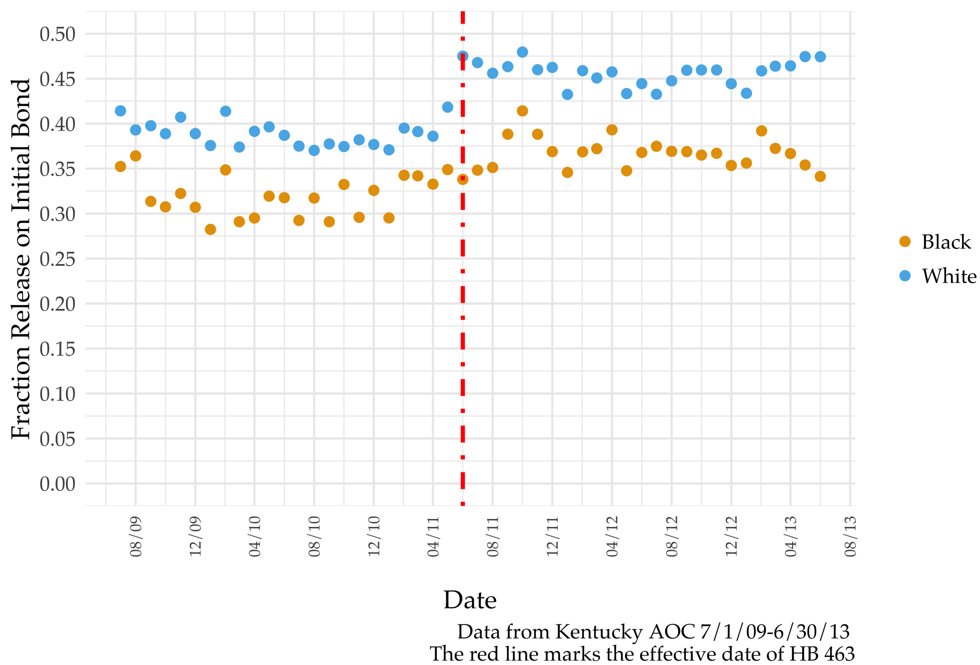
Time Period	Pr(nfb)	Pr(release | nfb)	Pr(fb)	Pr(release | fb)	Pr(release)
Pre-HB463	0.22	0.965	0.78	0.22	0.37
Post-HB463	0.34	0.95	0.66	0.18	0.43

In short, decreasing likelihoods of release for both non-financial bond and financial bond recipients watered down the ultimate initial release gains from HB463.

A.1.1 Decomposing Immediate Release Disparities

For more on release and other HB463 outcomes, see the thorough account of Stevenson (2017). Figure 15 shows that HB463 led to a small increase in racial disparities in initial release (increased to 8.9 percentage points from around 7.1 percentage points). This is substantially smaller than the change in non-financial bond disparities.

Figure 15: Initial Release Before and After HB463 by Race



The reasons that changes in racial disparities in initial release could be so different from those in non-financial bond should be clear from consideration of all possible moving parts in equation 3. In fact, the racial gap for $Pr(release|fb)$ decreased notably after HB463. Figure 16 shows that the gap in probability of release conditional on financial bond decreased meaningfully from 7.5 percentage points to 4.7 percentage points. This naturally leads to curiosity about how financial bond setting changed across the racial groups.

A.2 Financial Bond Setting

All financial bond amounts are not equally likely. There is significant bunching at certain round numbers. In fact, 75% of all financial bond amounts in the data are listed in the Table 5 below.

I use Figure 17 to plot out the density of financial bond amounts before and after HB463 (up to $10,000). Bonds of around $2,500 and below become less common relative to higher bonds, which makes sense as we'd think that the defendants given non-financial bond now were likely to have lower bond levels had they been in the pre-period.

Since white defendants experience a larger dip in likelihood of release on financial bond than black defendants after HB463, we might think that white defendants experienced larger increases in financial bond than black defendants after HB463. In regressing dummies for bond under clear cut-points ($500, $1,000, $2,500, $5,000) on the post indicator and its interaction with race, we see that defendants are 2-6 percentage points less likely

Figure 16: Pr(Release | Financial Bond) Before and After HB463 by Race

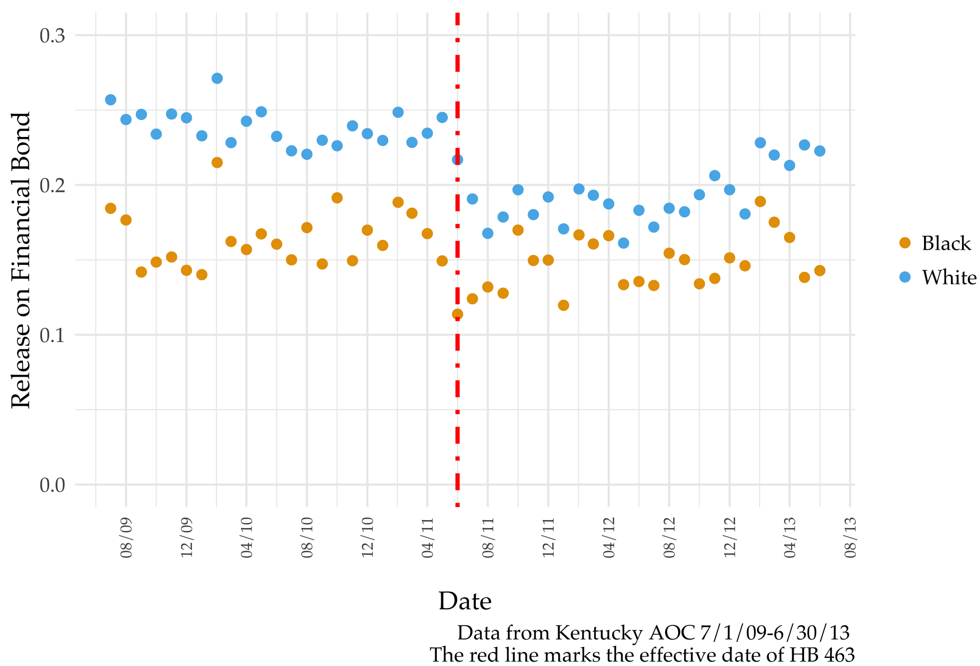
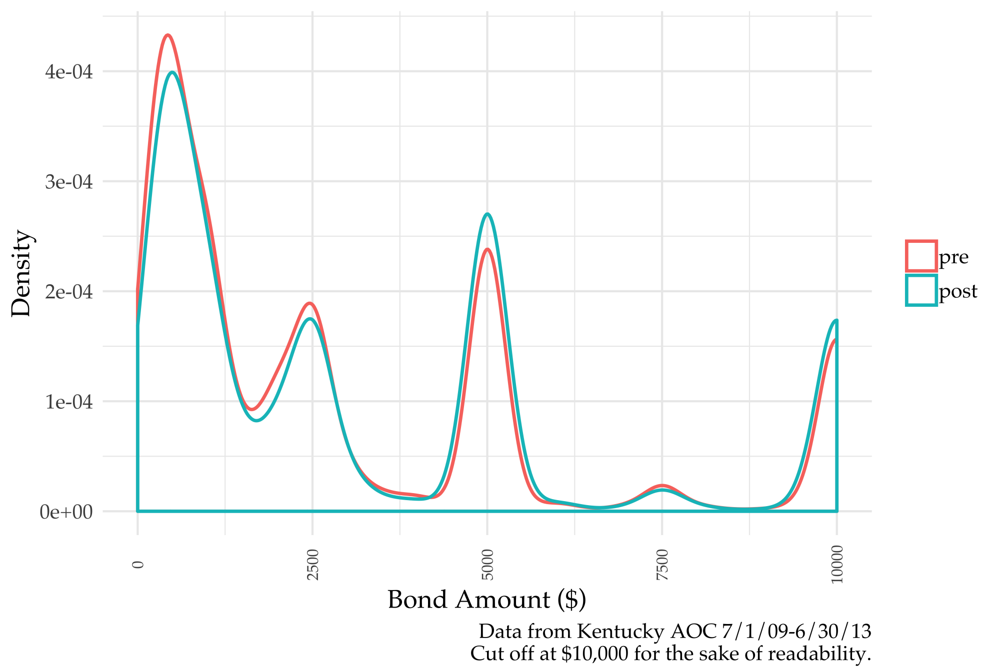


Table 5: Top 75 Percent of Financial Bond Amounts

Bond Amount	Observations	Pr(Release on Bond)
$250	10161	0.416
$500	32373	0.307
$1000	26302	0.265
$1500	6592	0.244
$2000	11477	0.284
$2500	23797	0.210
$5000	38185	0.127
$10000	25077	0.075
$20000	5143	0.042
$25000	9948	0.043
$50000	6224	0.023

Figure 17: Financial Bond Amount Densities Before and After HB463



to receive low non-financial bond (depending on the cut-point definition) after HB463. If judges who set non-financial bond more in the post-period did so by moving defendants from low financial bond to non-financial, then we would expect black defendants to be more likely to receive low financial bond in the post period than white defendants (since white defendants were receiving non-financial bond more in the post-period). However, there is no significant difference in likelihood for black and white defendants after HB463 to receive most low financial bond definitions. If anything (for under $1,000 bond), blacks become less likely to receive low financial bond relative to whites. This suggests that judges did not simply substitute out low-financial bond for non-financial bond after HB463.

The results are consistent with a story of non-linearity in ability to pay financial bond. Note that black defendants are more likely to have lower bonds than white defendants in the pre-period, however, they are less likely to be released on said bonds. Given a shift to financial bonds that affected both racial groups, the behavioral response to this based on ability to pay necessarily depends on the initial level of the bond. It seems likely that since white defendants were less likely to be receiving smaller financial bonds to begin with, their response to a shift out in financial bonds was larger, thus giving us the picture of differential trends in Figure 16.

Table 6: Likelihood of Low Financial Bond

	Under \$500	Under \$1000	Under \$2500	Under \$5000
	(1)	(2)	(3)	(4)
Post	-0.033^{***}	-0.024^{***}	-0.058^{***}	-0.066^{***}
	(0.001)	(0.002)	(0.002)	(0.002)
Black	0.028^{***}	0.032^{***}	0.0003	-0.017^{***}
	(0.002)	(0.003)	(0.003)	(0.003)
Black x Post	-0.007^{**}	-0.014^{***}	-0.006	-0.002
	(0.003)	(0.004)	(0.005)	(0.005)
N	261,590	261,590	261,590	261,590
R^2	0.004	0.002	0.004	0.005
Adjusted R^2	0.004	0.002	0.003	0.005

OLS estimates. *** p<0.01; ** p<0.05; * p<0.1.

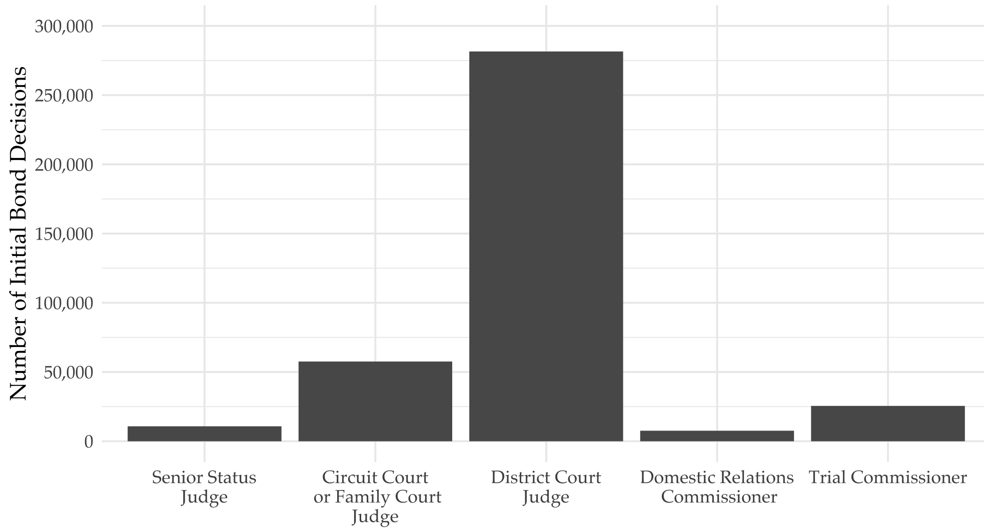
B Note on Judge Types

In my data, 563 distinct judges make the 383,080 initial bond decisions of interest. There are five different types of judges. The judge type for an initial decision is partially determined by the type of case. Recall that the data covers felonies and misdemeanors, both of which are originally under the jurisdiction of District court judges. However, if a felony defendant is indicted, the case is under the jurisdiction of a Circuit court judge. Moreover, the Family Division of Circuit Court handles cases related to domestic violence, and child abuse and neglect.

What this means for initial bond decisions is that District judges make most of the decisions. Figure 18 shows that 73.5% of decisions are made by District Court Judges while another 15% are made by Circuit or Family Court Judges.[76] The remaining three types of judges fill in for other judges: trial commissioners fill in for District Court judges, Domestic Relations Commissioners fill in for Family Court Judges (if a given county doesn't have a Family Court judge), and Senior Status judges (who are retired) fill in as needed.

[76]Judges in Kentucky are elected, while Commissioners are appointed by judges. District Court judges serve four-year terms, while Circuit Court and Family Court judges serve eight-year terms.

Figure 18: Initial Decision Count by Judge Type



Data from Kentucky AOC 7/1/09-6/30/13

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